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Abstract

We study product innovation in the UK mortgage market by analysing when and how attributes outside the traditional structure of mortgage contracts become pricing relevant. To do so, we develop a stylised framework that treats mortgage products as structured bundles of attributes, focusing on the two-part tariff, comprising interest rates and fees, to infer innovation from pricing patterns. Our empirical strategy first uses transaction-level data and exploits within-product variations over time to detect when new product features affect pricing, which we apply to the case of green mortgages. Matching Energy Performance Certificates (EPCs) to UK mortgage originations, we show that EPCs become pricing-relevant in 2018, with lenders starting to offer pricing discounts for loans to buy properties with higher energy efficiency. We also use offer-level data on advertised green products to precisely estimate pricing discounts. We detect considerable green discounts, which reach up to 15 basis points in 2022. Mortgages against high EPC properties are concentrated in new buildings, suggesting relaxed credit constraints and increased housing investment, with implications for the broader economy.

Key words: Product innovation, green mortgages, housing construction, economic growth.

JEL classification: G21, O31, R31.

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1 Introduction

Product innovation in the banking sector refers to the development and introduction of new financial instruments, services, or contractual features that expand choices available to customers (Tufano, 2003). Banks innovate to differentiate in competitive markets, respond to evolving borrower needs, and adapt to changing regulatory and macroeconomic environments. By expanding the menu of financial products, they can segment markets more effectively, tailor offerings to heterogeneous borrower profiles, comply with regulations, and improve the efficiency of credit allocation, with potential implications for economic growth.

We infer product innovation through its pricing footprint—which banks introduce new product features, when they do so, and how these changes influence equilibrium outcomes, particularly credit allocation. Beyond inference, we complement this approach by directly identifying new product features to estimate their pricing effects using complementary data on offered products. This perspective matters because prices are a central mechanism through which markets incorporate new information about risk and allocate capital efficiently (Dávila and Parlatore, 2025; Hayek, 1945), thereby influencing credit supply and shaping borrower incentives.

Our approach is related to dynamic pricing in that prices evolve over time, but the adjustment margin here is structural: it reflects the adoption of new product attributes (Shaked and Sutton, 1982) rather than solely repricing of the same products over time (Brogaard et al., 2014; Baldauf and Mollner, 2020). This perspective aligns with models of dynamic pricing under product differentiation, where innovation expands the product menu and pricing adjusts accordingly (Liu and Zhang, 2013).

Empirically, we leverage the UK mortgage market's two-part tariff, mortgage rates and lender fees, to estimate how new product attributes affect pricing, while flexibly controlling for product characteristics using high-dimensional fixed effects. The UK mortgage market offers a particularly clean empirical setting due to its scale, stable product definitions, and transparent pricing structures, allowing us to isolate the pricing footprint of innovation. More broadly, mortgages represent the largest asset class on banks' balance sheets (Jordà et al., 2016), play a central role in household wealth accumulation (Campbell, 2006), and can stimulate economic activity through their impact on housing investment and construction (Alberts, 1962). These features make the mortgage market a natural laboratory for studying how financial product innovation propagates through pricing and affects credit allocation.

Leveraging this setting, we examine the emergence of green mortgages—products that incorporate environmental criteria into loan pricing and eligibility—as a case shaped by the intersection of environmental policy, financial regulation, and market discipline. These products represent a targeted expansion of the mortgage offering, designed to align borrower incentives with environmental objectives while potentially reshaping lender pricing strategies and portfolio risk profiles. We focus specifically on the energy efficiency of underlying properties, a key dimension of credit risk (Guin et al., 2022; Billio et al., 2022), and check when this green attribute starts to be priced, and whether this timing reflects genuine risk signals.

For our empirical analysis, we match mortgage transaction records from the Product Sales Database (PSD), covering the universe of mortgage originations since 2005 (Cloyne et al., 2019), with property-level Energy Performance Certificates (EPCs), available in the UK since 2008. Building on Benetton (2021), who conceptualises mortgage products as structured bundles of attributes, and Benetton et al. (2025), who model pricing as a two-part tariff of rates and fees, we develop a stylised framework that accommodates evolution in product features. Our identification strategy exploits variation in pricing across otherwise identical products over time, isolating the effect of green property attributes while controlling for fees and product-level heterogeneity. The baseline specification links mortgage pricing to product structure via fixed effects, providing a robust foundation for identifying pricing-relevant features. Within this framework, we observe innovation in mortgage product features, with green property attributes emerging as distinct pricing drivers beyond conventional product characteristics during the sample period.

We then extend our framework incorporating the time dimension, enabling us to trace when green property features become pricing-relevant in response to external shocks and policy signals. From 2018 onwards, lenders begin offering measurable discounts of 7.5 basis points (bps) for mortgages against energy-efficient homes, with these discounts widening substantially by 2022. These adjustments are consistent with a risk-based pricing mechanism: policy signals and macroeconomic shocks may alter the perceived risk or funding cost associated with energy-efficient properties, prompting lenders to revise pricing. Specifically, our estimates for 2018 and 2022 align with two key moments that plausibly influenced lender behaviour. The implementation of Minimum Energy Efficiency Standards (MEES) in 2018 represents a salient regulatory intervention, coinciding with the initial emergence of green pricing discounts. In 2022, a sharp rise in energy prices marks a macroeconomic shock, corresponding with a notable widening of these discounts. We also examine responses to alternative events, including the 2015 announcement of MEES for rental properties and the Paris Agreement, as well as climate-related regulatory initiatives in 2021, such as the Bank of England's climate stress test of major UK banks.

We then examine which lenders introduced green product innovations post-2018. Our evidence indicates that this activity was concentrated among large, publicly listed institutions—those with greater exposure to regulatory and supervisory scrutiny and market discipline. This pattern is consistent with our theoretical priors: institutions facing more intense oversight and investor expectations may perceive stronger incentives to manage environmental risks, leading them to incorporate environmental attributes into product design and to price them earlier and more actively in response to external signals.

To support our identification strategy, we conduct a series of tests. We verify that, conditional on observed product features and fees, changes in mortgage rates reflect product innovation rather than shifts in other borrower characteristics. We test that green attributes are not confounded by other contemporaneous product changes. We mitigate concerns about interest rate shocks that could influence pricing dynamics, and we confirm that lenders primarily use mortgage rates, not cashback incentives, to price green mortgages. We also show that estimates in our pricing framework remain stable across samples, including the universe of all UK mortgage originations, even when EPC data are incomplete. These findings add credibility to the external validity of our baseline results.

To precisely estimate pricing discounts for green mortgage products, we leverage data on advertised products obtained from Moneyfacts. This alternative approach enables us to identify green lenders, those that incorporate environmental features in their offerings, abstracting from demand-side influences. For this subsample of lenders, like with transaction-level results, pricing responses are most pronounced in 2018 and 2022. Our estimates indicate discounts of approximately 15 basis points in 2022 and 5 basis points in 2018, averaging 7.5 basis points across the sample period. This magnitude is economically meaningful across our range of estimates. For a £200,000 mortgage, our best estimated discount of 7.5 bps using offer data translates into roughly £150 in annual interest savings, or a net present value (NPV) of around £2,612 over a 25-year term assuming a 3% discount rate. Expressed differently, the 7.5 bps discount corresponds to about 3.7% of the average mortgage spread in our sample (2.04%), highlighting its relevance in competitive pricing terms. Even our more modest 4.3 bps discount based on transaction-level data, yields approximately £90 in annual interest savings and an NPV of £1,566, equating to 2.2% of the average spread. This underscores that even small pricing adjustments can have meaningful financial implications for borrowers.[1] By analysing the full flow of new originations over a decade and adopting a dynamic framework that accurately accounts for the baseline product structure, our study reveals an emerging green discount.

Our findings have broader implications for housing markets and economic activity. Green mortgages are more frequently issued to finance purchases of newly built properties, compared to existing ones. Together with being priced at a discount, this observation suggests that credit constraints facing new-build borrowers were relaxed. Assuming elastic housing supply and stable construction costs (Günnewig-Mönert and Lyons, 2024; Hilber and Mense, 2021), this shift in credit conditions makes additional development projects financially viable. The marginal new building becomes profitable to construct, leading to increased construction activity. Over time, this reallocation of credit may support investment in housing stocks and, hence, contribute to GDP growth.

We contribute to three strands of literature. First, we speak to dynamic pricing and product innovation: lenders adjusting prices as attributes of mortgage products evolve (Liu and Zhang, 2013; Spann et al., 2015; Shaked and Sutton, 1982), as well as and the literature on high-frequency repricing in trading (Brogaard et al., 2014; Baldauf and Mollner, 2020). We develop a stylised product-space framework that uses the UK market's two-part tariff (rates and fees) to identify when new attributes become pricing relevant and trace their

[1]The average discount we estimate is comparable to the 7.5 basis point spread documented by Nguyen et al. (2022) for "brown" mortgages in U.S. zip codes fully exposed to sea-level rise risk, illustrating that environmental attributes can have pricing effects on par with salient climate risk exposures.

diffusion in equilibrium. This approach relates to the work on strategic product design and complexity in retail financial markets, which examines how firms may strategically design complex financial products (Carlin, 2009) to reduce transparency and preserve market power, with implications for consumer surplus and market efficiency (Henderson and Pearson, 2011; Carlin and Manso, 2011). We apply this framework to a transparent, policy-relevant attribute (energy efficiency) that introduces a new dimension of product differentiation with regulatory and ESG implications. This complements research on mortgage market design and pricing, including alternative mortgage products with flexible repayment structures (Cocco, 2013; Amromin et al., 2018; Garmaise, 2013) and studies emphasising borrower heterogeneity and non-traditional drivers of mortgage pricing (Bhutta and Hizmo, 2021; Bhutta et al., 2020; Deng and Gabriel, 2006).

Second, by applying our framework to green characteristics, we contribute to the emerging literature on green mortgage pricing. We build on Bell et al. (2023), who find no evidence of a discount in a cross-section of UK mortgages outstanding at end-2017, prior to the introduction of relevant financial regulation. Our analysis extends this line of research by moving from a static cross-sectional perspective to a dynamic, time-varying approach, enabling us to examine how the green discount evolves over time and how this is shaped by regulatory and market pressures. Our results are consistent with broader evidence that ESG and climate-related characteristics are increasingly priced as risk factors in equilibrium asset pricing models (Bolton and Kacperczyk, 2021; Pástor et al., 2022) and complements prior work on the pricing of "brown" mortgages, i.e. those that incorporate sea level rise into mortgage pricing (Nguyen et al., 2022). Beyond that, our findings provide new insight into the mechanisms through which environmental attributes become pricing-relevant in credit markets by documenting the timing and magnitude of the "green" discount and analysing heterogeneity across banks in terms of their exposure to regulatory pressure and market discipline.

Third, we contribute to the literature on the macroeconomic effects of mortgage product design. Prior studies have examined implications for financial crises (Mian and Sufi, 2010), household consumption (Gerardi et al., 2010), and house price dynamics (Dokko et al., 2019). We extend this by discussing how changes in mortgage pricing, in the case of green mortgages, affect housing supply and construction activity. Noting that green mortgages are disproportionately used to finance new-build properties, we argue that pricing advantages of the former can relax credit constraints for borrowers buying the latter, potentially stimulating investment in the housing stock. This mechanism connects to earlier work on mortgage finance and economic growth (Jaffee et al., 1979) and more the recent studies linking housing investment to the business cycle (Walentin, 2014; Leamer, 2015, 2007), offering a novel channel through which product innovation can influence aggregate outcomes.

We structure the remainder of the paper as follows. Section 2 provides background on the UK mortgage products and describes our framework for identifying product innovation. Section 3 describes the data. Section 4 outlines the empirical methodology. Section 5 presents the results using transaction-level data. Section 6 reports robustness checks, including tests for non-rate pricing via cashbacks, and external validity of our results using different samples. Section 7 introduces offer-level evidence, combining advertised products data with transacted outcomes to refine our estimates of the green discount. Section 8 discusses implications for housing markets and economic activity. Section 9 concludes.

2 Mortgage pricing in the UK and Product Innovation

This section introduces the UK mortgage market, formalises the product space and pricing structure and outlines our framework for identifying product innovation. We then show how this framework applies to any new product feature, with green mortgages as a salient representative case in the next section.

2.1 Product structure

The UK mortgage market offers a suitable environment for studying product innovation and pricing behaviour of lenders. The market is both competitive and diverse, with large, internationally active banks operating alongside smaller, domestic challenger lenders. It features a stable product structure and a high degree of standardisation across its components in terms of loan-to-value (LTV) bands, fixed rate promotional (fixation) periods and interest rate types. Moreover, as mortgages represent the largest asset class for most retail lenders, the mortgage market is subject to regulatory scrutiny by the Prudential Regulation Authority

(PRA), which enforces prudential policies such as capital requirements, and the Financial Conduct Authority (FCA), which enforces conduct regulations. These features create a stable yet dynamic environment for analysing how institutional and regulatory factors shape product design and pricing. As shown in Figure 1, lenders typically structure pricing menus by LTV bands and fixation periods, with two- and five-year fixed rate deals most common[2]. After the fixation period, mortgages revert to a (usually higher) variable rate (Cloyne et al., 2019). Lenders commission surveys to appraise the properties, which are conducted by independent appraisers and can differ from transaction prices. The property valuation that lenders employ to assess borrower leverage is based on the lower of the purchase price and the appraised value; we denote the ratio of the loan amount to this valuation as LTmV, calculated using the minimum of the appraised value and purchase price.

