How do lenders price energy efficiency?

Evidence from the French personal consumption loan market

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At least ex ante, energy efficiency improvements increase investor's solvency. Associated loans should therefore carry lower interest rates than do otherwise conventional loans. We test this hypothesis using unique panel data on posted interest rates scraped from loan simulators made available online by French credit institutions. Crucially, our data are immune from sorting bias based on borrower characteristics, which are not queried by online simulators. On average, we find that lenders charged a green premium in 2015 but offered a green discount in 2016. The latter effect was most pronounced for vehicles. We also find that, absent green attributes, interest rates are higher for home retrofit loans than for vehicle loans, which suggests that lenders use the loan purpose as a screening device of unobserved borrower characteristics. Our results together imply that loans for home energy renovation were consistently charged relatively high interest rates, with adverse consequences for scaling up home energy renovation.

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1 Introduction

Improving energy efficiency is recognized as the most cost-effective means of reducing carbon dioxide emissions at the source of anthropogenic global warming. This is particularly the case in the building and transportation sectors, which together contribute 30% of global emissions, two thirds of which come from households. The Intergovernmental Panel on Climate Change estimates that limiting global warming to 1.5°C above pre-industrial levels would require global investment in energy efficiency of $700 billion in 2050, an upscale by a factor of 4 to 5 compared to 2015 (IPCC, 2018). The International Energy Agency suggests even higher numbers of $1.3 trillion per year between 2026 and 2040 (IEA, 2018). As an attribute of long-lived assets, energy efficiency implies financing. In France alone, the average investment in home energy retrofit is 11,750€; 32% of retrofits involve credit, which typically covers over 50% of the upfront cost (ADEME, 2018). Meeting the 500,000 annual retrofit target set by the French Government thus creates annual borrowing needs of about one billion euros. Scaling up energy efficiency therefore requires that sizable borrowing needs be satisfied in an economically efficient manner. Despite its importance, however, the issue has received only little attention so far.

According to basic principles of finance, interest rates should reflect the risks associated with the underlying asset. As a first approximation, the risk associated with energy efficiency investments can be considered as low: by reducing energy expenditures, energy efficiency both increases the solvency of the investor and the resale value of the underlying asset – the latter phenomenon effect in particular is increasingly documented (e.g., Brounen and Kok, 2011; see Giraudet, 2018, for a review). A well-functioning credit market should therefore offer lower interest rates for energy efficient projects (hereafter "green projects") than for projects devoid of that attribute but otherwise similar (hereafter "conventional projects"). This simple prediction has recently been proved valid in the US market for commercial mortgages by An and Pivo (2018). Using ex post data from a loan programme, the authors find that those buildings that were certified green at loan origination obtained slightly but statistically significantly better loan terms than did their conventional counterparts.[1] To our knowledge, this is the only study that has investigated the matter. Its internal validity is however threatened by selection issues, as the authors could not control for borrowers' characteristics.

In this paper, we assess the validity of what we refer to as the "green discount" hypothesis in the French market for personal consumption loans. To this end, we assembled a unique panel dataset of loan terms posted on credit institutions' websites. The data were retrieved every week, for two years, from loan simulators made available online by 15 institutions which cover the near totality of the French market. Our approach differs from that of An and Pivo (2018) in several respects. First, we consider a different market. While An and Pivo (2018) studied mortgage loans for new commercial buildings, we study unsecured loans for household investment; when it comes to buildings, we are concerned with the renovation of existing

[1] The authors additionally find that greener buildings entail lower default rates. They thus corroborate an earlier finding of Kaza et al. (2014) in the US market for residential mortgages. This robust result confirms one assumption of the "green discount" prediction, namely that green projects are less risky than conventional projects. According to An and Pivo (2018), however, the green attribute has a much smaller effect on loan terms than on default rates.

ones rather than new constructions.[2] Our broader focus allows us to examine whether the green attribute varies with the designation of the project. In that regard, assuming that the risk associated with a home retrofit and a vehicle purchase does not particularly differ, we expect the green discount associated with each designation, if any, to be the same online. Second, and perhaps most importantly, our data are immune from sorting bias, as the online simulators which they originate from do not query any information about the prospective borrower's characteristics. We therefore avoid the selection issues faced by An and Pivo (2018). Third, these facilitating features come at the cost of handling ex ante, rather than ex post, data. This implies in particular that we cannot study default rates. Still, the fact that our posted data overestimate actual data by a mere 0.3 percentage point on average and that the two follow parallel trends lends external validity to our analysis.

