How do lenders price energy-efficiency loans? Evidence from France

Louis-Gaëtan Giraudet,[*] Anna Petronevich,[†] Laurent Faucheux[‡]

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First draft

Abstract

Scaling up home energy retrofits requires that associated loans be priced efficiently. We test this hypothesis using a novel dataset of posted interest rates for unsecured consumer credit in France. We designed a web-scrapping algorithm that collected interest-rate data every week, for two years, from loan simulators made available online by 15 lending institutions covering the near totality of the market. We examine potential pricing distortions with respect to energy-efficient versus non-energy-efficient principals on the one hand, home retrofit versus other household investments – automobiles in particular – on the other. We find that energy-efficient principals carry lower interest rates, which is consistent with efficient pricing and corroborates recent studies. We additionally find evidence of price differentiation of home retrofits and automobiles, which suggests that lenders use loan purposes as a screening device of unobserved borrowers' characteristics. This distortion can undermine efficient pricing along the energy-efficiency dimension.

JEL: D14, G21, Q41

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[*]Centre International de Recherche sur l'Environnement et le Développement (CIRED), Ecole des Ponts ParisTech. Email: giraudet@centre-cired.fr.

[†]Centre International de Recherche sur l'Environnement et le Développement (CIRED), Centre national de la recherche scientifique (CNRS). Email: petronevich@centre-cired.fr.

[‡]Centre International de Recherche sur l'Environnement et le Développement (CIRED), Centre national de la recherche scientifique (CNRS). Email: faucheux@centre-cired.fr.

1. **Introduction**

Home energy retrofits are encouraged by policy-makers from around the world to reduce carbon dioxide emissions and alleviate fuel poverty. As such measures involve high upfront costs, they necessitate financing. In the United States alone, the market for energy-efficiency finance is estimated to amount to $100 billion annually (Freehling and Stickles, 2016). Effective investment scaling-up however requires that energy retrofit loans be priced efficiently.

A variety of information asymmetries can be hypothesized that distort loan terms, along at least two characteristics of home energy retrofits. On the one hand, home energy retrofits are an energy-efficiency technology. As such, they are supposed to reduce energy expenditures. Compared to an otherwise conventional retrofit, say a home painting job, such an extra-return should lower the risk perceived by the lender, hence drive interest rates down. Yet a growing body of literature suggests that home energy retrofits produce fewer energy savings than predicted by engineering models (Metcalf and Hassett, 1999; Fowlie et al., 2015). Failure to observe lower interest rates for energy retrofits than for conventional retrofits would therefore suggest that lenders anticipate such issues. On the other hand, home energy retrofits are one among various household purchases that are financed by credit, including automobiles, major appliances or unexpected expenses. Whereas 75% of automobile purchases in France are financed by credit, this share is as low as 20% for home retrofits, despite comparable amounts borrowed (SOFINCO, 2010; ADEME, 2016). This suggests that borrowers have heterogeneous preferences for different loan purposes, which lenders can exploit to price discriminate. Observation of any purpose-based differentiation of loan terms would lend support to this hypothesis.

In this paper, we compare the pricing of energy retrofit loans to that of otherwise similar investments to test for the existence of information asymmetries in the market for energy retrofit loans. We thereby investigate a little-studied market failure that could explain why energy-efficiency technologies are too slowly adopted – a phenomenon known as the energy-efficiency gap (Jaffe and Stavins, 1994) that has recently gained renewed interest (Gillingham et al., 2009; Allcott and Greenstone, 2012; Gerarden et al., 2017). We also contribute to the literature on loan pricing by introducing purpose-based differentiation, thereby complementing previous studies that have identified discrimination based on gender (Peterson, 1981) and ethnicity (Duca and Rosenthal, 1993).

Research into the financing of building energy efficiency is scarce. The issue was first addressed by Palmer et al. (2012), who described government and utility financing programs implemented in the United States. The authors pointed to the fact that energy-efficiency loans are typically unsecured as the main potential market barrier. Kaza et al. (2014) provide the first comprehensive evaluation of an energy-efficiency loan program. Using U.S. data from the Home Energy Rating System (HERS), the authors found that more energy efficiency, as measured by ENERGY STAR ratings, is associated with lower default and prepayment rates in residential mortgages. Applying a similar research design to commercial mortgages, An and Pivo (2018) confirm that greener buildings are associated with lower default rates. The authors also find a smaller yet significant relationship between greener buildings and better loan terms. Altogether, these results can be interpreted as efficient loan pricing, implying that information asymmetries in energy-efficiency loans are not economically important.

While these studies have focused on the energy-efficiency attribute of building-backed loans, ours examines the interaction between energy efficiency and the purpose of a loan principal. That is, we compare loan terms across four categories of investments: home retrofit versus other household investments – automobiles in particular – each with or without an energy-efficiency attribute. We thus investigate a broader set of information asymmetries than Kaza et al. (2014) and An and Pivo (2018).

We use a unique panel dataset of posted interest rates for unsecured credit in France. We designed a web-scrapping algorithm that retrieved interest-rate data from loan simulators made available online by 15 credit institutions, covering the near totality of the French market. For two years, the algorithm generated data every week from queries about loan amount, duration and, crucially for our analysis, a menu of purposes, which we grouped into the four categories introduced above. Our dataset has several distinctive features compared to those used by Kaza et al. (2014) and An and Pivo (2018). First, we study home retrofits rather than new constructions; given the inertia of the building stock, the former are expected to be more decisive in meeting energy-savings targets. Second, focusing on unsecured credit allows us to isolate the information asymmetries under scrutiny from those associated with collateral in mortgages. Third, our data are immune from any observable information about borrower characteristics, which are not queried by online simulators; we can therefore concentrate on purpose-based differentiation without being confounded by other forms of discrimination. These facilitating features come at the cost of handling deterministic, posted data, instead of realized data. This implies in particular that we cannot study default rates. The fact that the average interest rate in our dataset closely matches that of contemporaneous realized loans however gives some credibility to our analysis.

Controlling for loan characteristics (amount, duration) and macroeconomic variables (government bonds, inflation, energy prices), we find that those institutions that differentiate green and non-green attributes for the same purpose tend to post lower interest rates for the former. This corroborates the finding of An and Pivo (2018), thereby lending further support to the notion that lenders do recognize the value of energy efficiency. Meanwhile, however, credit institutions exhibit no systematic behavior in the way they value home retrofits compared to other household investments. This suggests that some purpose-based discrimination might be at play, perhaps by using loan purpose as a screening device of borrowers' creditworthiness. Overall, our analysis illustrates that some market failures seemingly unrelated to energy efficiency might in fact affect energy-efficiency investments. Overlooking them can lead to under-estimate the energy-efficiency gap.