Benetton (2021a) defines a mortgage product as a unique combination of lender, interest rate type, fixation period, and LTV band (LTmV in our set-up). That is, the mortgage product space is the set P, where each element $\text{Product}_{i,k} \in P$ represents a differentiated offering defined by a combination of pricing-relevant attributes:

$$\text{Product}_{i,k} = (\text{lender}_k, \text{LTmV}_i, \text{fixation period}_i, \text{rate type}_i) \tag{1}$$

Each combination of product attributes defines a distinct option on a lender's menu. Benetton et al. (2025) model lender pricing as a two-part tariff, consisting of interest rate and fees, (Figure 1). At a given point in time, a static pricing tariff can be expressed as:

$$\text{Rate}_{i,k} = \theta(\text{Product}_{i,k}) + \delta\,\text{Fee}_{i,k} \tag{2}$$

where $\theta(\cdot)$ maps product attributes to rates, and δ captures the contribution of fees. This structure reflects the fact that pricing cannot be summarised by the interest rate alone—fees are also relevant [3]. As Equation (2) represents a snapshot in time, it does not consider the evolving nature of mortgage pricing. To account for the dynamic nature of mortgage pricing

[2]There are three-year and ten-year fixed rate deals, but they are less common than the two-year and five-year deals. Unlike many other markets, loans with fixed rate for the lifetime of the loan are highly uncommon in the UK mortgage market.

[3]Fees associated with mortgage loans in the UK vary in size and composition across lenders. They might include one or more of booking/reservation fees, arrangement fees, administration fees, and completion fees.

of product attributes, Benetton et al. (2025) allow for further flexibility:

$$\text{Rate}_{i,k,t} = \theta_t(\text{Product}_{i,k}) + \delta_t \, \text{Fee}_{i,k,t} \tag{3}$$

Figure 1: Pricing schedule by a UK lender published online

60% LTV | 85% LTV | 70% LTV | 75% LTV | 80% LTV | 80% LTV | 90% LTV | 90% LTV | 95% LTV

60% Maximum Loan to Value (LTV)

Mortgage	Initial interest rate	Followed by Variable Rate, currently	initial interest rate period	Overall cost for sompari-son (APRC)	Booking fee	Annual overpoym-ent allowance	Cashback	Maximum loan amoint (subject to LTV and Lending Poilcy)
2 Year Fixed Fee Saver	4.14% fixed	6.49%	2 Years fixed rate until 28.02.202	6.20% APRC	£0	10%	£0	£ 5,000,000
3 Year Fixed Standard	3.78% fixed	6.49%	2 Years fixed rate until 28.02.202	6.60% APRC	999	10%	£0	£ 5,000,000
5 Year Fixed Standard	4.05% fixed	6.49%	5 Years fixed rate until 28.02.2031	6.60% APRC	£0	10%	£0	£ 5,000,000
5 Year Fixed Standard	3.88% fixed	5.60%	5 Years fixed rate until 28.02.2031	5.80% APRC	999	10%	£0	£ 5,000,000

Source: https://www.hsbc.co.uk/mortgages/existing-customers/switch/rates, accessed on 15 Nov 2025

The dynamic extension allows the mapping from product attributes to rates and fees to vary over time. Yet, it still assumes a fixed product menu (i.e., the set of product attributes remains unchanged). This assumption restricts the framework's ability to capture how lenders adapt their offerings in response to emerging criteria, such as environmental features.

2.2 Expanding the Product Space

To capture product innovation, we extend Equation (3) allowing the mortgage product space to evolve over time. We define an augmented product space P^*, where each element is indexed by lender k, an expanded set of product attributes i, and time t:

$$\text{Product}_{i,k,t} = (\text{lender}_k, \text{LTmV}_i, \text{fixation period}_i, \text{rate type}_i, x_{i,t}) \tag{4}$$

where $x_{i,t}$ denotes potential product features that can vary, i.e., be added or removed, across baseline products and over time—this is our extension. Product innovation expands the contract menu as new features surface[4]. The augmented product space in Equation (4) allows us to identify when any new product features become pricing relevant given the two-part tariff structure of UK mortgages. As we observe both interest rates and fees, as well as the full set of product attributes, it enables us to isolate the incremental role of newly introduced features in pricing decisions. Formally, consider the mortgage rate $\text{Rate}_{i,k,t-1}$ associated with product at time $t-1$:

$$\text{Rate}_{i,k,t-1} = \theta_{t-1}(\text{Product}_{i,k,t-1}) + \delta_{t-1}\,\text{Fee}_{i,k,t-1} \tag{5}$$

Differencing rates within a lender-product configuration between periods t and $t-1$ gives:

$$\Delta\text{Rate}_{i,k,t} = \theta_t \Delta\text{Product}_{i,k,t} + \Delta\theta_t \text{Product}_{i,k,t-1} + \delta_t \Delta\text{Fee}_{i,k,t} \tag{6}$$

$\Delta\text{Product}_{i,k,t}$ captures changes in product attributes, including the introduction of new features or the removal of existing ones. Leveraging the two-part tariff structure, changes in mortgage rates can reflect either changes in the pricing of existing product features, $\text{Product}_{i,k,t-1}$, or the pricing of new product features, $\Delta\text{Product}_{i,k,t}$, conditional on fees.

2.3 Inferring Product Features from Salient Characteristics: The Case of Green Mortgages

Building on our framework, we illustrate how pricing of salient characteristics signals the introduction of new product features. Using green mortgages as a case study, we exploit

[4]In this notation, time is not itself a direct attribute of a product. However, since the addition (or removal) of product attributes happens at specific times, time can be viewed as an indirect attribute of the product to the extent it reflects changes in the product attributes defining the product space. Hence, Equation $\tilde{(}4)$ can also be expressed as follows:

$$\text{Product}_{i,k,t} = (\text{lender}_k, \text{LTmV}_i, \text{fixation period}_i, \text{rate type}_i, \text{t})$$

In general, t reflects product attributes that are being added (or removed) by lenders at timet.

time variation in the pricing of energy-efficient properties, conditional on detailed product characteristics and fees, to infer when lenders incorporate green attributes into mortgage product structure. This approach can detect innovation before formal product labels emerge and illustrates how observable attributes can systematically reveal shifts in product features.

Identification logic. Product innovation becomes observable when a previously non-pricing-relevant characteristic starts influencing rates or fees. In our transaction-level data, we do not observe whether a mortgage is labelled as green. Instead, we infer the emergence of such product features from pricing behaviour, leveraging the two-part tariff structure of UK mortgage contracts. The key assumption is that, conditional on detailed product characteristics and fees, any incremental discount for energy-efficient properties reflects the pricing of green product innovation.

We define the green characteristic based on a property's energy efficiency:

$$\text{Green characteristic}_i = \mathbf{1}\{\text{EPC rating} \in \{A, B\}\} \tag{7}$$

This binary variable equals one for loans secured against properties with EPCs of A or B, and zero otherwise. This threshold aligns with industry practice for advertising green mortgages[5].

Empirical specification. To detect the introduction of green product features, we estimate the following equation:[6]

$$\text{Rate}_{i,k,t} = \beta_t \,\text{Green characteristic}_i + \theta_t \,\text{Product}_{i,k,t} + \delta \,\text{Fee}_{i,k,t} \tag{8}$$

where $\text{Rate}_{i,k,t}$ denotes the mortgage rate for product i offered by lender k at time t. The specification controls for detailed product characteristics and fees, isolating any incremental discount associated with energy-efficient properties. The coefficient β_t captures the time-varying pricing relevance of the green characteristic in year t. We estimate the

[5]Banks publicly announce green products based on EPC ratings of A and B – which is the typical green mortgage product in our Moneyfacts sample. It coincides with anecdotal evidence. See, for example: https://www.ftadviser.com/mortgages/2018/04/04/barclays-launches-first-green-mortgage, retrieved on 15 October 2025

[6]Equation (8) in levels in t can be derived by summing up equations (5) in levels in t-1 and (6) in first differences between t and t-1. We infer the expansion of the product space, $\Delta\text{Product}_{i,k,t}$, from a non-zero coefficient β_t of the salient Green characteristic$_i$

specification both in a regression pooling all years and by separate year-by-year regressions. The pooled model captures overall pricing relevance, while the yearly estimates trace the timing of product innovation. A statistically significant β_t over time indicates the emergence of green product features.

Interpretation. This empirical strategy allows us to detect innovation before formal product labels appear, offering a systematic approach to monitor emerging trends in mortgage markets. Beyond the case of green mortgages, the framework demonstrates how observable attributes can reveal underlying shifts in product design, providing a tool for studying product innovation in financial markets more broadly.

2.4 Hypotheses

We interpret green mortgage product innovation as a form of product differentiation in the UK mortgage market, where discounts reflect risk-based pricing. We complement this idea with a mechanism driven by regulatory and market scrutiny, where certain lenders choose to innovate to proactively manage compliance costs and adapt to evolving supervisory and market expectations.

1. **Risk-pricing channel (Intensive Margin):** explains why green mortgage products may carry pricing discounts.
2. **Pressure channel (Extensive Margin):** explains why some lenders adopt green product features while others do not.

Risk-pricing channel (Intensive Margin). In standard models of banking competition, lenders set prices to reflect expected default risk and funding costs (Freixas and Rochet, 2008; Crawford et al., 2018). Adding a green attribute, such as energy efficiency, introduces a new dimension that can reflect both default probabilities and collateral recovery values. This addition aligns with evidence that ESG and environment-related characteristics are increasingly priced as risk factors (Bolton and Kacperczyk, 2021; Pástor et al., 2022).

Energy-efficient homes can reduce credit risk through two mechanisms:

1. **Cash-flow resilience.** Lower energy costs ease household liquidity constraints, particularly during energy price volatility (Guin et al., 2022; Billio et al., 2022).

2. **Collateral quality.** Cost savings capitalise into higher property valuations, improving recovery prospects (Eichholtz et al., 2010; Ferentinos et al., 2023).

However, these benefits can be offset by higher purchase prices and loan-to-value (LTV) ratios. We control for LTmV in our empirical analysis to isolate the pricing effect of green attributes.

Hypothesis 1 (Risk - Pricing Discount). *Conditional on offering, green mortgage products carry lower credit spreads than otherwise similar loans.*

Formally, we expect the coefficient on the green attribute to be negative in our pricing regression. We examine year-by-year pricing patterns to examine if lenders adjust rates in response to external risk signals such as policy changes or macroeconomic shocks.

Pressure channel (Extensive Margin). Beyond direct risk considerations, banks face increasing regulatory and market pressure to manage environmental risks and align with broader sustainability objectives. These pressures are unevenly distributed, with systemically important and publicly listed banks subject to heightened scrutiny.

Regulatory pressure. Regulatory and supervisory authorities can require banks to integrate environmental risks into stress testing, disclosure frameworks, and risk management practices. Offering dedicated green mortgage products can help banks proactively manage regulatory risks and pre-empt potential[7] compliance costs associated with supervisory expectations.

Market pressure. Investors, credit rating agencies, and other stakeholders not only demand transparency around environmental exposures, but also increasingly favour institutions that support green investment. Failure to meet these expectations can raise funding costs or restrict market access. Green mortgage offerings can help banks address two dimensions:

[7] For example, in November 2025, the European Central Bank (ECB) fined Spanish lender ABANCA for non-compliance with climate-related risk disclosure and risk-management requirements (www.reuters.com/sustainability/climate-energy/ecb-fines-abanca-noncompliance-with-climate-decision-2025-11-10/), accessed on 26 November 2025

- **Risk management.** By demonstrating strong governance and proactive management of environmental risks, banks can reduce external financing and compliance costs, and better position themselves against changing consumer preferences toward green products.
- **Sustainability alignment.** By aligning with investor and societal preferences for environmental responsibility, banks can mitigate the risk of increased funding costs or restricted market access, even when these preferences are not directly tied to risk.

Hypothesis 2 (Pressure - Adoption). *The likelihood of offering a green mortgage product increases with regulatory and market pressure.*

This pressure hypothesis is consistent with both the signalling perspective (Heinkel et al., 2001), where banks adopt green products to demonstrate risk governance and sustainability, and the regulatory tax perspective (Posner, 1971), where regulation imposes costs that banks seek to minimise. Offering green mortgage discounts can be a cost-effective way for banks to pre-empt or reduce regulatory burdens, when these discounts are less costly than non-compliance.

3 Data

3.1 Data Sources and Sample Construction

Our analysis combines two primary datasets: the Energy Performance Certificates (EPC) from the Ministry of Housing, Communities and Local Government, and the Product Sales Database (PSD) provided by the UK Financial Conduct Authority (FCA). Energy Performance Certificates (EPCs) were introduced in 2007 as part of a UK government initiative to improve energy transparency in the housing market. EPCs are mandatory whenever a property is built, sold, or rented. They provide an estimate of typical energy costs for lighting, heating, and ventilation, and assign an energy efficiency rating between A (most efficient) to G (least efficient). These ratings are designed to inform buyers and tenants and to incentivise investment in energy-saving improvements. EPCs have become increasingly salient in policy discussions around housing, sustainability, and financial regulation, making them a natural basis for identifying green mortgage products. The EPC dataset reports the energy performance of buildings register for all domestic properties in England and Wales. It includes information on the EPC rating, property type, internal floor area, postcode, sale price, and transaction date.

The FCA maintains the Product Sales Database (PSD), which contains detailed loan-level information on all regulated mortgage originations in the UK since April 2005. It includes borrower characteristics (e.g., income, age), loan terms (e.g., interest rate, amount, duration), and property details (e.g., purchase price, surveyor's valuation and postcode). PSD has been widely used in academic and policy research (Cloyne et al., 2019; Benetton et al., 2022). Its comprehensive coverage and granularity make it a valuable source for studying lender behaviour, product design, and pricing dynamics in the UK mortgage market. We match EPCs to PSD records using transaction date, property price, and postcode. Our final matched sample spans 2012 to 2023 and includes over 4.6 million mortgage originations.

We complement our analysis of transacted mortgages with offer-level data from Moneyfacts Group plc ("Moneyfacts"), an independent data provider that records information on products offered by a subset of lenders in the UK mortgage market. This data is widely used by consumers, lenders, and regulators, and has been employed in previous academic research (Benetton et al., 2025). The dataset contains daily product-level information, including lender identity, sales channel (direct or brokered), broker commission, and green status along with eligibility requirements, allowing us to identify environmentally targeted products. It also provides detailed product characteristics—such as maximum LTV, interest rate, fees, mortgage type (fixed or variable rate, interest rate fixation period), early repayment charges, and whether the property is a new build—as well as financial benefits like cashback incentives. These granular features make the products directly comparable to our definition of mortgage offerings and reinforce our approach to conceptualizing product-level variation in the market.

We use the Moneyfacts data in two distinct ways to enhance our empirical exercise. First, we identify a subsample of "green banks", or lenders who publicly offer green mortgage products. Specifically, we classify a lender as offering a green mortgage if the product eligibility criteria explicitly require the underlying property to have an EPC rating of A or B[8]. This

[8] We classify green lenders as those offering mortgage products for properties with EPC ratings of A or B, as well as those offering products for properties rated A, B, or C. In robustness checks, we exclude mixed lenders—those offering both A/B and A/B/C products—and alternatively define green lenders as those offering products for EPC A, B, or C properties.

classification allows us to establish a clean estimate of green mortgage discount and supports our identification strategy built around the two-part tariff structure. Second, we use the fee information in Moneyfacts to supplement PSD data. While lender fees are directly observed in PSD from 2015 onward, they are unavailable in earlier years. To address this issue, we map product-level fee data from Moneyfacts into PSD for the pre-2015 period. This enables us to construct a measure of total upfront cost, which we incorporate into our pricing model. By adjusting for fees, we assess whether green mortgage products differ not only in interest rate spreads but also in fee structure, and whether pricing reflects the total cost of borrowing.

3.2 Summary Statistics

Table 1 reports summary statistics for key variables used in our analyses. We use mortgage spread to capture mortgage pricing. Mortgage spread is the difference between mortgage rate, averaging 2.7 percent, and SONIA, with a mean of 2.0 percent over our sample period. In robustness tests, we also use the spread of the mortgage rate over the 5-year sterling swaps rate ("mortgage spread (alt.)"), which averages 1.3 percent. Lender fees, defined as the total upfront cost charged by the lender, average £991. Mortgage-level variables include *Government support*, capturing participation in schemes such as Help-to-Buy, which applies to 6% of mortgages in the sample. Loan-to-value ratio, calculated using the minimum of the appraised value and purchase price (LTmV), has a mean of 74%. We observe that the maximum of LTmV is 100%, implying that in some cases borrowers had no down payment. In terms of the fixation period, the number of years before a mortgage reverts to the standard variable rate (SVR) typically priced higher.

We observe that most mortgages have 2-year fixation (48%) or 5-year fixation periods (41%). Rate type is a binary indicator equal to one for products which offer fixed reversion rates (i.e., non-floating, after the fixation period), which account for around 94% of the sample.

Borrower characteristics include gross income, averaging £60,000, with some high-wealth borrowers being able to take out mortgages with (reported) zero income. The average age at origination is around 36 years. Joint-application buyer status is flagged by a binary indicator and applies to 21% of borrowers.

Table 1: Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min	Max
Mortgage pricing					
Mortgage spread	4,619,541	2.0354	1.0622	-4.3450	13.3460
Mortgage rate	4,619,541	2.6536	1.0270	0.7500	13.8000
Mortgage spread (alt.)	4,619,541	1.2708	1.1450	-4.6774	12.0709
Lender fees (£000)	4,619,541	0.9909	0.9719	0.0000	43.2364
Loan characteristics					
Government support	4,619,541	0.0621	0.2413	0.0000	1.0000
LTmV	4,602,993	73.8359	18.6639	6.0000	100.0559
Fixation period (2 years)	4,619,541	0.4811	0.4996	0.0000	1.0000
Fixation period (5 years)	4,619,541	0.4127	0.4923	0.0000	1.0000
Fixation period (10 years)	4,619,541	0.1062	0.3081	0.0000	1.0000
Rate type (Fixed)	4,619,541	0.9347	0.2471	0.0000	1.0000
Rate type (Variable)	4,619,541	0.0653	0.2471	0.0000	1.0000
Borrower characteristics					
Gross income (£000)	4,570,033	59.7460	36.1737	0.0000	257.4170
Age of borrower (years)	4,619,541	35.7780	8.9930	18.0000	60.0000
Joint application	4,619,541	0.2112	0.4081	0.0000	1.0000
Property characteristics					
Green characteristic	3,730,512	0.1826	0.3864	0.0000	1.0000
New build	4,619,541	0.1180	0.3227	0.0000	1.0000
Price/Value	4,619,320	0.9975	0.1105	0.0830	2.8889
Lender characteristics					
Systemic bank	4,619,541	0.7923	0.4057	0.0000	1.0000
Listed bank	4,619,541	0.9120	0.2833	0.0000	1.0000

Note: This table provides summary statistics of variables employed in the analyses, from PSD, Land Registry and EPC data.

Property-level variables include a binary indicator for the green characteristic of the property, equal to one for loans issued against properties with EPC ratings of A or B. On average, 18% of properties in our sample classify as green. The binary indicator for new build equals to one for newly constructed properties and has a mean of 2%. The price-to-value ratio (Price/Value) shows that on average appraisal values are very close to purchase prices. In addition, we observe lender identity for each mortgage, allowing us to classify banks by institutional characteristics. Our sample includes 56 distinct banks, of which 23 are listed banks that are defined as institutions with publicly traded equity, which originated around 91% of mortgages. By contrast, 16 are designated as domestically systemic ("D-SIB") or globally systemic ("G-SIB") by the UK Prudential Regulation Authority or by a foreign regulator based on size, interconnectedness, and substitutability, which originate 79% of mortgages. This classification allows us to examine heterogeneity in pricing behaviour across bank types, particularly in response to policy and macroeconomic signals and reputational incentives.

4 Empirical Strategy

Descriptive statistics in Section 3.2 reveal substantial variation in mortgage pricing, product configurations, and borrower characteristics. As indicated above, our first approach is to infer product innovation by observing pricing behaviour. Specifically, we test whether mortgage spreads systematically reflect energy efficiency conditional on detailed product characteristics. To do so, we estimate a baseline pricing model that relates spreads to product-level features and lender fees, while absorbing residual heterogeneity through high-dimensional fixed effects. This approach allows us to interpret any incremental discount for energy-efficient properties as evidence of green product innovation being priced into contracts.

4.1 Baseline Pricing Model

Establishing the link between product structure and mortgage pricing. We begin by establishing the link between mortgage product structure and pricing. Our goal is to understand how lenders adjust spreads in response to product characteristics and fees.

Specifically, we estimate the following baseline regression:

$$\text{Spread}_{i,k,t} = \beta_1 \,\text{Gov't support}_i + \delta \,\text{Fee}_i + \text{Product FE}'_{i,k,t}\gamma + \varepsilon_{i,k,t} \tag{9}$$

The dependent variable is the mortgage spread (the difference between the mortgage rate and SONIA). The model relates this spread to whether the loan is part of a government support scheme, the upfront fee charged by the lender, and a set of high-dimensional product fixed effects.

We model government support separately from the product fixed effects. Although it alters the borrower's effective leverage, it does not vary across product configurations offered by individual lenders. Under schemes such as Help-to-Buy, borrowers receive a second-charge equity loan from the government, which supplements the primary mortgage.[9] This structure allows the borrower to receive more funding while reducing the lender's downside risk, as the government shares the equity of the property. As discussed in Benetton et al. (2022), this shifts part of the risk-return profile to the public sector. To preserve its independent effect on pricing, we include government support as a separate regressor.

We progressively expand the dimensionality of the fixed effects to capture heterogeneity in mortgage offerings. The baseline specification includes interactions between lender identity, fixed rate bucket, and loan-to-market value (LTmV) bucket. We then add year-month fixed effects to control for time-specific shocks, followed by interest rate type (fixed vs. variable). Our final specification includes a five-way product fixed effects structure: *lender* × *fixed rate bucket* × *LTmV bucket* × *year-month* × *interest rate type.*

Identification relies on within-product variation in pricing across loans with and without government support, conditional on detailed product characteristics. This allows us to isolate the pricing effect of policy interventions while controlling for institutional and market-level heterogeneity. We also explicitly discuss the role of possible other concurrent product innovations, such as mortgages against new builds in our identification strategy. Section 6 discusses the key identifying assumptions and robustness tests supporting our results.

[9] A second charge equity loan is a second mortgage or junior loan. It uses home's equity as collateral, like your first mortgage, but it has a lower seniority for repayment if the home is sold or foreclosed.

Measuring green product innovation. Building on the baseline pricing model, we examine whether energy efficiency is priced into mortgage contracts. To do so, we introduce a binary indicator for the green characteristic, defined as equal to one if the property securing the loan has an Energy Performance Certificate (EPC) rating of A or B. We estimate the following extended pricing model:

$$\text{Spread}_{i,k,t} = \beta_1 \,\text{Green characteristic}_i + \beta_2 \,\text{Gov't support}_i + \delta \,\text{Fee}_i + \text{Product FE}'_{i,k,t}\gamma + \varepsilon_{i,k,t} \tag{10}$$

This specification retains the high-dimensional product fixed effects used in the baseline model (*lender* × *fixed rate bucket* × *LTmV bucket* × *year-month* × *interest rate type*), ensuring that the estimated green effect is identified conditional on detailed product characteristics.

The coefficient on *Green characteristic* is our focal parameter. A statistically significant estimate of β_1 indicates that energy efficiency is priced into mortgage contracts, consistent with the emergence of green mortgages as a distinct product innovation. A negative and significant β_1 suggests that loans for purchase of energy-efficient properties receive preferential pricing.

In addition, we examine model fit to assess whether the inclusion of the green variable improves explanatory power. An increase in adjusted R^2 in the specifications with the green characteristic would suggest that energy efficiency contributes meaningfully to explaining variation in mortgage spreads. Such a finding supports the interpretation of green mortgages as a product feature being priced in the UK market.

4.2 Identification of Green Product Innovation

Time variation. To trace the emergence of green mortgage pricing, we estimate year-specific effects by interacting *Green characteristic* with annual indicators. This approach is equivalent to estimating separate baseline regressions (Equation 10) by year, allowing us to assess when energy-efficient properties began receiving pricing discounts relative to comparable non-green loans. We begin the sample in 2012 to avoid confounding effects from the Global Financial Crisis. Our sample ends in 2023, as this year corresponds to the end of the merged EPC–Land Registry dataset at the time we integrated it with the PSD data (UCL, 2024).[10]

[10] Updates are difficult to obtain due to the confidential nature of the data and the complexity of the associated procedures.

The resulting yearly coefficients capture the marginal effect of green status in each year, identified from within-product-year variation. Identification relies on high-dimensional product fixed effects (*lender* $\times$ *fixed rate bucket* $\times$ *LTmV bucket* $\times$ *year-month* $\times$ *interest rate type*) which absorb product-level heterogeneity and market conditions. This structure ensures that the estimated time-varying effects reflect changes in pricing behaviour rather than shifts in product composition or lender mix.

To interpret the timing of these effects, we contextualise the estimates using key external developments (Annex 1), including the implementation of the Minimum Energy Efficiency Standard (MEES) in 2018 and the 2022 energy price shock. Our set-up allows us to contrast these events with the Paris Agreement in 2015 and consider regulatory interventions such as the PRA's Supervisory Statement 3/19 and the Bank of England's CBES exercise, which formalised expectations around climate risk management.

Lender heterogeneity. Building on the regulatory and market pressures discussed above, we examine whether green product innovation is concentrated among a subset of lenders. Identifying which lenders offer green discounts provides insight into how institutional characteristics shape responsiveness to policy signals and macroeconomic shocks. To explore this heterogeneity, we estimate Equation 10 on the post-2018 data. Specifically, we interact *Green characteristic* with indicators for (i) listed banks, (ii) systemic banks, and (iii) listed but non-systemic banks. These categories capture variation in exposure to regulatory scrutiny and market discipline—two key drivers of signalling incentives. We include high-dimensional product fixed effects to ensure that estimated effects reflect changes in pricing behaviour rather than shifts in product mix or market structure. This approach allows us to test whether pricing differentials associated with green attributes are more pronounced among lenders facing stronger external pressures, consistent with the mechanism outlined previously in section 2.4.

5 Results

5.1 Mortgage Pricing: Baseline Product Structure

We begin by estimating the baseline pricing framework to establish core relationships between mortgage product characteristics and pricing outcomes. Columns (1) to (4) of Table 2 report our results. They demonstrate how progressively granular fixed effects improve model fit. Column (1) includes individual fixed effects for lender identity, fixation period, and loan-to-market value (LTmV) buckets. Column (2) introduces 3-way product fixed effects: lender × fixed rate bucket × LTmV bucket—which captures heterogeneity in pricing across lenders and product types. Column (3) adds year-month fixed effects, forming a 4-way structure that captures macroeconomic and policy variation. Column (4) incorporates interest rate type, distinguishing between fixed and variable rate products, yielding a 5-way fixed effects structure (lender × fixed rate bucket × LTmV bucket × year-month × interest rate type). This expansion of fixed effect combinations leads to a substantial increase in explanatory power, with R^2 rising from 0.736 in Column (1) to 0.844 in Column (4). These increases underscore the importance of detailed product definitions in explaining mortgage pricing variation and reassure us of the validity of our baseline product definition.