The analysis proceeds as follows. Section 2 formulates testable hypotheses. Section 3 describes the data collection procedure. Section 4 provides some descriptive statistics of loan terms. Section 5 details the empirical approach. Section 6 discusses the results. Section 7 concludes.

2. Testable hypotheses

When setting interest rates, the lender adds to the borrowing rate a spread meant to reflect the risk perceived in relation to the project. Risks can stem from several sources – the maturity of the loan, the characteristics of the underlying asset, or purpose, and the borrower's characteristics. While the relationship between the maturity and the interest rate is determined by the so-called yield curve, the other two risks must be appraised by the lender. In the context of home energy retrofits, they can both be subject to information asymmetries.

To begin with, compared to a conventional asset, a home energy retrofit produces an extra-return in the form of reduced energy expenditures. In a perfectly functioning credit market, the associated loan should therefore carry a lower interest rate. Yet an increasing number of studies point to energy retrofit projects that fail to deliver predicted energy savings (Metcalf and Hassett, 1999; Fowlie et al., 2015; Graff Zivin and Novan, 2016). While these studies attribute the missing savings to modeling flaws in engineering calculations, Giraudet et al. (2018) propose an alternative explanation rooted in information asymmetries. Evaluating a home weatherization program conducted in Florida, they provide evidence that retrofit contractors engage in moral hazard by under-providing quality in partly unobservable measures such as insulation installation or duct sealing. If such problems make lenders unable to appraise the extra-return supposedly associated with energy efficiency, then the associated loans will be priced the same as those associated with conventional, non-energy-efficient assets.

Hypothesis 1. *If energy efficiency is unobservable, then the interest rate for such projects will be the same as for projects that have no energy-efficiency attribute.*

Preliminary analysis by Kaza et al. (2014) and An and Pivo (2018) reject this hypothesis, thereby failing to provide evidence of information asymmetries surrounding energy efficiency. Note that the extra-return can materialize in two ways. First, reduced energy expenditures increase the borrower's creditworthiness. Second, if housing markets recognize the value of energy efficiency – which existing analyses suggest they do (Brounen and Kok, 2011) – then an energy retrofit generates a rental or resale premium. An and Pivo (2018) emphasize this second mechanism by identifying a loan-to-value channel where the risk is lowered by an energy-efficiency premium.

Turning to the second information asymmetry, if lenders cannot observe borrowers' characteristics, they might use the purpose of the loan as a screening device. Different purposes would then lead to different interest rates, depending on the lender's perception of the associated risk. In the area of interest, the respective size of the markets for auto loans and retrofit loans suggests that the latter is a more exclusive purchase. In fact, while car purchases are largely disconnected from borrowers' tenure type, home energy retrofits are overwhelmingly conducted by homeowners, who tend to be wealthier. All other things being equal – in particular, absent any energy-efficiency attribute – a price-discriminating lender might therefore consider a home retrofit a less risky project than an automobile.

Hypothesis 2. *If borrowers' characteristics are unobservable, lenders might engage in price discrimination by offering lower interest rates for home retrofits than for automobiles.*

In practice, loans terms are negotiated between the lender and the borrower during the underwriting process, at which time the lender does observe key applicants' characteristics. Purpose-based differentiation probably becomes irrelevant at that stage. It is more likely to occur earlier on when loan terms are posted, then generating differences in interest rates that subsequent negotiation might not completely clear. This early process is the one studied in our analysis.

3. Data

3.1. Collection procedure

Our dataset consists of a weekly record of posted interest rates collected from online credit simulators. We designed an algorithm that retrieved interest-rate data for unsecured credit from queries about loan size, maturity, and a menu of designations. Importantly, all simulation results were accessible without providing further information about the applicant's characteristics. The algorithm was run automatically for 93 weeks, from January 2015 to October 2016. All credit institutions which, to our knowledge, offer online credit simulators in France were surveyed. This includes 15 institutions of different nature, which altogether represent the six main French banking groups (Table 1). The dataset thus covers the near totality of the French market for consumer credit. The panel is unbalanced due to occasional difficulties in accessing some banks' simulators.

Type of institution	**Institution**	GroupGroups
Public bank	**La Banque postale**	La Banque postale
Private banks	**BNP Paribas**	BNP Paribas
	LCL	Groupe Crédit agricole
	Société générale	Société générale
	Crédit agricole	Groupe Crédit agricole
	Caisse d'épargne	Groupe BPCE
	Crédit mutuel	Groupe Crédit mutuel
Credit finance establishments	**Cofinoga**	BNP Paribas
	Cofidis	Groupe Crédit mutuel
	Prêt d'union	Groupe Crédit mutuel
	Domofinance	BNP Paribas
	Franfinance	Société générale
	Financo	Groupe Crédit mutuel
	Cetelem	BNP Paribas
	Sofinco	Groupe Crédit agricole

Table 1. Characteristics of the credit institutions surveyed

Each week, for a given institution, for each designation, loans were simulated for a combination of 11 different amounts – ranging from 5,000€ to 32,500€, with a step of 2,500€ – and 8 different maturities – ranging from 12 to 108 months, with a step of 12. The average loan size and maturity over the whole dataset are 16,785€ and 47 months, respectively.[1] Figure

[1]To put these numbers in perspective, the average national averages are 11,449€ and 47 months, respectively.

1 displays summary statistics of amounts and maturities, by institutions and designations. It shows that sampling was not homogeneous across institutions, due to heterogeneity in the range of amounts and maturities they offered for simulation. Yet averaging the data by loan purpose tends to attenuate these biases.

Overall, the panel comprises 240,962 simulations, or observations, all of which are 4-tuples of institution, designation, amount and maturity. Four outputs were recorded per simulation: the nominal interest rate; the fees; the *taux effectif global*, i.e., annual percentage rate (APR), which expresses the yearly cost of the loan, including the fees; and the *taux annuel effectif global*, i.e., annual percentage yield (APY), which compounds the APR.