Across all specifications, loans linked to government support schemes attract statistically significantly higher spreads (between 25 to 27 basis points), despite their supposed goal of reducing risk profile. Such premium can reflect increased borrower leverage, administrative costs, or lender perceptions of scheme-related risk. At the same time, the negative and significant coefficients on lender fees across columns (1) to (4) indicate that products with higher upfront fees tend to have lower interest rate spreads. This inverse relationship, in line with findings by Benetton et al. (2025), suggests lenders balance pricing across fees and rates, underscoring the need to consider total loan cost when evaluating mortgage pricing.

Column (5) of Table 2 introduces *Green characteristic*, identifying loans secured against energy-efficient properties (EPC rating A or B). The coefficient is negative and statistically significant, pointing to a green discount of approximately 4.3 basis points over the sample period. The inclusion of this variable yields a modest but consistent increase in adjusted R^2 of around 0.003, reinforcing its explanatory value even within a saturated model.[11] This discount suggests that lenders had begun to systematically differentiate pricing based on energy efficiency during the sample period—even though we do not observe formal product launches or branding in our transaction data. Taken together, the findings provide strong

[11] Unreported robustness tests confirm that green discount remains significant under 3- & 4-way fixed effects specifications.

empirical evidence for the existence of a green mortgage product feature, indicating that sustainability considerations are increasingly embedded in lender pricing strategies.

Table 2: Mortgage Pricing: Baseline Product Structure

Dependent variable	Mortgage spread				
	(1)	(2)	(3)	(4)	(5)
Green characteristic					-0.043***
					(0.007)
Gov't support	0.273***	0.257***	0.251***	0.250***	0.265***
	(0.038)	(0.046)	(0.050)	(0.051)	(0.045)
Lender fees	-0.305***	-0.306***	-0.331***	-0.337***	-0.344***
	(0.035)	(0.037)	(0.032)	(0.032)	(0.028)
Constant	2.320***	2.323***	2.346***	2.352***	2.342***
	(0.035)	(0.037)	(0.031)	(0.032)	(0.028)
Individual FE's	YES	NO	NO	NO	NO
Product FE (3-way)	NO	YES	NO	NO	NO
Product FE (4-way)	NO	NO	YES	NO	NO
Product FE (5-way)	NO	NO	NO	YES	YES
Observations	4,619,541	4,619,515	4,606,865	4,595,741	3,707,282
Number of banks	57	57	57	56	56
R^2 (adj.)	0.736	0.759	0.828	0.841	0.843
Clustered S.E.	YES	YES	YES	YES	YES

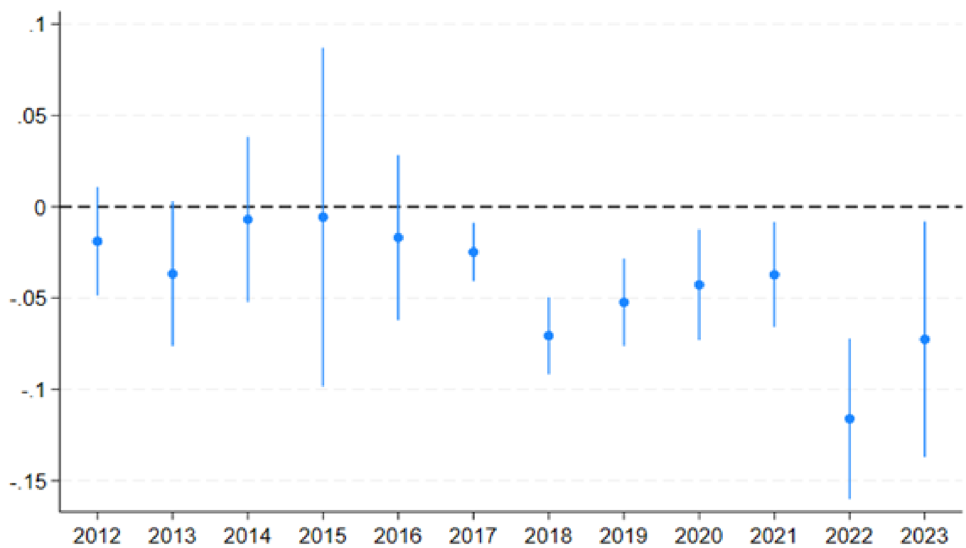
Notes: This table presents the results from the mortgage pricing model specified in Equations (9) and (10). The dependent variable is the Mortgage spread, and the key explanatory variables are Gov't support and Lender fees. Column (1) includes individual fixed effects, which control for lender, fixation period, and loan-to-market value (LTmV) buckets. Columns (2) through (5) progressively introduce more granular product fixed effects. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

5.2 Product Innovation: Timing

Consistent with the risk-pricing channel outlined in Hypothesis 1, we next examine the timing of green mortgage product adoption by estimating when lenders began incorporating energy efficiency into pricing decisions. Specifically, we estimate year-specific effects to trace the emergence and evolution of the green pricing discount over time.

Figure 2 presents the resulting coefficients from a specification that interacts *Green characteristic* with annual indicator variables—effectively equivalent to estimating separate regressions by year. This approach allows us to identify the timing of product innovation by estimating the marginal effect of the green feature in each year. That is, whether mortgages secured against energy-efficient properties have lower spreads relative to comparable non-green loans.

Figure 2: Timing of Green Mortgage Discount



Notes: This figure plots the estimated annual coefficients from a specification that interacts *Green characteristic* with year-specific indicator variables. Each coefficient captures the marginal effect of green status on mortgage spreads each year, relative to comparable non-green loans. The specification includes the full set of 5-way product fixed effects (*lender* × *fixed rate bucket* × *LTmV bucket* × *year-month* × *interest rate type*), as in Table 2 Column (5). Standard errors are clustered at the lender-by-time level. The figure traces the emergence and evolution of green mortgage pricing, identifying when lenders began offering green products and whether energy-efficient properties were priced at a discount. Estimates include 95% confidence intervals.

The year-specific estimates reveal that a statistically and economically meaningful green discount begins to emerge around 2018. This timing coincides with the implementation of the Minimum Energy Efficiency Standard (MEES), which required rental properties to meet a minimum EPC rating of E. The estimated discount in that year is approximately 7 basis points, suggesting that formal policy enforcement reinforced earlier policy signals and served as a catalyst for product innovation. Although MEES came into force in April 2018, it had been announced earlier, introducing direct compliance risk for landlords. This regulatory shift likely altered the perceived risk profile of mortgage collateral—particularly in the buy-to-let segment—with potential spillovers to the owner-occupied segment (Ferentinos et al., 2023). While the visual estimates suggest a temporary decline in the discount following 2018, pairwise t-tests indicate that these changes are not statistically significant, implying no structural break or regime shift during that period.

A second notable inflection point occurs in 2022, when the estimated green discount widens to approximately 12 basis points. This shift follows a sharp increase in energy prices (driven by post-pandemic recovery and geopolitical tensions), which appears to have served as a salient macroeconomic shock. The magnitude and timing of the response suggest that lenders recognised the financial materiality of energy efficiency, as rising energy costs directly affected household budgets and asset valuations. Importantly, rising utility costs disproportionately impacted borrowers in low-EPC properties, increasing credit risk and reducing affordability, while high-EPC homes offered relative insulation from these shocks (Guin et al., 2022). This shift in borrower risk profiles likely contributed to the repricing of green mortgage products, as lenders adjusted spreads to reflect differential exposure to energy-related financial stress.

By contrast, we find no evidence of a pricing response in 2015, despite the announcement of MEES and the adoption of the Paris Agreement. This absence of early adjustment implies that lenders did not respond pre-emptively to policy signals but instead waited until regulatory implementation became imminent or market conditions shifted. Taken together, these results support the risk-pricing hypothesis: lenders began pricing green mortgage products more favourably in response to evolving policy and market signals that altered the perceived riskiness of energy-inefficient properties. The emergence of a green discount around 2018, and its amplification in 2022, reflects a growing recognition of energy efficiency as a risk factor in mortgage markets. This timing variation explains the difference to Bell et al. (2023). They estimate the discount using the stock of mortgages mostly reflecting the flow of new mortgages pre-2017 that are not repaid or defaulted. For these years, we neither find any significant discount.

5.3 Product Innovation: Lender Heterogeneity

While Section 5.2 establishes when lenders began pricing green attributes into mortgage spreads, it does not explain which lenders led this shift or why some institutions responded quicker than others. To address this, we turn to the pressure channel outlined in Hypothesis 2, which posits that banks facing greater regulatory and market scrutiny, such as systemically important or publicly listed institutions, have stronger incentives to adopt green mortgage products.

These institutions are subject to heightened expectations. Listed banks must meet investor-facing ESG mandates and disclosure requirements (Mudalige, 2023), while systemically important banks face enhanced supervisory oversight, including the integration of environmental risks into credit risk frameworks (Gunningham, 2020). Together, these pressures may accelerate product innovation and pricing differentiation.

To examine this, we estimate Equation (10) on the post-2018 subsample, interacting *Green characteristic* with indicators for listed and systemic banks. This specification captures whether responsiveness to environmental attributes varies systematically with institutional structure and external oversight. As in previous specifications, we include high-dimensional product fixed effects to ensure that estimated coefficients reflect changes in pricing behaviour rather than shifts in product mix or market structure.

Table 3 presents the results. Column (1) reports the baseline specification, capturing the average green pricing effect across all lenders. The coefficient on *Green characteristic* is negative and statistically significant at the 1% level, indicating that loans secured against energy-efficient properties (EPC rating A or B) are associated with lower mortgage spreads. The estimated discount (4.3 basis points) is larger than in the full sample period, suggesting that pricing differentiation intensified following the 2018 inflection point.

Columns (2) to (4) introduce interaction terms to assess heterogeneity in lender behaviour. Column (2) interacts *Green characteristic* with an indicator for listed banks. The interaction term is negative and statistically significant at the 10% level, corresponding to an incremental discount of roughly 4.3 basis points. This result aligns with the expectation that heightened market discipline encourages banks to expand their product offerings, offering discounts against the green product characteristic.

Table 3: Mortgage Pricing: Bank Heterogeneity (Post-2018)

Dependent variable	Mortgage spread			
	(1)	(2)	(3)	(4)
Green characteristic	-0.049***	-0.006	-0.025**	-0.047***
	(0.008)	(0.022)	(0.011)	(0.009)
Green characteristic × Listed		-0.043*		
		(0.023)		
Green characteristic × Systemic			-0.026**	
			(0.012)	
Green characteristic × Listed				0.011
& not systemic				(0.009)
Gov't support	0.209***	0.208***	0.209***	0.208***
	(0.023)	(0.024)	(0.023)	(0.024)
Lender fees	-0.319***	-0.341***	-0.341***	-0.341***
	(0.018)	(0.018)	(0.018)	(0.018)
Constant	1.833***	1.846***	1.846***	1.846***
	(0.012)	(0.012)	(0.012)	(0.012)
Product FE (5-way)	YES	YES	YES	YES
Observations	2,101,744	2,101,744	2,101,744	2,101,744
Number of banks	51	51	51	51
R^2 (adj.)	0.807	0.806	0.806	0.806
Clustered S.E.	YES	YES	YES	YES

Notes: This table presents results from the baseline mortgage-pricing model specified in Equation (10) using post-2018 data. Dependent variable is the Mortgage spread, and the key explanatory variables are Green characteristic as well as Gov't support and Lender fees. All regressions use 5-way fixed effects: lender × fixed rate bucket × LTmV bucket × year-month × interest rate type. Each column interacts Green characteristic with a different subsample of banks: Column (1) shows the un-interacted results; Column (2) interact with listed banks; Column (3) interact with systemic banks which is largely identical with UK systemic banks; Column (4) interact with listed but not systemic. All regressions are estimated using Ordinary Least Squares. Standard errors clustered at the lender-by-time level, where time is defined as a year-by-month combination. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Column (3) focuses on systemic banks, where the interaction term is again negative but of lower magnitude (≈ 2.6 basis points), consistent with banks facing regulatory pressures being more responsive. The results are identical to just UK systemic banks, those that were subject to the first Climate Stress Test (C-BES) in 2021 and therefore exposed to direct regulatory pressure[12].

Column (4) isolates listed but non-systemic banks. Here, the interaction term is statistically insignificant, suggesting that investor-facing pressure alone may not be sufficient to induce pricing adjustments in response to environmental attributes, at least among smaller institutions with limited regulatory exposure.

Taken together, these results support Hypothesis 2. Banks under greater regulatory and market pressure are more likely to engage in green mortgage pricing. Systemic importance, as a proxy for regulatory pressure, appears to be the dominant driver of responsiveness, while market discipline plays a more selective role. The lack of significance for listed but non-systemic banks reinforces the idea that offering discounts is only worthwhile for banks with both the capability and the incentive to bear its costs. This heterogeneity in responsiveness underscores the importance of institutional scale and oversight in shaping the trajectory of green product innovation in mortgage markets.

6 Discussion of Identifying Assumptions

Our identification strategy relies on the following assumptions:

1. Conditional on observed attributes and fees, mortgage rate changes reflect a change in product structure rather than shifts in borrower risk.

2. The introduction of green products is not perfectly collinear with other concurrent product innovations.

3. Other economic shocks did not convolute the identification of product innovation.

4. Lenders use mortgage rates to price green mortgages rather than cashback incentives.

[12]See www.bankofengland.co.uk/stress-testing/2021/key-elements-2021-biennial-exploratory-scenario-financial-risks-climate-change, accessed on 25 November 2025.

In the following sections, we analyse each assumption in detail and provide evidence on the external validity of our results.

6.1 Borrower Risk

Collateral quality. To assess borrower risk more accurately, we introduce the Price-to-Value (Price/Value) ratio as a supplementary measure of collateral quality, alongside our existing loan-to-value measure (LTmV). The Price/Value ratio captures discrepancies between market transaction prices and appraised property values. These discrepancies could arise, at least partially, when energy efficiency characteristics are capitalised into market prices but not fully reflected in appraisals, or vice versa. Such mismatches are particularly relevant for energy-efficient buildings. To account for this, we augment the baseline specification by adding the Price/Value ratio:

$$\begin{aligned}\text{Spread}_{i,k,t} = {} & \beta_1 \,\text{Green characteristic}_i + \beta_2 \,\text{Gov't support}_i + \beta_3 \,\text{Fee}_i \\ & + \beta_4 \,\text{Price/Value}_i + \text{Product FE}'_{i,k,t}\gamma + \varepsilon_{i,k,t} \end{aligned} \tag{11}$$

As shown in Table 4, Column 2, the coefficient on Price/Value ratio is negative and statistically significant: higher ratios are associated with lower spreads. This observation suggests that lenders adjust pricing based on the expectation that transaction prices offer a more accurate signal of recoverable collateral value than appraisals alone. The coefficient on Green characteristic remains stable and significant, indicating that the observed pricing benefit for energy-efficient properties is not driven by valuation gaps. Instead, it reflects a distinct and consistent lender response to sustainability attributes, over and above any collateral valuation effects.

Observable borrower risk. In the UK mortgage market, lenders post mortgage product rates at the product level, with LTmV reflecting borrower risk, and do not vary with other borrower-specific characteristics, mitigating concerns about discretionary pricing. Nevertheless, the green mortgage discount could reflect differences in borrower composition if energy-efficient homes attract systematically lower-risk households.

Table 4: Mortgage Pricing: Borrower Risk

Dependent variable	Mortgage spread			
	(1)	(2)	(3)	(4)
Green characteristic	-0.043***	-0.043***	-0.037***	-0.044***
	(0.007)	(0.007)	(0.007)	(0.007)
Gov't support	0.265***	0.264***	0.253***	0.261***
	(0.045)	(0.045)	(0.045)	(0.045)
Lender fees	-0.344***	-0.344***	-0.329***	-0.342***
	(0.028)	(0.028)	(0.027)	(0.028)
Price/Value		-0.094**		
		(0.045)		
Gross income			-0.001***	
			(0.000)	
Joint application			0.010	
			(0.006)	
Age			-0.000**	
			(0.000)	
LTI > 4.5				-0.034***
				(0.007)
Constant	2.342***	2.436***	2.408***	2.344***
Product FE (5-way)	YES	YES	YES	YES
Observations	3,707,282	3,707,107	3,672,065	3,707,282
R^2 (adj.)	0.843	0.843	0.845	0.843

Notes: This table presents the results from the baseline mortgage-pricing model specified in Equation (10). The dependent variable is the *Mortgage spread*, and the key explanatory variables are *Green characteristic* as well as *Gov't support* and *Lender fees.* All regressions use five-way fixed effects: lender × fixed rate bucket × LTmV bucket × year-month × interest rate type. Column (1) replicates the baseline specification (Table 2). Column (2) adds the price-to-valuation ratio (Price/Value) as an additional collateral quality control. Column (3) introduces borrower-level controls: gross income, joint application status, and age. Column (4) includes an indicator for LTI > 4.5. Column (5) extends the sample to include remortgaging transactions and adds borrower–property fixed effects. Standard errors are clustered at the lender-by-time level (year-month). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

For example, higher-income or lower-risk borrowers may self-select into green properties, causing the green characteristic to proxy for borrower quality rather than product design. To address this concern, we augment the baseline specification with borrower-level controls (gross income, joint application status, and age), which capture heterogeneity in repayment capacity and household composition:

$$\begin{aligned}\text{Spread}_{i,k,t} = {} & \beta_1 \,\text{Green characteristic}_i + \beta_2 \,\text{Gov't support}_i + \beta_3 \,\text{Fee}_i + \text{Controls}'_{i,k,t}\phi \\ & + \text{Product FE}'_{i,k,t}\gamma + \varepsilon_{i,k,t}\end{aligned} \tag{12}$$

As shown in Table 4, Column 3, age and gross income are negatively correlated with mortgage spreads, consistent with lower-risk borrower profiles receiving more favourable pricing. The coefficient on the green characteristic is robust to the inclusion of these controls, indicating that observable borrower risk factors do not drive observed pricing.

We further account for the Loan-to-Income (LTI) flow limit, which restricts lenders from issuing more than 15% of new residential mortgages at LTI ratios of 4.5 or higher (Peydró et al., 2024). This regulation limits the scope for risk-based pricing at high LTI levels, but residual concerns remain if borrowers above this threshold differ on unobservable dimensions such as wealth or liquidity[13]. To address this concern, we include an indicator for LTI > 4.5 in the baseline specification. Table 4, Column 4 shows that the estimated green mortgage discount remains virtually unchanged, reinforcing the interpretation that the discount reflects lender response to sustainability attributes rather than borrower selection.[14]

Unobservable borrower risk. Beyond observable borrower characteristics, credit scores are not included in PSD data. Following Benetton (2021), this omission is unlikely to bias results because UK mortgage pricing primarily reflects product characteristics rather than credit scores. Robles-Garcia (2019) provides supporting evidence, showing that credit scores have negligible impact on UK mortgage rates once product features are controlled for. This feature of UK mortgages contrasts with the US case, where credit scores play a more prominent role alongside LTV bands. Overall, the estimated green mortgage discount remains robust

[13] This LTI flow limit was introduced in 2014 and applied to lenders whose annual mortgage lending exceeds £100 million (increased to £150 million in July 2025). As such, all 56 lenders in our sample are subject to the limit.

[14] In unreported robustness tests, we re-estimate the model on the subsample of loans with LTI ¡ 4.5, which leaves the *Green coefficient* unchanged

across specifications that control for collateral quality, observable borrower characteristics, and regulatory constraints on high-LTI lending. These results suggest that neither observable nor unobservable borrower risk factors are likely to explain the observed pricing differences of green mortgages, supporting the interpretation of the green mortgage discount as a product-level feature rather than a reflection of borrower selection.

6.2 Concurrent Product Innovations

A second identification concern is that the introduction of green mortgage products can coincide with other product innovations that occur around the same time. If these innovations correlate with both pricing and the green label, the estimated discount could reflect broader changes in product structure rather than the green characteristic itself. Our empirical design mitigates this risk by exploiting within-lender, within-time variation across narrowly defined product cells. Any confounding innovation would therefore need to occur contemporaneously within the same lender, product category, and time period.

To further probe this assumption, we augment the baseline five-way fixed effects (*lender* $\times$ *fixed rate bucket* $\times$ *LTmV bucket* $\times$ *year-month* $\times$ *interest rate type*) with a sixth dimension, introduced sequentially across specifications. We consider four plausible sources of confounding heterogeneity: (i) regional pricing schedules[15], (ii) preferential pricing for new-build properties, (iii) government support schemes, and (iv) interacting *Green characteristic* itself. Table 5 reports the results.

Across all specifications, the coefficient on Green characteristic remains negative and statistically significant, indicating that the estimated green mortgage discount is robust to alternative definitions of product heterogeneity. The magnitude of the discount is broadly stable when adding region-level fixed effects (Column 2) but declines when controlling for new-build status (Column 3) and government support (Column 4), consistent with partial overlap between these features and green products. This attenuation suggests that some of the green discount reflects correlated product attributes, though the effect of remains economically and statistically meaningful, reassuring us about our inference on product innovation. Column (5) introduces a sixth fixed-effect dimension that interacts the baseline structure with *Green*

[15] We measure region at the 2-digit postcode level.

characteristic itself. This specification does not aim to re-estimate the green discount but rather to test whether explanatory power improves when green status is treated as part of the product definition.

Table 5: Mortgage Pricing: Other Product Innovation

Dependent variable	Mortgage spread				
	(1)	(2)	(3)	(4)	(5)
Green characteristic	-0.043***	-0.044***	-0.023***	-0.024**	
	(0.007)	(0.007)	(0.005)	(0.011)	
Gov't support	0.265***	0.266***	0.323***		0.287***
	(0.045)	(0.046)	(0.045)		(0.048)
Lender fees	-0.344***	-0.369***	-0.341***	-0.335***	-0.344***
	(0.028)	(0.020)	(0.028)	(0.028)	(0.028)
Constant	2.342***	2.315***	2.330***	2.349***	2.331***
Product FE (5-way)	YES	NO	NO	NO	NO
Product FE (6-way, region)	NO	YES	NO	NO	NO
Product FE (6-way, new-build)	NO	NO	YES	NO	NO
Product FE (6-way, gov't support)	NO	NO	NO	YES	NO
Product FE (6-way, green)	NO	NO	NO	NO	YES
Observations	3,707,282	2,857,090	3,692,693	3,703,567	3,689,945
Number of banks	56	55	56	56	56
R^2 (adj.)	0.843	0.850	0.846	0.847	0.845

Notes: This table reports estimates from the baseline mortgage-pricing model in Equation (10). The dependent variable is the mortgage spread (in percentage points). Column (1) includes five-way fixed effects: *lender* $\times$ *fixed-rate bucket* $\times$ *LTmV bucket* $\times$ *year-month* $\times$ *interest rate type.* Columns (2) – (5) introduce a sixth fixed-effect dimension interacting the baseline structure with additional product attributes: region (Column 2), new-build status (Column 3), government support (Column 4), and the green characteristic (Column 5). The purpose of columns (1) – (4) is to test whether the estimated green discount is robust to alternative definitions of product heterogeneity. The purpose of column (5) is to demonstrate that the explanatory power of including the green characteristic in the product fixed effect does not increase the explanatory power of the model. Observations vary due to data availability for each attribute. All regressions are estimated using OLS with standard errors clustered at the lender-by-time level (year-month). Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

The adjusted R^2 only marginally increases, reinforcing our interpretation that *Green characteristic* is a pricing-relevant product feature. Taken together, these findings suggest that the observed green mortgage discount is unlikely to be driven by concurrent product innovations.

6.3 Fiscal and Economic Shocks: The Case of the 2022 UK Mini-Budget

A potential challenge in interpreting the post-2022 effect arises from the fiscal shock associated with the so-called "mini budget." On 23 September 2022, the then-Chancellor Kwasi Kwarteng announced a package of large tax cuts that marked a sharp departure from prior fiscal policy. Financial markets reacted immediately: 30-year gilt yields rose by approximately 130 basis points within days (Alfaro et al., 2024), and swap rates—commonly used as a reference in mortgage pricing—also spiked sharply. This episode raises the possibility of a structural break in mortgage pricing, potentially complicating identification under our two-part tariff framework. While swap rates are not formally embedded in lenders' pricing rules, they influence the sensitivity of pricing to product attributes. Our empirical design, as specified in Equations (10) and (11), accommodates such shifts by interacting time fixed effects with baseline product indicators. This structure allows for temporal variation in the pricing of identical product attributes, ensuring that the fixed effects absorb common shocks to interest rates or pricing sensitivity.

To further assess whether our results are potentially confounded by the mini-budget shock, we test whether our results are sensitive to the construction of the dependent variable. We re-estimate the baseline specification using the raw mortgage rate rather than the spread over SONIA rate. Because our model includes time fixed effects, this specification absorbs common variation in interest rates, due to in monetary policy and macroeconomic conditions:

$$
\begin{aligned}
\text{Mortgage rate}_{i,k,t} = \beta_1 \,\text{Green characteristic}_i + \beta_2 \,\text{Gov't support}_i + \beta_3 \,\text{Fee}_i \\
+ \text{Product FE}'_{i,k,t}\gamma + \varepsilon_{i,k,t} \qquad (13)
\end{aligned}
$$

Second, we construct an alternative spread measure by replacing SONIA with the sterling 5-year swap rate. This benchmark captures a different segment of the yield curve and allows us to test whether our results depend on the choice of this alternative mortgage spread:

$$\begin{aligned}\text{Mortgage spread (alt.)}_{i,k,t} = \beta_1 \,\text{Green characteristic}_i + \beta_2 \,\text{Gov't support}_i + \beta_3 \,\text{Fee}_i \\ + \text{Product FE}'_{i,k,t}\gamma + \varepsilon_{i,k,t} \end{aligned} \tag{14}$$

Table 6: Mortgage Pricing: Alternative Dependent Variables

Dependent variable	Mortgage spread	Mortgage rate	Mortgage spread (alt.)
	(1)	(2)	(3)
Green characteristic	-0.043***	-0.042***	-0.044***
	(0.007)	(0.007)	(0.007)
Gov't support	0.265***	0.265***	0.266***
	(0.045)	(0.045)	(0.044)
Lender fees	-0.344***	-0.345***	-0.345***
	(0.028)	(0.028)	(0.028)
Constant	2.342***	2.962***	1.584***
	(0.028)	(0.028)	(0.028)
Product FE (5-way)	YES	YES	YES
Observations	3,707,282	3,707,282	3,707,282
Number of banks	56	56	56
R^2 (adj.)	0.843	0.833	0.860
Clustered S.E.	YES	YES	YES

Notes: This table reports robustness checks using alternative dependent variables based on the model specified in Equation (10). The key explanatory variables are *Green characteristic* as well as *Gov't support* and *Lender fees.* All columns include five-way product fixed effects: *lender* × *fixed rate bucket* × *LTmV bucket* × *year-month* × *interest rate type.* The dependent variable changes across columns to test sensitivity. Column (1) uses the *Mortgage spread* as the dependent variable. Column (2) switches to the *Mortgage rate.* Column (3) reports the baseline *Mortgage spread (alt.).* All regressions are estimated using Ordinary Least Squares (OLS), with standard errors clustered at the lender-by-time level, where time is defined as a year-by-month combination. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6 reports the results. Column (1) reports results for the baseline mortgage spread over SONIA (for comparison), Column (2) uses the raw mortgage rate, and Column (3) uses the spread over the sterling 5-year swaps rate. Across all specifications, the coefficient on Green characteristic remains negative and statistically significant, with an estimated discount of 4.3 basis points in Column (1) compared to 4.2 basis points in Column (2) and 4.4 basis points in Column (3). This stability indicates that our findings are not sensitive to the choice of benchmark or to the heightened volatility in interest rates following the mini-budget shock.