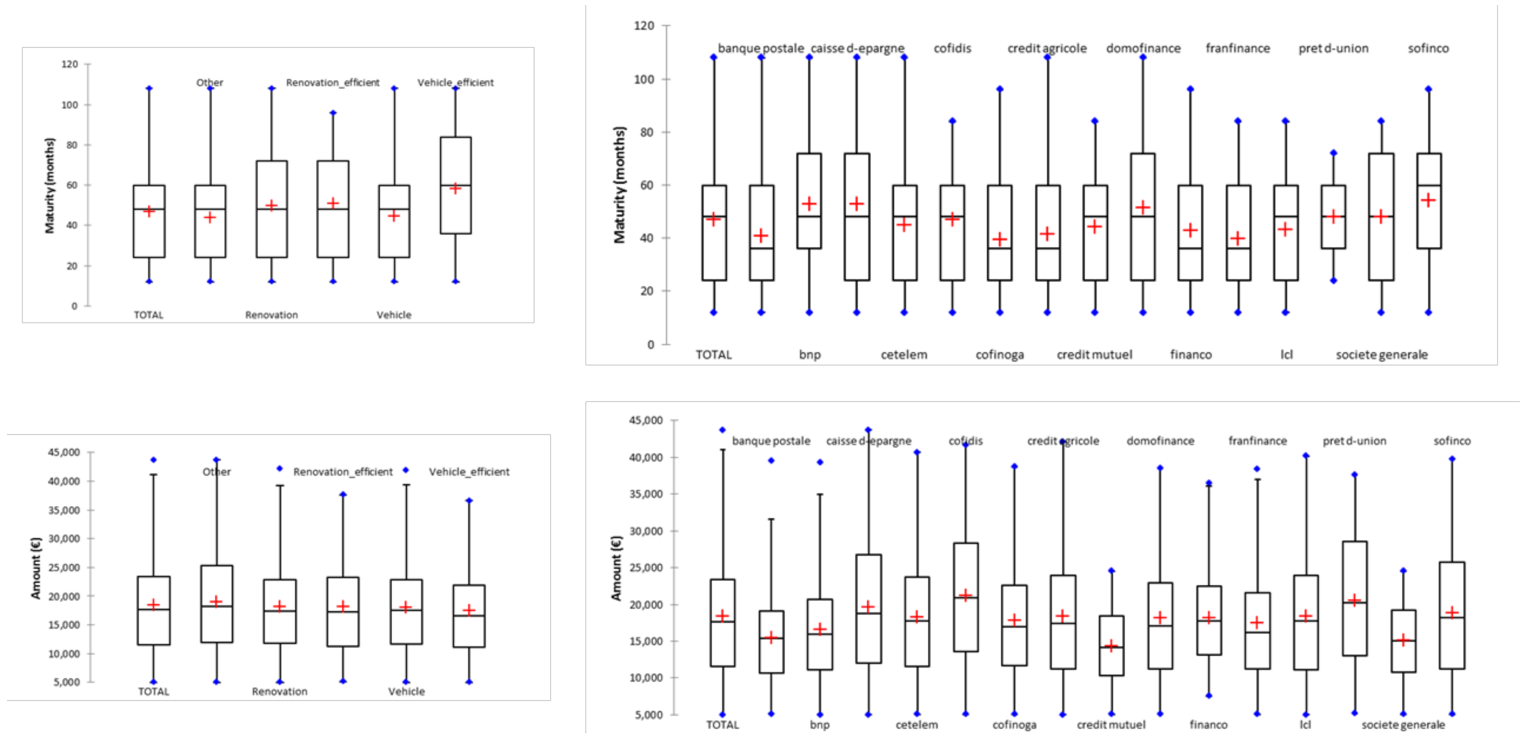

FIGURE 1. Summary statistics of simulated amounts and maturities

Collected entries (90)	Categorization 0	Categorization 1	Categorization 2	Categorization 3
Car, motorcycle	Auto	Auto	Auto	Normal
Used car, used vehicle, used boat, used camping car, used trailer, used motorcycle	Auto_used	Auto	Auto	Normal
Brand new vehicle, Brand new car, Brand new or less than 2-year-old car, brand new or less than 2-year-old camping car, brand new or less than 2-year-old trailer, brand new or less than 2-year-old motorcycle	Auto_new	Auto	Auto	Normal
Brand new efficient car	Auto_efficient	Auto_efficient	Auto	Green
Other works, decoration, construction, veranda, indoor/outdoor design	Retrofit	Retrofit	Retrofit	Normal
Boiler, wood boiler, electrical heating, water heating, windows, insulation, heat pumps, heating, home improvement	Retrofit_efficient	Retrofit_efficient	Retrofit	Green
Other project, consumption, relocation, wedding, birth, DIY supplies, holidays, event, leisure	Consumption	Other	Other	Normal
Health, Family problems	Health	Other	Other	Normal
Need for money, Need for cash, budget	Liquidity	Other	Other	Normal
Student loan	Student	Other	Other	Normal
Electronic device, appliances, Hi-fi, furniture, computer accessories	Equipment	Other	Other	Normal

Table 2. Categorization of loan designations

3.2. Loan categorization

The number of options offered by the institutions in their menu of loan designations vary widely. Over the period, the algorithm captured 90 different designations across all institutions (Table 2). Many options only differ from one another through slight variations in labeling. We group redundant labels into broad categories, thereby restricting designations to auto loans, home retrofit loans, equipment loans, consumption loans, student loans, health loans and cash loans (categorization 0).[2]

As our empirical analysis intends to compare home energy retrofits to non-energy retrofits on the one hand, all retrofits to other investments on the other hand, we further restrict the number of categories. In doing so, we sort out auto loans from non-retrofit investments, for

[2]To put these numbers in perspective, in France, in 2017, 47% of consumer credit issued was dedicated to auto purchase, 19% to equipment purchase, 10% to home retrofits, 8% to consumption, 8% to liquidity, 4% to credit restructuring and 4% to tax payments (Mouillard, 2018).

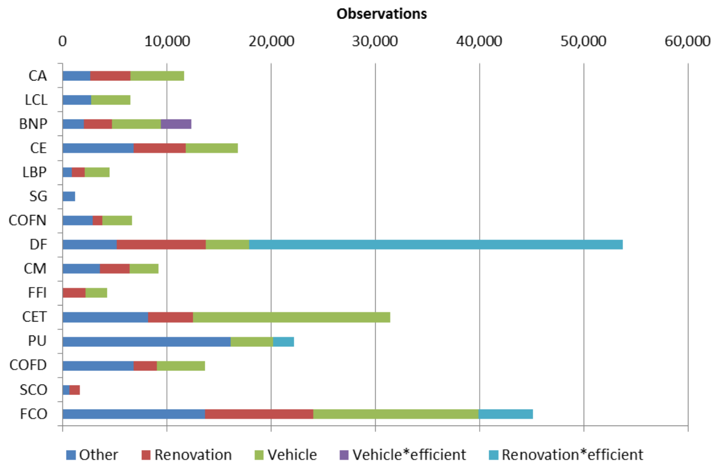

FIGURE 2. Observations, by issuing institution and loan designation

two reasons: first, auto loans form the bulk of non-retrofit investments; second, our dataset has the interesting feature of including a green automobile designation. Ultimately, our workable dataset includes five categories: energy retrofits, other retrofits, green automobiles, other automobiles, and other investments (categorization 1). As will be discussed later, we subject this categorization to robustness checks.