Taken together, these results confirm that the estimated green mortgage discount is robust to alternative benchmark choices and remains unaffected by macro-financial shocks, such as the 2022 mini budget, reinforcing the validity of our identification strategy.

6.4 Cashback Incentives

Lenders can use cashback incentives, rather than mortgage rates, as a mechanism to price mortgages. If so, omitting cashback features could bias estimates of the green discount. In the offer data from Moneyfacts we observe that many lenders offer cashback incentives to potential borrowers. Yet, it remains unclear whether such incentives materially influence borrower selection or pricing outcomes in practice, as borrowers often overlook cheaper options even when available (Coen et al., 2023), and hence, have implications for our conclusions.

This issue can be tackled using our dataset on transacted mortgages, which captures the terms of originated loans. This distinction is important: offer menus reflect lender intentions, whereas transacted data reveal equilibrium outcomes and borrower choices. In our dataset, we observe a binary indicator for whether a mortgage included a cashback offer, though not the monetary value. While this restriction limits quantification, the presence of a cashback feature allows us to test whether such offers are systematically associated with green mortgage pricing or uptake.

We conduct two empirical tests. First, we present our baseline pricing regression (Equation 10). We then extend it by introducing a cashback indicator variable together with *Green characteristic*. These specifications allow us to assess whether the estimated green discount is sensitive to the inclusion of cashback controls and whether model fit improves. Second, we estimate regressions where the dependent variable is the presence of a cashback offer, testing whether a green characteristic predicts cashback incidence, both with and without controls for interest rates and fees. Table 7 summarises the results.

Columns (1)–(3) use mortgage spread as the dependent variable. Column (1) replicates the baseline result from Table 2, while Columns (2) and (3) introduce indicators for cashback

Table 7: Mortgage Pricing: Cashback Incentives

Dependent variable	Mortgage spread			Cashback	
	(1)	(2)	(3)	(4)	(5)
Green characteristic			-0.043***		0.005
			(0.007)		(0.011)
Gov't support	0.250***	0.246***	0.261***	0.060**	0.057*
	(0.051)	(0.052)	(0.046)	(0.029)	(0.032)
Lender fees	-0.337***	-0.334***	-0.341***	-0.040***	-0.041***
	(0.032)	(0.032)	(0.028)	(0.015)	(0.015)
Cashback		0.078***	0.075***		
		(0.022)	(0.022)		
Constant	2.352***	2.333***	2.323***	0.251***	0.254***
	(0.032)	(0.034)	(0.029)	(0.014)	(0.013)
Product FE (5-way)	YES	YES	YES	YES	YES
Observations	4,595,741	4,595,741	3,707,282	4,614,916	3,722,154
Number of banks	56	56	56	56	56
R^2 (adj.)	0.841	0.841	0.843	0.599	0.598
Clustered S.E.	YES	YES	YES	YES	YES
Method	OLS	OLS	OLS	OLS	OLS

Notes: This table examines the relationship between mortgage pricing and cashback incentives. Columns (1) to (3) use the *Mortgage spread* as the dependent variable. Column (1) replicates the baseline results without the green characteristic from Table 2. Columns (2) and (3) introduce indicators for cashback offers and green characteristic as additional explanatory variables. In columns (4) and (5), we use the presence of a cashback offer as the dependent variable. Column (4) shows the baseline results and column (5) adds the green characteristic indicator to assess whether property characteristics are systematically associated with cashback incentives. All specifications employ five-way fixed effects: lender × fixed-rate bucket × loan-to-value bucket × year-month × interest rate type. Regressions are estimated using Ordinary Least Squares (OLS), with standard errors clustered at the lender-by-time level, where time is defined as a year-month combination. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

offers and *Green characteristic*, respectively. Across all specifications, controlling for cashback has negligible impact on the estimated green discount, and model fit remains unchanged.

Columns (4)–(5) examine the incidence of cashback offers. The *Green characteristic* is not significantly associated with cashback, even after controlling for rates and fees, implying that green mortgages are not systematically bundled with cashback in realised transactions.

Taken together, these findings suggest that while offer-level data highlight strategic bundling, cashback incentives do not materially affect pricing outcomes in equilibrium, confirming that the estimated green mortgage discount is not confounded by non-rate incentives and reinforcing our interpretation that interest rates remain the primary channel through which lenders differentiate green products.

6.5 External Validity of Our Approach

Our baseline analysis relies on a sample of UK mortgage originations that can be matched to property EPCs. This matching is essential for studying the pricing relevance of environmental attributes but naturally restricts the sample. Although EPCs have been mandatory for property transactions since 2008, their coverage is incomplete. Remortgage transactions often rely on previously issued EPCs, which may not be updated or available in administrative data. Similarly, some initial purchases prior to 2008 did not require EPCs and are therefore excluded. We do not impute missing EPC values but instead drop observations without EPCs from the baseline estimation.

To assess whether our findings generalise to the broader mortgage market, we conduct a two-step exercise. First, we expand the sample to include remortgage transactions, regardless of whether EPCs are available. Second, we incorporate the full universe of mortgage originations from PSD, including both purchase and remortgage loans, even when EPC ratings are unavailable. In these expanded samples, we exclude *Green characteristic*, as it cannot be reliably measured, and focus on the stability of other coefficients, particularly those on fees, government support schemes, and core product attributes. The objective is not to re-estimate the green discount but to test whether our pricing framework remains valid when applied to a broader set of transactions. Table 8 compares estimates across three samples: (i) the baseline

EPC-matched sample, (ii) an expanded sample including remortgages, and (iii) all mortgage originations in PSD.

Table 8: Mortgage Pricing: Representativeness

Sample	Baseline (PSD-EPC)	Baseline + Remortgage	All Originations
	(1)	(2)	(3)
Gov't support	0.250***	0.247***	0.240***
	(0.051)	(0.050)	(0.047)
Lender fees	-0.337***	-0.337***	-0.329***
	(0.032)	(0.032)	(0.031)
Constant	2.352***	2.353***	2.275***
	(0.032)	(0.032)	(0.030)
Product FE (5-way)	YES	YES	YES
Observations	4,595,741	4,634,734	6,867,945
Number of banks	56	57	72
R^2 (adj.)	0.841	0.840	0.827
Clustered S.E.	YES	YES	YES

Notes: This table reports estimates from the baseline mortgage-pricing model in Equation (10) across increasingly inclusive samples. The key explanatory variables are *Green characteristic* as well as *Gov't support* and *Lender fees.* The table assesses the robustness of the pricing model across increasingly inclusive samples. Column (1) uses the baseline sample of PSD mortgages matched to EPC data. Column (2) adds remortgage transactions, regardless of EPC availability. Column (3) includes all mortgage originations in PSD, including those without EPC data. All regressions include five-way product fixed effects: *lender* $\times$ *fixed rate bucket* $\times$ *LTmV bucket* $\times$ *year-month* $\times$ *interest rate type.* All regressions are estimated using Ordinary Least Squares (OLS), with standard errors clustered at the lender-by-time level, where time is defined as a year-by-month combination. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Coefficients on non-environmental variables remain highly stable: the effect of government support ranges between 24 and 25 basis points, and the effect of lender fees between -33 and -34 basis points. The adjusted R^2 declines only slightly from 0.841 to 0.827 despite a near 50% increase in sample size, indicating that the model retains strong explanatory power in a broader market setting. This suggests that our pricing framework generalises beyond EPC-matched loans and that EPC coverage does not materially distort the estimated role of core product attributes.

While EPC availability can correlate with borrower or property characteristics, which we cannot fully observe, the robustness of our results across expanded samples supports the external validity of our conclusions. Future work could explore the missingness mechanism or leverage complementary datasets to further validate these findings. Taken together, these results indicate that our pricing framework remains stable across broader samples, reinforcing the representativeness of our baseline findings and supporting the external validity of our conclusions.

7 Offer-Level Evidence on Green Mortgage Pricing

7.1 Identifying Offered Discounts: Evidence from Offer Data

Our baseline analysis defines *Green characteristic* at property level, using an indicator variable for properties with EPC ratings of A or B. This classification allows us to estimate average pricing differences across transacted mortgages. However, our PSD data does not distinguish between lenders that explicitly offer green mortgage products and those who do not. Our estimated discount can therefore potentially understate the true discount offered by green lenders.

To refine our estimates, we incorporate offer-level data from Moneyfacts, which records advertised mortgage products regardless of whether they were transacted. A key advantage of this dataset is that it allows us to identify lenders that explicitly market green mortgages, typically restricted to properties with EPC ratings of A or B, and to observe the timing of product introduction.

Using this subsample, we estimate pricing differences of mortgages against properties with EPC ratings of A or B and those against other properties, applying the same five-way fixed effects as in our baseline. Column (1) of Table 9 shows an average discount of 7.5 basis points, substantially larger than the 4.3 basis point discount estimated across all lenders (Table 2, Column 2), and larger than the 3.8 basis point discount observed among non-green lenders in both Moneyfacts (Column 3) and PSD (Column 4). These findings suggest that some lenders offer green discounts even without explicit product labelling, but that formal product adoption is associated with a stronger pricing response.

Table 9: Mortgage Pricing: Estimating the Discount

Dependent variable	Mortgage spread				
Sample of lenders	Moneyfacts Green	Moneyfacts Non-green	PSD w/o Moneyfacts Green	Moneyfacts (only)	All
	(1)	(2)	(3)	(4)	(5)
Green characteristic	-0.075***	-0.038***	-0.038***	-0.039***	-0.039***
	(0.021)	(0.006)	(0.006)	(0.007)	(0.007)
Gov't support	0.302***	0.262***	0.261***	0.265***	0.264***
	(0.052)	(0.048)	(0.047)	(0.044)	(0.044)
Lender fees	-0.302***	-0.351***	-0.349***	-0.346***	-0.344***
	(0.035)	(0.032)	(0.032)	(0.028)	(0.028)
Green characteristic ×				-0.030*	-0.030*
Green lender (offered)				(0.017)	(0.017)
Constant	1.716***	2.400***	2.415***	2.328***	2.342***
	(0.022)	(0.032)	(0.032)	(0.027)	(0.028)
Product FE (5-way)	YES	YES	YES	YES	YES
Observations	379,221	3,000,821	3,328,025	3,380,078	3,707,282
Number of banks	11	49	56	49	56
R^2 (adj.)	0.800	0.840	0.843	0.841	0.843
Clustered S.E.	YES	YES	YES	YES	YES

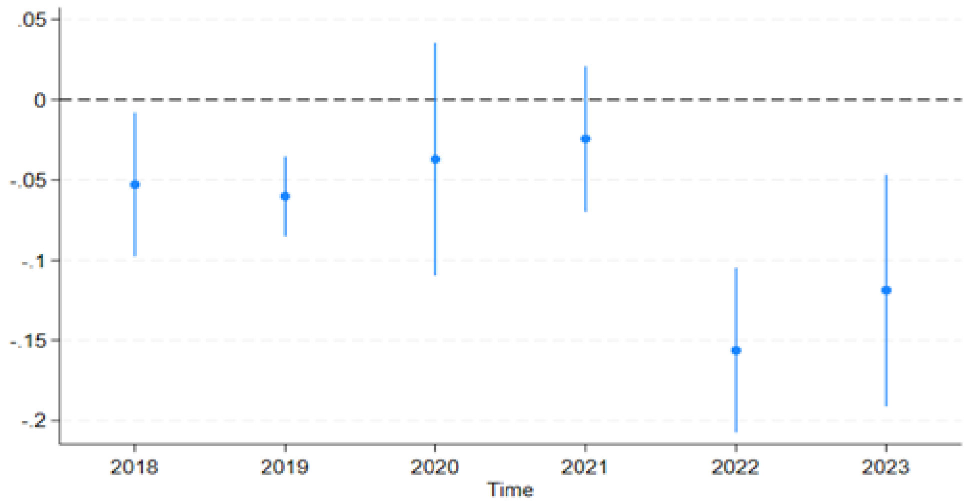
Notes: Columns (1) – (3) of this table present the results from the mortgage pricing model specified in Equation (10). The dependent variable is the *Mortgage spread*, and the key explanatory variables are *Green characteristic* as well as *Gov't support* and *Lender fees.* All regressions use 5-way fixed effects: *lender × fixed rate bucket × LTmV bucket × year-month × interest rate type.* Column (1) restricts the sample to lenders that begin offering green mortgage products in the Moneyfacts sample. Column (2) includes lenders in Moneyfacts that never offer a green mortgage. Column (3) includes lenders in PSD that are not identified as green lenders in Moneyfacts. Columns (4) and (5) implement difference-in-differences specifications comparing the sample of lenders used in column (1) to those used in columns (2) and (3), respectively. *Green Lender (Offered)* is a treatment-time indicator equal to one from the first month a lender publicly advertises a green characteristic in Moneyfacts, and zero otherwise. All regressions are estimated using Ordinary Least Squares (OLS), with standard errors clustered at the lender-by-time level, where time is defined as a year-by-month combination. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

These patterns confirm the findings from the PSD sample but suggest a more pronounced pricing response among lenders that formally adopt green products. Our results remain qualitatively similar when we exclude mixed-product lenders—those offering products for both EPC A/B and A/B/C properties—as shown in Annex 4.[16]

[16] Appendix 4 also presents robustness checks using alternative definitions of green lenders. Figure 6 includes lenders offering products for EPC A, B, or C properties, including those with mixed offerings (A/B and A/B/C). Figure 7 excludes all mixed lenders, focusing only on those with consistent EPC A/B/C offerings.

Overall, the offer-level evidence reinforces our main findings: lenders began advertising green mortgage products from 2018 and did not subsequently withdraw them. The pricing effect is more precisely estimated in this subsample and becomes significantly more pronounced in 2022, highlighting the role of product-level targeting in amplifying the green discount.

Figure 3: Timing of Green Mortgage Discount (Moneyfacts Sample)



Notes: This figure plots annual estimates of the green mortgage discount for lenders that introduced green products for properties with EPC rating A or B, as identified in Moneyfacts. We exclude lenders that only offer green products for properties with EPC rating A, B or C. Estimates are based on transaction-level data from the PSD and include 95% confidence intervals. Estimation begins in 2018, when the first lenders in the Moneyfacts sample introduced green products. The discount appears in 2018, becomes statistically insignificant after 2020, and re-emerges more strongly in 2022.

Figure 3 presents the corresponding year-by-year estimates for the Moneyfacts subsample of lenders following the first introduction in 2018. The estimated discount is statistically significant in 2018. Whilst the pricing discount becomes insignificant after 2020, we observe in Moneyfacts that products continue to exist. The effect re-emerges in 2022 following the energy price shock. Compared to the full sample (Figure 2), the 2022 discount is notably larger—rising from 12 (in our baseline) to over 15 basis points—while the 2018 discount is slightly smaller, at approximately 5 basis points.

Both figures show that the timing and magnitude of the green discount remain broadly consistent, with a re-emergence of the discount in 2022.

These patterns confirm the findings from the PSD sample but suggest a more pronounced pricing response among lenders that formally adopt green products. Our results remain qualitatively similar when we exclude mixed-product lenders—those offering products for both EPC A/B and A/B/C properties—as shown in Annex 4.[17]

Overall, the offer-level evidence reinforces our main findings: lenders began advertising green mortgage products from 2018 and did not subsequently withdraw them. The pricing effect is more precisely estimated in this subsample and becomes significantly more pronounced in 2022, highlighting the role of product-level targeting in amplifying green discount.

7.2 Quantity Responses to Product Innovation

To complement the pricing analysis, we examine lending volumes to assess whether green mortgage discounts are associated with shifts in credit allocation. To the extent that these discounts are economically meaningful, we would expect to observe an increasing flow of credit both toward energy-efficient properties and toward lenders offering dedicated green products. We combine PSD transacted mortgage data with lender-level information from Moneyfacts to examine quantity responses to green mortgage pricing. For each quarter, we calculate:

1. The share of mortgage lending against properties with *Green characteristic* relative to total mortgage lending (blue solid line), capturing the overall penetration of energy-efficient properties in the mortgage market.

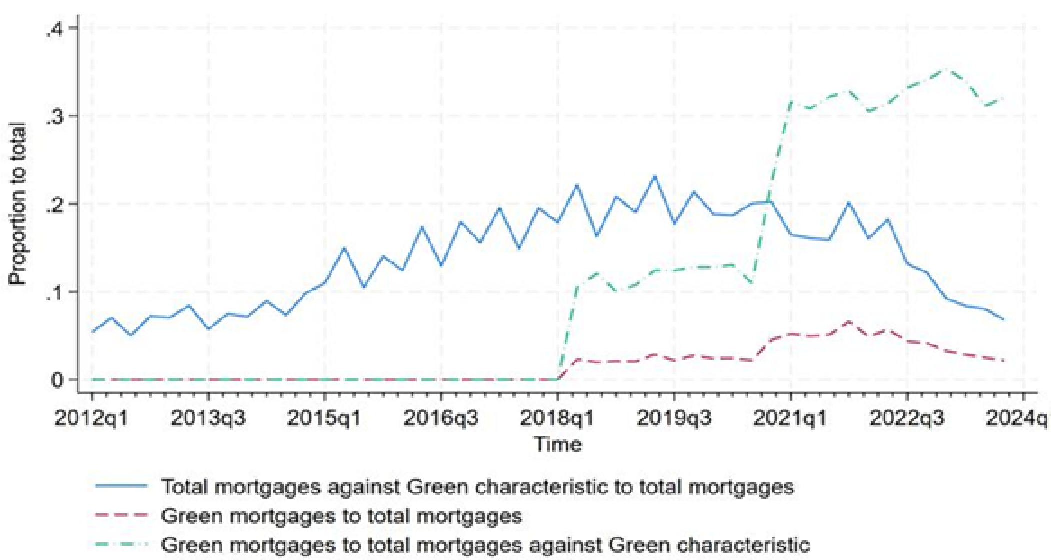
2. The share of "green mortgages"—loans against properties with a *Green characteristic* originated by green lenders—relative to total mortgage lending (red dashed line), isolating the contribution of institutions offering green products to the flow of credit for energy-efficient homes.

3. The share of "green mortgages" relative to total lending against properties with a *Green characteristic* (green dash-dot line), measuring the extent to which green lenders dominate the energy-efficient segment.

[17] Appendix 4 also presents robustness checks using alternative definitions of green lenders. Figure 6 includes lenders offering products for EPC A, B, or C properties, including those with mixed offerings (A/B and A/B/C). Figure 7 excludes all mixed lenders, focusing only on those with consistent EPC A/B/C offerings. Both figures show that the timing and magnitude of the green discount remain broadly consistent, with a re-emergence of the discount in 2022.

Figure 4 plots the evolution of the three quantity-series. The overall share of lending against properties with a Green characteristic (those with an EPC rating of A or B) rises steadily from below 10% in 2012-2014 to approximately 20% by 2018-2021, reflecting broader improvements in housing energy efficiency (blue solid line). More notably, the share of "green mortgages" (loans against properties with Green characteristic originated by green lenders) increases sharply beginning in 2018 (red dashed line), coinciding with the emergence of dedicated green mortgage offerings and the pricing discount documented earlier. A further rise is visible in 2021, aligning with the reappearance of the discount in 2022. The share of "green mortgages" relative to total lending against properties with Green characteristic also increases over time (green dash-dot line), peaking around 2022.

Figure 4: Evolution of Green Lending Shares (Moneyfacts Sample of Lenders)



Notes: This figure plots three series related to the quantity of mortgage lending, highlighting both the overall penetration of green lending and the increasing relevance of green lenders. The blue solid line shows the share of mortgage lending against properties a *Green characteristic*, i.e. those with an Energy Performance Certificate (EPC) rating of A or B, relative to total mortgage lending. The red dashed line shows the share of "green mortgages", those against properties a *Green characteristic* by green lenders, those that advertise green products, relative to total mortgage lending. The green dash-dot line shows the share of "green mortgages" relative to total mortgage lending against properties with a *Green characteristic,* i.e. those with an Energy Performance Certificate (EPC) rating of A or B.

These patterns suggest that the introduction of green mortgage products is not only associated with broader lender participation in energy-efficient lending, but also with a reallocation of market share toward institutions offering dedicated green products. Taken together, the pricing and quantity evidence points to green mortgages as a meaningful form of product innovation, emerging in response to salient policy and market signals and primarily driven by lenders more exposed to regulatory and investor pressure.

8 Implications for Economic Growth

Green mortgage innovation has the potential to influence real economic activity through its impact on housing finance. Our earlier analysis shows that lenders expand their product menus by introducing green mortgages at a discount. If these products disproportionately finance new builds rather than existing properties, they can relax credit constraints for buyers of new builds. Lower borrowing costs shift the demand curve outward; under a relatively elastic supply curve and stable construction costs, this shift makes marginal projects financially viable, leading to an increase in housing supply and construction activity, ultimately contributing to economic growth.

To explore this channel, we examine whether green mortgages are more frequently issued against new builds. Table 10 presents the distribution of mortgage issuance by building age and product category.

Table 10: Share of Green vs New Buildings

	Green characteristic	**No green characteristic**
New building	68%	3%
Existing building	32%	97%
Total	100%	100%

Notes: This table shows the share of green mortgages against properties with EPC rating of A or B (vs. C or D) by building age in the sample period 2013–2023.

Among mortgages against properties with the green characteristic, 68% finance new build purchases, compared to only 3% for baseline mortgages. Conversely, 97% of mortgages with baseline products finance existing properties. This result means mortgages against green characteristic are over 20 times more likely to fund new build purchases than standard loans. Given that these products are priced at a discount, this concentration suggests that green mortgage product innovation primarily benefits new build buyers, reducing financing costs and potentially stimulating construction activity.

While these patterns are descriptive and do not establish causality, they highlight a plausible mechanism through which financial product innovation can amplify policy signals and influence real economic outcomes.

9 Conclusion

In this paper, we develop a framework that treats mortgage contracts as structured bundles of attributes and allows the product space to evolve over time. Leveraging the two-part tariff structure of UK mortgage pricing, we detect when new attributes become pricing-relevant and quantify their effects. We examine product innovation in the UK mortgage market by implementing our framework on the case of green mortgages—products that incorporate environmental attributes into pricing and eligibility. Using linked transaction-level data and offer-level evidence, we document the emergence of a green discount in 2018, the timing of the MEES policy implementation. The discount widens in 2022, coinciding with energy price surge, reaching up to 15 basis points among lenders actively marketing green products. Notably, there was no comparable pricing response to earlier policy announcements or the international Paris Agreement, suggesting that lenders tend to wait for tangible policy action or significant market changes before adjusting product features, rather than responding pre-emptively to high-level policy signals. Pricing responses are heterogeneous with activity being concentrated among large, publicly listed institutions, as they face greater regulatory and supervisory as well as market scrutiny. Mortgages against properties with Green characteristic are disproportionately issued against new builds, suggesting that product innovation can influence credit allocation in ways that can affect housing supply and investment.

From a broader perspective, our findings underscore three insights. First, product innovation may amplify policy signals and economic shocks. By altering credit terms, innovation can shape credit allocation and amplify the effects of regulatory initiatives or macroeconomic events on real activity. Green mortgages illustrate this mechanism in the environmental domain: by embedding energy efficiency into pricing, lenders reinforce climate policy objectives and accelerate the decarbonisation of housing stock. Second, the dynamics of product innovation can serve as an early-warning indicator for supervisors and policymakers. Monitoring how new attributes become pricing relevant provides forward-looking insights into market behaviour and emerging risks, enabling the design of 'future-proof' regulatory frameworks. Historical evidence highlights the cost of neglecting such signals: the rapid growth of adjustable-rate and low-documentation loans in the US subprime market signalled rising fragility well before systemic stress became evident (Demyanyk and Van Hemert, 2011). Third, future research could quantify these channels and examine whether similar dynamics arise in other credit markets, such as SME finance, where targeted product design can influence investment and productivity. Finally, while our focus is on the pricing footprint and diffusion of new product attributes, several related questions remain open. For example, we do not estimate welfare effects, model strategic interactions among lenders, or identify causal impacts on borrower outcomes. Nor do we formally analyse the mechanisms behind banks' innovation decisions. We leave these dimensions to future research, as they would require additional data and methodological approaches.

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Appendix 1. List of Events

Public Policy Signals

- **March 2015 – MEES announced:** The UK government introduced the Minimum Energy Efficiency Standard (MEES), signalling future restrictions on substandard rental properties. This announcement likely raised awareness among lenders about the regulatory risks associated with low-efficiency housing stock.

- **December 2015 – Paris Agreement adopted:** The global commitment to limit warming to well below 2°C marked a turning point in climate policy. For financial institutions, this introduced long-term expectations around carbon exposure and sustainability, potentially influencing how green assets are valued.

- **April 2018 – MEES implemented:** The regulation came into force, making it unlawful to let properties with energy ratings below E unless exempt. This created direct compliance risk for landlords and indirectly affected lenders by altering the risk profile of collateral.

Regulatory Changes

- **April 2019 – PRA Supervisory Statement 3/19:** The Prudential Regulation Authority required banks and insurers to embed climate risk into governance, risk management, and disclosures. This formalised regulatory expectations and may have incentivised institutions to differentiate pricing for green versus non-green products.

- **2021 – Climate Biennial Exploratory Scenario (CBES):** The Bank of England conducted climate stress tests using 2020 balance sheet data. Although applied to a subset of institutions, CBES reinforced regulatory scrutiny of climate risk and may have influenced broader market behaviour and pricing practices.

Economic Shock

- **H2 2022 – Energy price surge:** A sharp rise in energy prices, driven by post-pandemic recovery and geopolitical tensions, highlighted the financial relevance of energy efficiency. This increased credit risk for less energy-efficient homes, while high-EPC properties benefited from lower running costs and improved affordability.