Figure 2 displays the number of observations by institution and designation. Eleven institutions offer both auto and retrofit loans; four institutions – Cetelem, Domofinance, Financo and Prêt d'Union – differentiate energy and non-energy retrofits; one institution only – BNP Paribas – differentiates energy-efficient cars from other cars.

4. Descriptive statistics

We focus below on the average percentage yield (APY), which summarizes all characteristics of the loan, including the fees.

4.1. Cross-section

Figure 5 shows that the average APYs vary widely across institutions. This highlights heterogeneity in pricing strategies, which is probably related to differences in consumer portfolios.

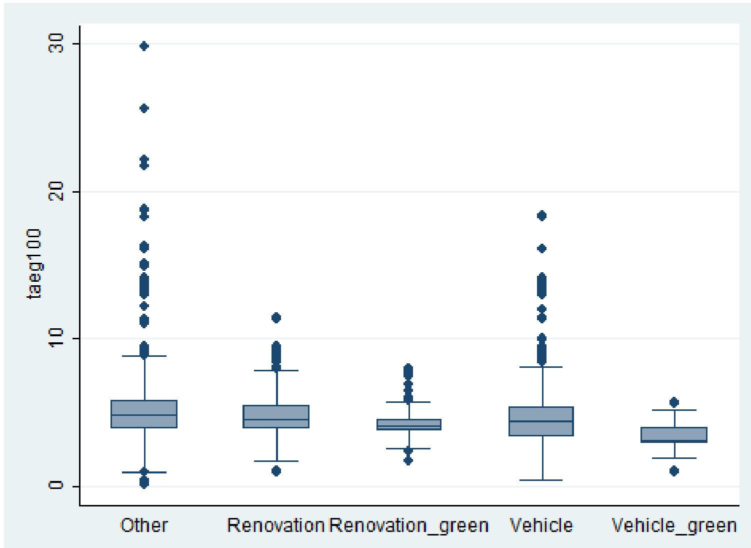

FIGURE 3. Average APY by designation

Figure 6 approximates the average yield curve of the market. While increasing maturities yield higher interest rates, the relationship is noisy. The 12-month maturity stands out as linked to particularly low rates. As the data are deterministic, we could in theory recover the online simulators' algorithms. While this occasionally occurs, as Figure 9 illustrates, it is not systematic. Our categorization, in particular, might introduce some averaging that creates noise.

On average, energy-efficient loans carry lower interest rates than loans of other types. Importantly, the standard deviation of the spread is also smallest for energy-efficient loans, suggesting that credit institutions recognize the value of energy efficiency (see Figure 3). Yet a closer look at the data shows that this behavior is not consistent across institutions. In particular, Cetelem prices green loans on average 0.83 percentage points (p.p.) higher while BNP Paribas is 0.58 p.p. cheaper.

4.2. **Time series**

Figure 4 compares the trend of the average posted rate in the dataset and the average interest rate provided by the Banque de France (BdF) for realized consumer loans. The former somehow parallels the latter with a lag of approximately three weeks.

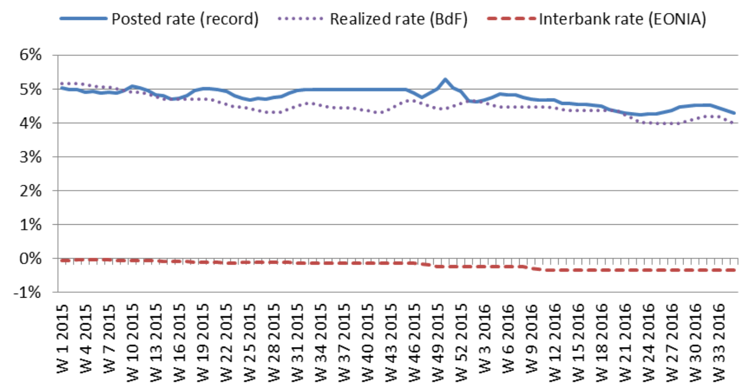

FIGURE 4. Average APY by maturity

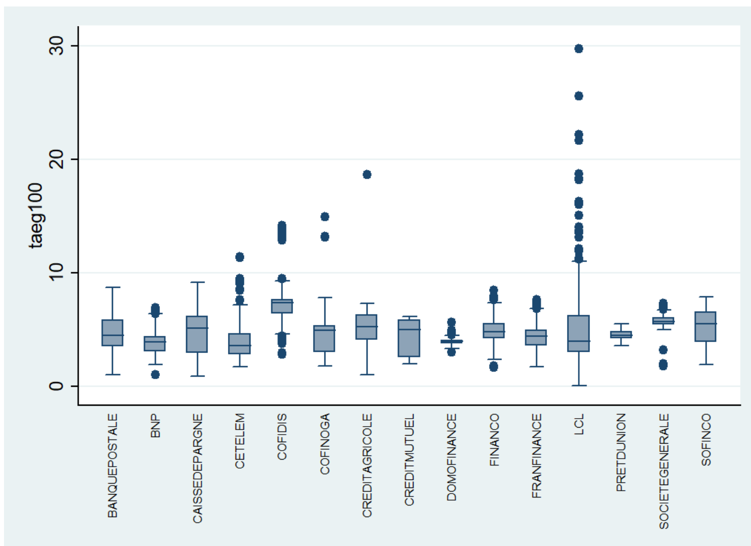

FIGURE 5. Average APY by institution

Figure 7 is the dynamic version of Figure 6. It shows that from early 2016 on, the interest rate of loans with a 12-month maturity diverges from that of loans with other maturities.

Figure 8 shows that some differences between loan designations are stable over time, but not all. Energy-efficient automobiles – for which specific loans are only offered by BNP Paribas – consistently carry low interest rates. In contrast, the differences between autos and retrofits are not consistent.

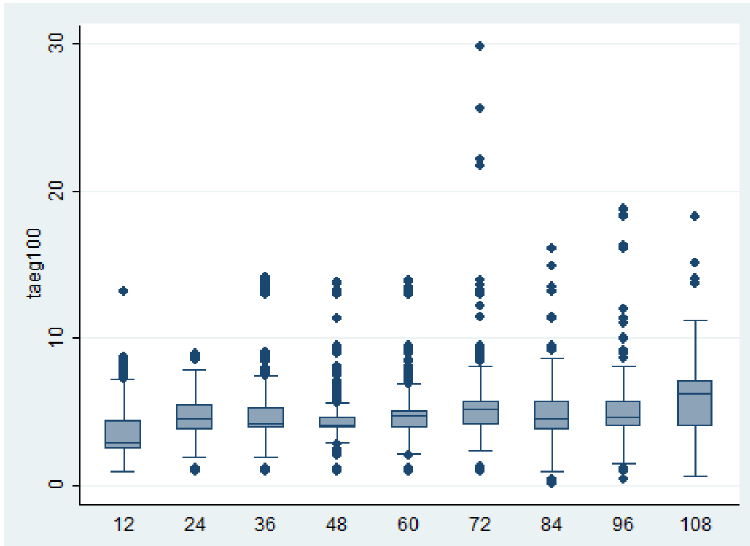

FIGURE 6. Average APY by maturity

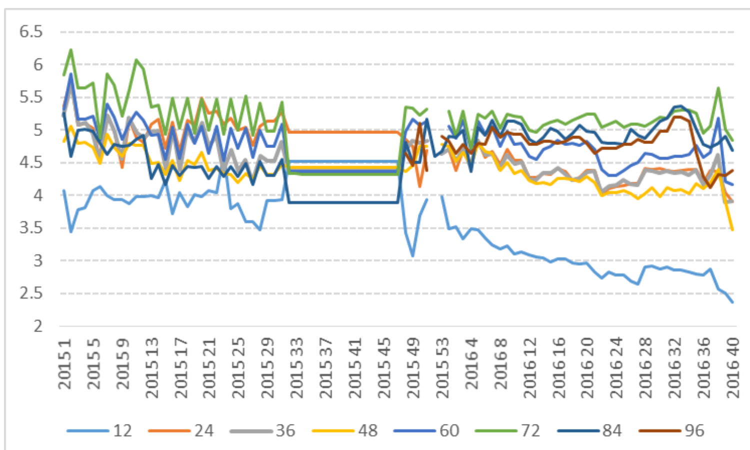

FIGURE 7. Dynamics of average APY by maturity

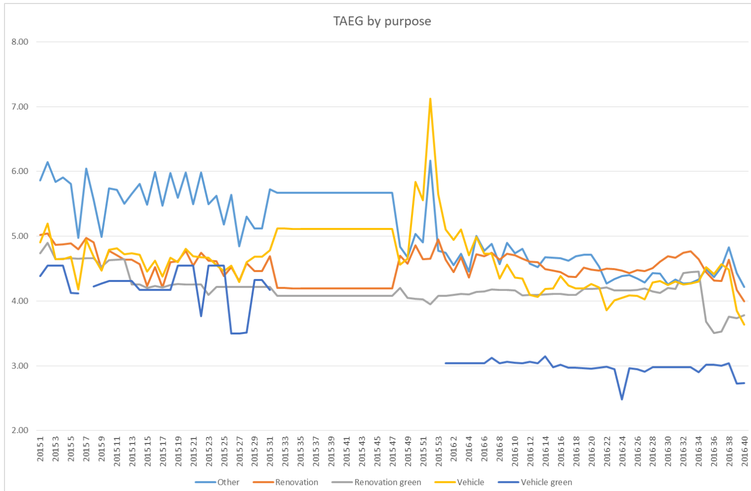

FIGURE 8. Average of average APY by designation

5. Empirical strategy

5.1. Dependent variable

We consider the spread s defined as the difference between the interest rate (APY) i and the spot yield of the government bond b of the same maturity:[3]

$$s_{kamtc} = i_{mt} - b_{mt}, \tag{1}$$

where $k \in \{1, ..., 15\}$ denotes the lending institution, $a \in \{5000, 6500, ..., 32500\}$ the amount simulated, $c \in$ {Other,Retrofit,RetrofitGreen,Auto,AutoGreen} the category of the principal, $m \in \{12, 24, ..., 108\}$ the maturity of the loan and t the week on which the loan was simulated.

By focusing on the spread, we intend to make inference on how institutions assess the risks associated with different loan designations. Using that metric rather than the interest rate allows us to address potential endogeneity problems that may arise due to the omission of factors simultaneously affecting loan terms and government bonds.

Since our data is deterministic, we could in theory recover the exact functional form of the pricing equation for each institution. Yet a preliminary analysis of the spread[4] as a function of durations and amounts *ceteris paribus* suggests that the data provide little

[3]Source: ECB, Data Source in SDW: Government bond, nominal, all issuers whose rating is triple A - Svensson model - continuous compounding - yield error minimisation - Yield curve spot rate - Euro, provided by ECB

[4]The same analysis was performed on the APR and APY series.

insight into such a functional form. If anything, the shape of the obtained curves (peaks and level shifts) indicates that the interest rate is determined as some function plus arbitrary mark-ups defined by the current price policy of an institution. We do occasionally observe a neat dependence, for instance with green-auto loans simulated from BNP Paribas, the yield curve of which is non-linear with the duration (Figure 9). Yet in most cases, the amount simulated does not impact the APY and so the spread.

In the absence of a clear insight from the data, we use functional forms derived from classical models of credit scoring for consumer loans. Specifically, we use logistic regressions (i.e., logit models), which are the most widely used owing to their parsimony and good performance (see Finlay (2012)). The common measure of risk in credit-score models is the odds ratio, i.e., the ratio between the potential number of defaults and the potential number of non-defaults, the latter being characterized by a linear combination of the borrower's characteristics and economic conditions. For any vector of risk factors x, the probability of default is given by the logistic function:

$$F(x) = \frac{1}{1 + \mathrm{e}^{-(\beta_0 + \beta_1 x)}}, \tag{2}$$

where β_0 β_1 is the vector of coefficients reflecting the log of percentage change of odds of defaulting on a loan in response to a unit change in the corresponding elements of x. The logit function is the inverse of that logistic function, that is, a function $g(F(x))$ such that:

$$g(F(x)) = \ln \frac{F(x)}{1 - F(x)} = \beta_0 + \beta_1 x. \tag{3}$$

The term in the logarithm is the odds ratio, which approximates the creditworthiness of the borrower or the risk attached to the loan. Assuming that the APY is constructed as the sum of the interest rate on a riskless bond of the same maturity and a measure of risk, the APY spread should therefore be described by the odds ratio. For this reason, we use a simple linear model in our analysis of spreads.

5.2. **Explanatory variables**

A distinctive feature of our dataset is that it is made up of data generated by credit institutions without factoring in the borrower's characteristics which in practice affect the terms of the realized loan. We therefore consider usual explanatory variables for credit pricing (e.g., Gambacorta (2008), Thomas et al. (2002), An and Pivo (2018)), less borrowers' characteristics. The retained variables, emphasized below, fall into several categories. Descriptive statistics are provided in Table 6.