Appendix 2. Baseline Product Structure

Table 11: Mortgage Pricing: Baseline Product Structure (Green characteristic (A–C))

Dependent variable	Mortgage spread		
	(1)	(2)	(3)
Green characteristic		-0.043***	
		(0.007)	
Green characteristic (A–C)			-0.016***
			(0.003)
Gov't support	0.250***	0.265***	0.246***
	(0.051)	(0.045)	(0.046)
Lender fees	-0.337***	-0.344***	-0.346***
	(0.032)	(0.028)	(0.028)
Constant	2.352***	2.342***	2.345***
	(0.032)	(0.028)	(0.028)
Individual FE's	NO	NO	NO
Product FE (3-way)	NO	NO	NO
Product FE (4-way)	NO	NO	NO
Product FE (5-way)	YES	YES	YES
Observations	4,595,741	3,707,282	3,707,282
Number of banks	56	56	56
R^2 (adj.)	0.841	0.843	0.843
Clustered S.E.	YES	YES	YES

Notes: This table presents the results from the mortgage pricing model specified in Equations (9) and (10). The dependent variable is the *Mortgage spread,* and the key explanatory variables are *Gov't support* and *Lender fees.* Column (1) shows baseline results with 5-way fixed effects: *lender × fixed rate bucket × LTmV bucket × year-month × interest rate type.* Column (2) introduces *Green characteristic.* Column (3) introduces *Green characteristic* (A-C), those mortgages against properties with EPC A-C. All regressions are estimated using Ordinary Least Squares (OLS), with standard errors clustered at the lender-by-time level, where time is defined as a year-by-month combination. . Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix 3. Bank Heterogeneity (Pre-2018)

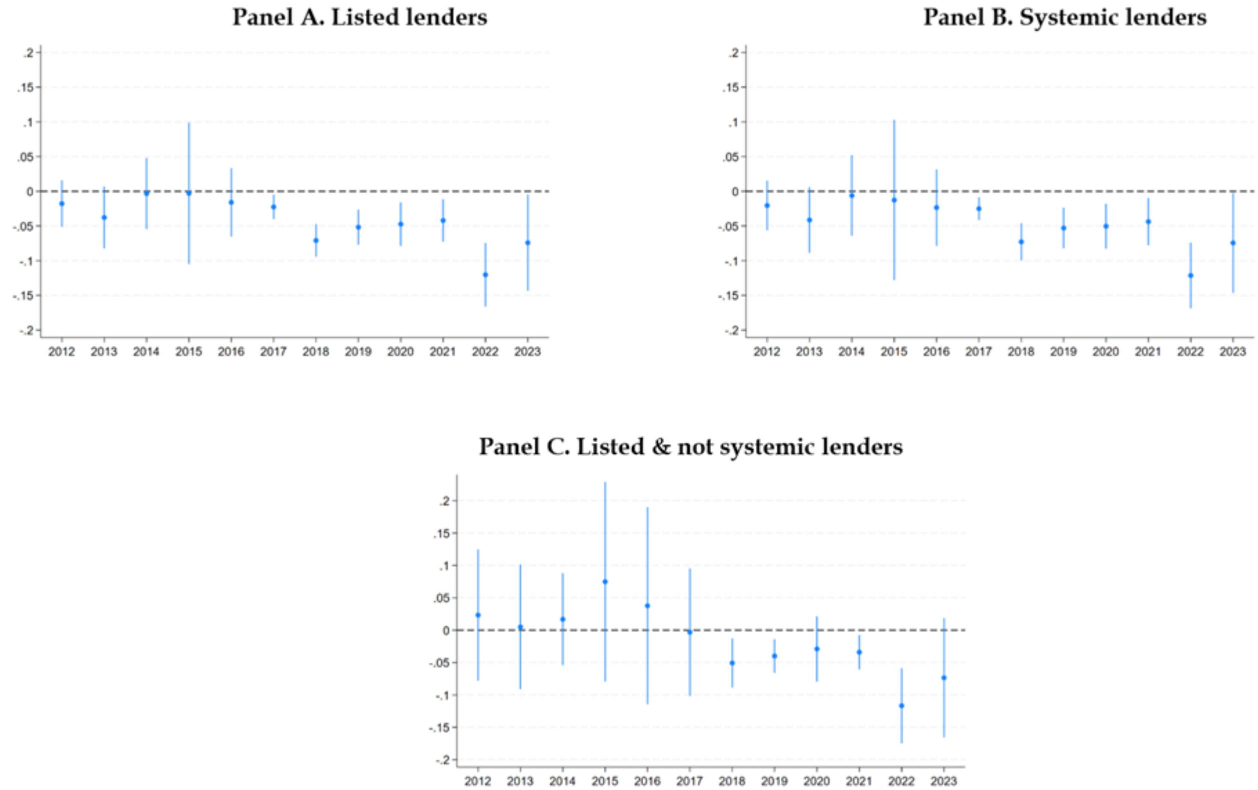
Table 12: Mortgage Pricing: Bank Heterogeneity (Pre-2018)

Dependent variable	Mortgage spread			
	(1)	(2)	(3)	(4)
Green characteristic	-0.034***	-0.001	-0.046***	-0.041***
	(0.012)	(0.028)	(0.013)	(0.012)
Green characteristic × Systemic		-0.040		
		(0.033)		
Green characteristic × Listed			0.013	
			(0.021)	
Green characteristic × Listed				0.064
& not systemic				(0.042)
Gov't support	0.356***	0.357***	0.355***	0.357***
	(0.084)	(0.083)	(0.083)	(0.083)
Lender fees	-0.349***	-0.349***	-0.349***	-0.349***
	(0.060)	(0.060)	(0.060)	(0.060)
Constant	2.992***	2.992***	2.992***	2.992***
	(0.084)	(0.084)	(0.084)	(0.084)
Product FE (5-way)	YES	YES	YES	YES
Observations	1,605,538	1,605,538	1,605,538	1,605,538
Number of banks	52	52	52	52
R^2 (adj.)	0.813	0.813	0.813	0.813
Clustered S.E.	YES	YES	YES	YES

Notes: This table presents the results from the baseline mortgage-pricing model specified in Equation (10) using pre-2018 observations. The dependent variable is the Mortgage spread, and the key explanatory variables are *Green characteristic* as well as Gov't support and Lender fees. All regressions use 5-way fixed effects: lender × fixed rate bucket × LTmV bucket × year-month × interest rate type. Each column interacts *Green characteristic* with a different subsample of banks: Column (1) shows the un-interacted results; Column (2) interact with systemic banks; Column (3) interact with listed banks; Column (4) interact with listed but not systemic. All regressions are estimated using Ordinary Least Squares (OLS), with standard errors clustered at the lender-by-time level, where time is defined as a year-by-month combination. Statistical significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

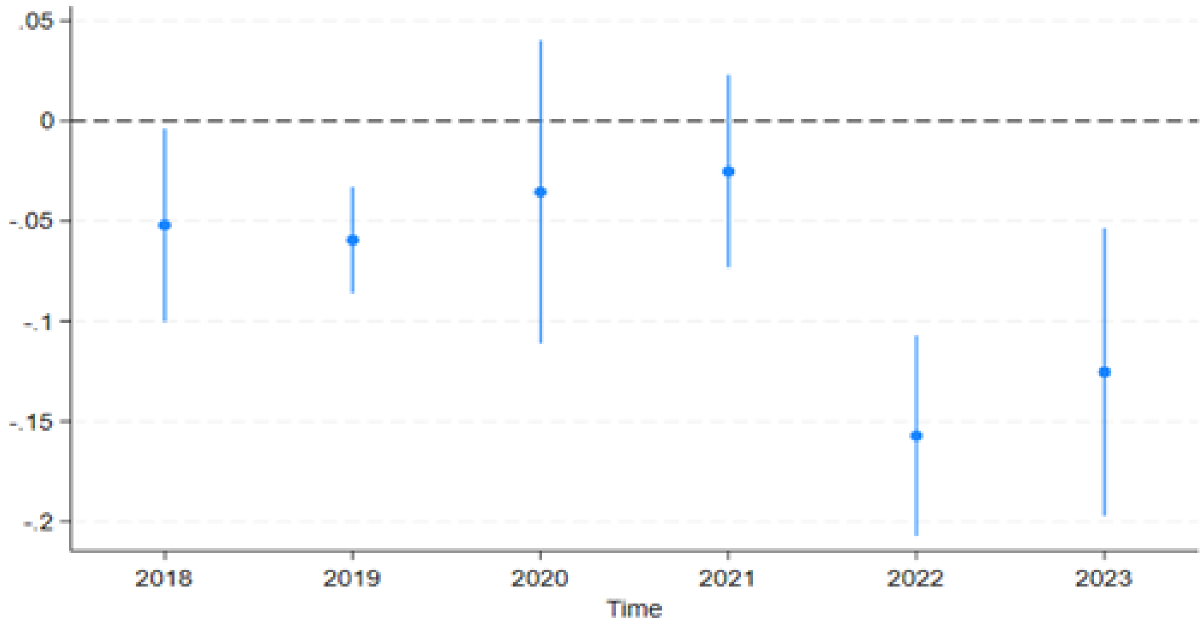
Appendix 4: Additional Timing Effect Figures

Figure 5: Timing of Green Mortgage Price Discount (Sample splits)



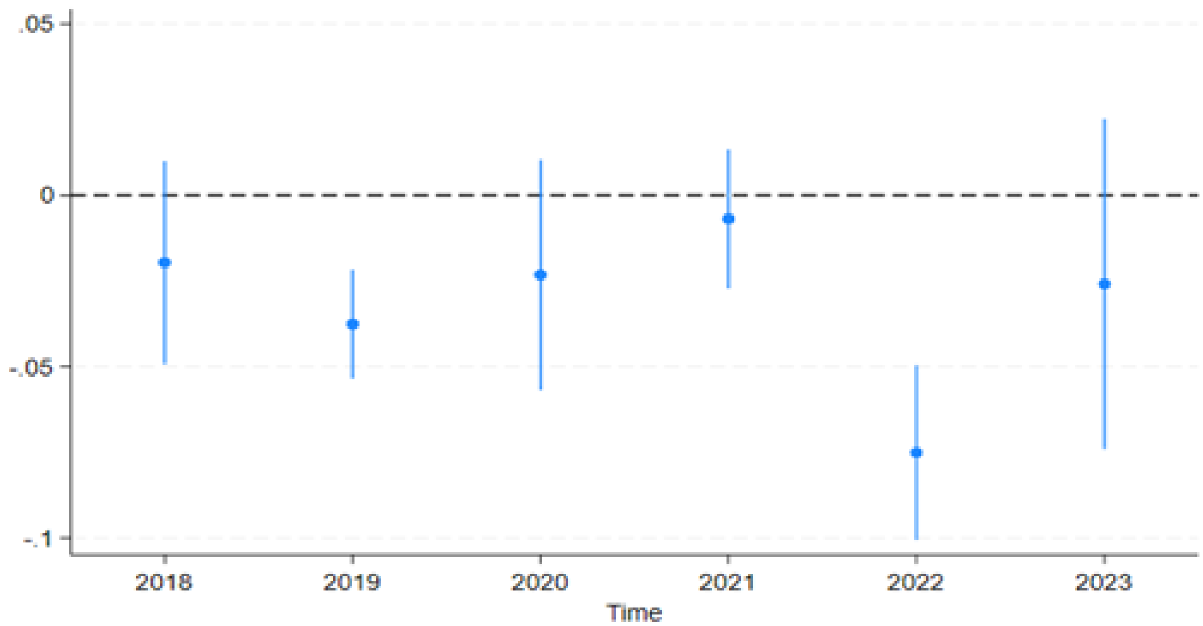
Notes: These figures plot the estimated annual coefficients from a specification that interacts *Green characteristic* with year-specific indicator variables. Panel A shows results for listed lenders. Panel B shows results for systemic lenders and Panel C shows results for listed by not systemic lenders. Each coefficient captures the marginal effect of green status on mortgage spreads in a given year, relative to comparable non-green loans. The specification includes the full set of 5-way product fixed effects (lender × fixed rate bucket × LTmV bucket × year-month × interest rate type), as in Column (5) of Table 2. Standard errors are clustered at the lender-by-time level. The figure traces the emergence and evolution of green mortgage pricing, identifying when lenders began offering green products and whether energy-efficient properties were priced at a discount. Estimates include 95% confidence intervals.

Figure 6: Timing of Green Mortgage Discount (Moneyfacts sample; no mixed lenders)



Notes: This figure plots annual estimates of the green mortgage discount for lenders that introduced green products for properties with EPC rating A or B, as identified in Moneyfacts. We exclude all lenders that offer green products for properties with EPC rating A, B or C (even if they offer both). Estimates are based on transaction-level data from the PSD and include 95% confidence intervals. Estimation begins in 2018, when the first lenders in the Moneyfacts sample introduced green products. The discount appears in 2018, becomes statistically insignificant after 2020, and re-emerges more strongly in 2022.

Figure 7: Timing of Green Mortgage Discount for EPC A–C (Moneyfacts sample; with mixed lenders)



Notes: This figure plots annual estimates of the green mortgage discount for lenders that introduced green products for properties with EPC rating A or B, as identified in Moneyfacts. We exclude all lenders that offer green products for properties with EPC rating A, B or C (even if they offer both). Estimates are based on transaction-level data from the PSD and include 95% confidence intervals. Estimation begins in 2018, when the first lenders in the Moneyfacts sample introduced green products. The discount appears in 2018, becomes statistically insignificant after 2020, and re-emerges more strongly in 2022.