Loan characteristics. We expect a longer *duration* to increase cumulative risks, thus implying a higher spread. Building on the non-linear relationship fitted in Figure 9, we include the second- and third-order terms. Similarly, we consider a greater *amount* to be more difficult to repay and therefore command a higher spread. The *loan type* dummies are central to our analysis. As formulated in Section 2, we use them to investigate information asymmetries potentially associated with energy-efficiency projects on the one hand, applicants' characteristics on the other. We include *lender* fixed-effects, assuming that different lenders might adopt different pricing strategies, depending on their client portfolio, size or capitalization. The interaction between loan types and lender types allows us to reveal the peculiar behavior of each institution in pricing each type of loan. The coefficients associated with the *loan type * lender* term can be interpreted as the additional effect of a particular institution for a particular loan type with respect to the average effect for this institution and the average effect of this type of loan.

Macroeconomic factors. To approximate the *inflation rate* and the *phase of the business cycle*, we use respectively the harmonized index of consumer prices (hicp) and the unemployment rate (u). As unemployment is likely to be a crucial determinant of default rates in consumer credit, we conduct robustness checks in which we alternatively approximate it by the growth rate of the index of industrial production and the temporary component of the index of industrial production. Regarding the *macroeconomic policy*, the period considered is remarkable in that the European Central Bank (ECB) massively engaged in quantitative easing. We therefore include the interest rates on one-year Euro area government bonds (ir_1y). We approximate investor's *expectations* by the yield-curve slope (yc_slope), defined as the yield difference between ten-year and one-year government bonds (see, for example, Chinn and Kucko (2015)). A higher slope implies more optimistic expectations on future risks. Presumably, positive expectations drive interest rates down.

Financial conditions. We approximate the *volatility in the stock market* by the spread between the return on CAC40 index and the interest rate on one-year government bonds (CAC40_spread), reflecting the current perception of risk in the stock market, which may translate into higher loan interest rates. We approximate the *volatility in the bond market* by the ciss_stress index provided by the ECB.[5]

Energy prices. Energy prices can intuitively be an important determinant of the demand for green loans, with a higher price increasing the demand for both fuel-efficient cars and home energy retrofits. We therefore include the gasoline price (e_s95) in the main regressions and add the prices of electricity and natural gas in robustness checks.

5.3. Econometric model

We model the APY spread as a linear combination of its determinants:

$$s_{jt} = \alpha_0 + \alpha_1 L_j + \alpha_2 M_t + \alpha_3 F_t + \beta_1 C_j + \beta_2 I_j + \beta_3 C_j * I_j + \gamma E_t * C_j + \varepsilon_{jt}, \tag{4}$$

where j is the 4-tuple (k, a, m, c), L_j the vector of loan characteristics, M_t the vector of macroeconomic variables, F_t the vector of financial conditions, E_j the energy price, C a set of loan-category dummy variables and I_j a set of institution dummy variables.

We estimate the unknown parameters α_0, α_1, α_2, α_3, β_1, β_2, β_3 and γ. By analyzing the sums of the relevant elements in β_1, β_2 and β_3, we can make inference, for each institution, on the hypotheses formulated in Section 2:

H 1. $\beta_1^{green} = \beta_1^{nongreen}$

H 2. $\beta_1^{retrofit} \leq \beta_1^{automobile}$

6. Results

6.1. Estimation

The results are given in the Table 3 below. The columns correspond to six different specifications characterized by an expanding set of explanatory variables. Specification (1) basically includes loan characteristics, macro factors and financial conditions; Specification (2) adds loan type dummies; Specification (3) further adds lender dummies; Specification (4) adds the interaction term loan type * lender dummies; Specification (5) adds an interaction term loan type * energy price; Specification (6) adds time fixed-effects.

[5] Euro area (changing composition), Stress subindice - Bond Market - realised volatility of the German 10-year benchmark government bond index, yield spread between A-rated non-financial corporations and government bonds (7-year maturity bracket), and 10-year interest rate swap spread, Contribution.

Table 3. Estimation results

Dependent variable	Model					
Spread APY	(1)	(2)	(3)	(4)	(5)	(6)
intercept	4.449***	3.757***	4.305***	4.029***	1.612***	-2.304
	(28.34)	(24.33)	(29.63)	(28.67)	(7.83)	(-0.00)
Loan characteristics						
duration	0.100***	0.0985***	0.102***	0.102***	0.103***	0.103***
	(68.68)	(69.00)	(81.34)	(86.67)	(87.01)	(87.88)
$duration^2$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-50.16)	(-51.36)	(-63.24)	(-67.60)	(-67.97)	(-68.89)
$duration^3$	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(39.03)	(41.88)	(54.35)	(58.18)	(58.57)	(59.58)
amount	-0.020***	-0.020***	-0.025***	-0.025***	-0.025***	-0.025***
	(-50.70)	(-52.52)	(-74.11)	(-77.62)	(-77.26)	(-77.18)
Macroeconomic factors						
ir_1y	-0.343***	-0.155***	-0.219***	-0.266***	-0.380***	1.611
	(-14.53)	(-6.68)	(-10.48)	(-13.47)	(-16.63)	(0.00)
hicp	-0.234***	-0.241***	-0.201***	-0.203***	-0.229***	0.124
	(-43.02)	(-45.29)	(-42.51)	(-45.91)	(-45.09)	(0.00)
u	-0.082***	-0.002	-0.069***	-0.030*	-0.027*	-0.022
	(-5.79)	(-0.17)	(-5.43)	(-2.52)	(-2.25)	(-1.85)
Financial factors						
CAC40_spread	0.022	0.096***	0.103***	0.092***	0.079***	3.082
	(1.78)	(8.05)	(9.64)	(9.17)	(7.75)	(0.01)
ciss_stress	-2.918***	-3.069***	-1.599***	-1.314***	-1.075***	-28.65
	(-12.80)	(-13.75)	(-8.11)	(-7.11)	(-5.75)	(-0.00)
yc_slope	-0.388***	-0.413***	-0.407***	-0.417***	-0.406***	-0.468
	(-21.74)	(-23.61)	(-26.38)	(-28.78)	(-28.03)	(-0.00)
Indicator variables						
loan type		X	X	X	X	X
lender			X	X	X	X
loan type*lender				X	X	X
loan type*fuel price (S95)					X	X
time dummy						X
N	240962	240962	240962	240962	240962	240962
R-sq	0.083	0.121	0.321	0.404	0.405	0.410
R-sq adj.	0.083	0.121	0.321	0.404	0.405	0.410

t-statistics in parentheses

p<0.1, **p<0.01, ***p<0.001

The estimates are comparable in value and sign across Specifications 1 to 5, but differ substantially in Specification 6. The loss of significance for many variables when the time dummy is added is due to the fact that most temporal effects are already captured in time-varying variables. We therefore focus our attention on Specifications 1 to 5.

We find that loan characteristics and economic factors explain a very modest part of the variation of the spread, which is consistent with previous findings (e.g., Gambacorta (2008)). As expected, the APY spread is positively related to the duration, though at a decreasing rate. In contrast, the loan amount has a negative but weak impact. The effect of quantitative easing and inflation is negative, which we attribute to expectations of economic recovery. The effect of unemployment is negative but low in absolute value, suggesting that unemployment insurance offered by the lender during the negotiation process can mitigate risks (similar results was obtained by Hsu et al. (2012)). Surprisingly, the systemic risk indicator $ciss_stress$ contributes negatively to the APY spread. Higher risks in the equity market, as approximated by the CAC40 spread, are positively related to the APY spread, implying that lenders transfer part of the portfolio risks to their clients. As expected, the impacts of the inflation rate and the yield curve slope are negative.

The inclusion of loan type dummies in Specification 2 helps explain slightly more variation – the R^2 rises from 0.08 to 0.12 – but it is mainly the institution fixed-effects that contain most of the information on pricing policies – the R^2 rises further up to 0.32. Adding interactions in Specification 4 helps further disentangle the variation across institutions and designation – with an R^2 of about 0.4. The energy price has a significant impact on the spread, largest for green autos and then on other purposes, green retrofits, retrofits and automobiles. Yet the energy price does not have much explanatory power.

Table 4 shows average effects by institutions (last column), loan type (last line) and additional institution-loan type effects (body of the table). The estimates suggest that loans for energy-efficiency projects are priced at a lower rate than their less energy-efficient counterparts. We therefore reject H1, thereby confirming the results of Kaza et al. (2014) and An and Pivo (2018). In addition, the institutions appear to price retrofit loans at lower rates than auto loans (both conventional), suggesting that H2 is verified.

Regarding institutions' idiosyncratic policies, Cofinoga appears to be the most expensive institution, followed by Credit Mutuel, Societe Generale and Financo. At the opposite end, Caisse d'Epargne, BNP Paribas and Cetelem offer the lowest rates.

Table 4. Effects by loan type and lender

	retrofit	retrofit green	automobile	automobile green	Average lender effect
BNP	0.16		-0.27	0.00	-0.81
CAISSEDEPARGNE	1.39		1.85		-1.13
CETELEM	0.38	0.52	-0.20		-0.73
COFIDIS	0.00		0.17		2.00
COFINOGA	-0.59		-0.51		0.34
CREDITAGRICOLE	0.00		-0.19		0.47
CREDITMUTUEL	-3.53		-0.78		1.01
DOMOFINANCE	-0.32	-0.29			-0.52
FINANCO	-0.33	-0.52	-0.63		0.41
FRANFINANCE	0.48				-0.53
LCL			1.09		-0.68
PRETDUNION			0.11		-0.23
SOCIETEGENERALE					0.42
SOFINCO	1.21				-0.18
Average designation effect	1.87	1.59	2.13	-6.99	

The Banque Postale and "Other" were omitted from the analysis to avoid the multicollinearity problem. The empty cells refer to cases with no observations on the corresponding bank and designation or also omitted due to multicollinearity.

6.2. Robustness checks

We subject Specification 5 of the model to a series of robustness checks (see Table 5).

Loan categorization. We use a three-fold categorization of loans (categorization 2: Other, Retrofit, Auto) and a further restrictive two-fold one (categorization 3: Green and Normal) and find little impact on regression coefficients.

Institution category. We verify that grouping institutions by the group they belong to or the type of ownership does not affect the result. However, using institution-type fixed-effects instead of lender fixed-effect reduces the explanatory power, with the bank ownership type even becoming less informative than the bank group.

Energy prices. Using residential fuels, namely electricity and natural gas (*e_elec* and *e_gnat*, respectively), instead of the gasoline price, we find the CAC40 spread to become insignificant. Other results are little affected, so the fuel type is in general irrelevant for the APY spread when controlling for energy price.

Proxies for the business cycle. We replace the unemployment rate by the growth rate of the index of industrial production *d_ipi* and the temporary component of the index of industrial production *ipi* and find industrial production to be positively associated with the APY spread, thereby confirming the negative sign of the unemployment rate coefficient. Otherwise, there is little impact on the coefficients of the other explanatory variables.

In general, the previously obtained estimates prove to be robust to alternative specifications. H1 is still rejected when using the two-fold categorization (Specification 2), green loans being priced 0.49 p.p. lower. However, with the three-fold categorization, retrofit loans entail a slightly higher spread than auto loans, therefore questioning the validity of H2.

The estimates reveal substantial differences in the behavior of banking groups. In particular, Credit Mutuel and Societe Generale charge on average 1.6 p.p. and 1.3 p.p. higher than BCPE group. Meanwhile, BCPE stands out by charging highest spreads on "Other" loans and lowest spreads on auto loans. Private institutions on average set the lowest rates, whereas credit establishments charge a 0.9 p.p. higher rate. In addition, only credit establishments do not differentiate retrofit projects, while the maximum discount is offer by cooperative banks, which charge on average 0.8 p.p. less. Overall, H2 is verified only for two bank groups – BPCE and Credit Mutuel – and two types of bank ownership – cooperative banks and private banks.

Table 5: Estimation results - robustness check

	Model						
2-11Dependent variable	Loan categorization		Institution category		Energy prices		Business cycle proxy
Spread APY	(1)	(2)	(3)	(4)	(5)	(6)	(7)
intercept	1.605***	3.039***	-1.679***	-4.384***	9.891***	1.554***	1.128***
	(7.79)	(15.10)	(-7.93)	(-18.51)	(28.45)	(5.00)	(6.77)
Loan characteristics							
duration	0.102***	0.103***	0.0948***	0.0988***	0.102***	0.102***	0.103***
	(86.48)	(81.65)	(71.49)	(70.40)	(86.83)	(86.87)	(87.04)
$duration^2$	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-67.43)	(-63.63)	(-55.21)	(-52.85)	(-67.79)	(-67.74)	(-67.97)
$duration^3$	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(57.98)	(54.69)	(47.69)	(43.72)	(58.40)	(58.29)	(58.56)
amount	-0.025***	-0.025***	-0.022***	-0.020***	-0.025***	-0.025***	-0.025***
	(-77.22)	(-73.92)	(-60.10)	(-53.60)	(-78.07)	(-77.40)	(-77.21)
Macroeconomic factors							
ir_1y	-0.371***	-0.333***	-0.370***	-0.317***	-0.426***	-0.479***	-0.368***
	(-16.23)	(-13.66)	(-14.44)	(-11.68)	(-19.65)	(-13.82)	(-14.61)
hicp	-0.233***	-0.219***	-0.262***	-0.301***	-0.174***	-0.150***	-0.238***
	(-45.81)	(-40.59)	(-46.24)	(-49.93)	(-37.48)	(-18.12)	(-45.12)
u	-0.026*	-0.055***	0.042**	0.042**	-0.031**	-0.029*	
	(-2.20)	(-4.32)	(3.24)	(3.04)	(-2.64)	(-2.45)	
Financial factors							
CAC40_spread	0.080***	0.088***	0.040***	0.089***	0.126***	0.019	0.090***
	(7.83)	(8.05)	(3.54)	(7.34)	(12.41)	(1.26)	(8.59)
ciss_stress	-1.090***	-1.288***	-2.123***	-2.941***	-1.905***	-0.805***	-1.153***
	(-5.82)	(-6.46)	(-10.09)	(-13.20)	(-10.19)	(-4.01)	(-5.98)
yc_spread	-0.408***	-0.408***	-0.341***	-0.405***	-0.424***	-0.357***	-0.429***

Continued on next page

Table 5 – *Continued from previous page*

	Model						
Dependent variable	Loan categorization		Institution category		Energy prices		Business cycle proxy
Spread APY	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(-28.11)	(-26.38)	(-20.93)	(-23.50)	(-29.29)	(-22.28)	(-27.46)
Controls							
d_ipi							0.009***
							(5.07)
ipi_t							0.023**
							(3.16)
loan type, 5 categories			X	X	X	X	X
loan type, 3 categories	X						
loan type, 2 categories		X					
lender	X	X			X	X	X
bank type			X				
bank group				X			
loan type(5 cat)*lender					X	X	X
loan type (3 cat)*lender	X						
loan type (2 cat)*lender		X					
loan type (5 cat)*bank type			X				
loan type (5 cat)*bank group				X			
loan type (5 cat)*S95 price			X	X			X
loan type (3 cat)*S95 price	X						
loan type (2 cat)*S95 price		X					
loan type (5 cat)*electricity price					X		
loan type (5 cat)*gas price						X	
N	240962	240962	240962	240962	240962	240962	240962
R-sq	0.404	0.321	0.243	0.151	0.405	0.405	0.405

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Table 5 – *Continued from previous page*

	Model						
Dependent variable	Loan categorization		Institution category		Energy prices		Business cycle proxy
Spread APY	(1)	(2)	(3)	(4)	(5)	(6)	(7)
R-sq adj.	0.404	0.321	0.243	0.151	0.405	0.405	0.405

t-statistics in parentheses
*p<0.1, **p<0.01, ***p<0.001

7. Conclusion

We have assembled a unique dataset from web-scrapped loan simulations to investigate two information asymmetries that might affect consumer loans dedicated to home energy retrofits in France. Our data have the interesting feature of being immune to borrowers' characteristics that lenders realistically take into account in the underwriting process. Exploiting the data has led us to two conclusions.

On the one hand, we find that energy-efficient principals carry lower interest rates than other principals devoid of such an attribute. The results established by Kaza et al. (2014) and An and Pivo (2018) for mortgages issued in the residential and commercial sectors, respectively, therefore seem to carry over to consumer credit, at least in the loan terms posted by credit institutions on their websites. This echoes the finding consistently established in the building sector that more energy-efficient units sell or rent with a premium (Brounen and Kok, 2011). Taken at face value, these findings together suggest that the information asymmetries at the source of missing energy savings (Fowlie et al., 2015; Giraudet et al., 2018) do not necessarily propagate to credit suppliers nor the buyers and renters of building units.

On the other hand, we reject the hypothesis that home retrofits and automobiles, all other things being equal, are priced the same. This suggests that lenders use loan purposes as a screening device of unobserved borrowers' characteristics. Yet substantial heterogeneity across lending institutions prevents us from concluding unequivocally on the type of differentiation. Moreover, this result is not robust to changes in the definition of loan categories and therefore requires further investigation. Nevertheless, this finding contributes to the literature on loan pricing, in line with previous studies that have identified discrimination based on gender (Peterson, 1981) and ethnicity (Duca and Rosenthal, 1993).

Combining the two findings, we conclude that purpose-based screening can in fact undermine efficient pricing of energy efficiency in home energy retrofits. This illustrates the need to take a broad view of energy-efficiency investments, taken into account ancillary characteristics apparently unrelated to energy use, to correctly assess the importance of the energy-efficiency gap. The economic implications are important, as home energy retrofits are central to developed countries' commitments to carbon-dioxide emission reductions.

Given the variation across lending institutions observed in our results, a priority avenue for further research is to include institution characteristics as explanatory variables to better understand loan pricing behavior

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Appendix A. Explanatory variables

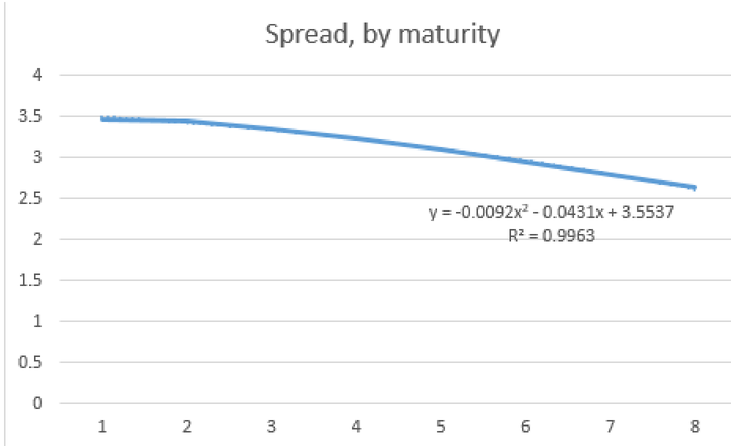

FIGURE 9. Interest rate spread by maturity, BNP bank, Ecological automobiles

TABLE 6. Descriptive statistics

Variable	Obs	Mean	Std.dev.	Min	Max
spread	240962	4.79	1.43	-0.34	29.58
duration	240962	46.87	24.04	12.00	108.00
amount	240962	16.78	7.31	5.00	32.50
ir_1y	240962	-0.50	0.17	-0.74	-0.10
hicp	240962	0.16	0.55	-1.30	0.80
u	240962	10.17	0.20	9.90	10.60
d_ipi	240962	-0.12	1.34	-1.90	2.70
ipi_t	240962	0.18	0.51	-0.92	0.77
CAC40_spread	240962	4.93	0.24	4.48	5.47
ciss_stress	240962	0.06	0.02	0.03	0.10
yc_slope	240962	0.83	0.24	0.43	1.32
eonia	240962	0.00	0.00	0.00	0.00
e_gnat	240962	12.39	0.36	11.99	13.24
e_elec	240962	19.61	0.28	19.21	20.32
e_s95	240962	1.32	0.06	1.24	1.44

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