In order to fully capture the interaction between the green dimension of the asset and its designation, we investigate two hypotheses – whether green projects are offered lower interest rates than their conventional counterparts on the one hand, and whether renovation and vehicle projects are priced the same, regardless of any green attribute, on the other. We do so by estimating a parsimonious econometric model of interest rate margin that includes time and institution fixed effects and controls for loan characteristics. When considering the period as a whole, we fail to reject the first hypothesis and find higher interest rates for renovations than for retrofits, which leads us to reject the second hypothesis. Overall effects are small (except for green vehicles) but statistically significant and confirmed by statistical tests and robustness checks, including placebo tests. Looking at each year separately, we find that both results hold for 2016 but were reversed in 2015. In other words, the market seems to increasingly value the lower risk associated with green projects while increasingly offering higher interest rates for renovation projects than for vehicles. This has important consequences for green renovation projects, which, owing to the interaction between these two trends, constantly carry relatively high interest rates. This is especially true for short-term loans (12 months).

Our contribution is two-fold. One speaks to the energy efficiency field. By documenting relatively high interest rates for home energy retrofits, we contribute to the literature on the factors causing under-investment in energy-efficient technologies – a phenomenon known as the energy-efficiency gap (Jaffe and Stavins, 1994). While most research into the issue has focused on behavioural factors on the demand side (Gillingham et al., 2009; Allcott and Greenstone, 2012; Gerarden et al., 2017), we focus on less-studied supply-side factors. Specifically, we add to the scarce literature on energy efficiency loans (Palmer et al., 2012; Kaza et al., 2014; An and Pivo, 2018) by emphasizing the interaction between the green attribute and other dimensions of the underlying asset. Given the high sensitivity of loan demand to loan terms (as estimated in credit cards by Gross and Souleles, 2002, and Ponce et al., 2014), removing premia on interest rates could significantly increase investment in home energy retrofit. Our second contribution is more general and relates to the literature on unsecured credit market (Artheya et al., 2012, Sánchez, 2018, Crawford et al., 2018). We document an anomaly, namely systematic differences in the interest rates offered for renovation- and vehicle-backed loans, whereas the risks associated with each project should

[2] Given the slow turnover of building stocks (typically 1% every year), the renovation of existing buildings is much more crucial for carbon dioxide emission reductions than are new constructions. This is especially true in the residential building stock, which is typically 50% larger than the commercial building stock.

not particularly differ. Considering that our data are immune from sorting bias, we interpret this finding as lenders using loan designations as a screening device of unobserved borrower characteristics in a way conducive to rationing. Our finding echoes Einav et al. (2012)'s one that down payments can also be used as screening device. Altogether, these findings contribute to the scarce literature on price discrimination by lenders facing ex ante hidden information on borrower characteristics (Zinman, 2014; Allen et al., 2014a,b).

The analysis proceeds as follows. Section 2 formulates testable hypotheses. Section 3 describes the data. Section 4 details the empirical approach. Section 5 discusses the results. Section 6 provides robustness checks. Section 7 discusses welfare implications and concludes.

2 Testable hypotheses

Here we discuss in greater length the hypotheses that our dataset allows us to test. As stated in the introduction, basic principles of finance imply the following:

Hypothesis 1: *Green projects carry lower interest rates than do conventional projects.*

Rejection of this hypothesis can be interpreted as evidence of an energy efficiency gap. An increasing number of studies point to energy retrofit projects that fail to deliver predicted energy savings (Metcalf and Hassett, 1999; Graff Zivin and Novan, 2016; Fowlie et al., 2018). 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, the authors provide evidence that retrofit contractors engage in moral hazard by under-providing quality in hard-to-observe measures such as insulation installation or duct sealing. Thus confronted with a so-called lemons problem (Akerlof, 1970), the lender might internalize it and price energy-efficient assets the same as conventional, non-energy-efficient assets.

Now regardless of any energy efficiency consideration, a renovation and a vehicle are two household investments which, as a first approximation, carry comparable risk. In a well-functioning credit market, the following hypothesis should therefore hold:

Hypothesis 2: *The interest rates for renovation and vehicle projects are identical.*

This hypothesis may however be rejected if the lender uses the loan designation as a screening device of unobserved borrower characteristics.[3] In this perspective, a plausible conjecture formed by the lender is that households borrowing money to retrofit their home are wealthier than those borrowing money to purchase a vehicle. Indeed, vehicle purchases are largely disconnected from borrowers' home ownership status, while home energy retrofits are overwhelmingly conducted by homeowners (79% in France,

[3] In practice, loans terms are negotiated between the lender and the borrower during the underwriting process, at which time the lender does observe many of the applicant's characteristics. Screening 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 here.

according to ADEME, 2018), who tend to be wealthier.[4]Such a conjecture can have two countervailing effects. On the one hand, a wealthier borrower can be perceived as having a higher willingness to pay, which a price-discriminating lender may want to exploit by charging higher interest rates. This effect, which we refer to as the "WTP channel," is common to the supply of any good. On the other hand, a wealthier borrower might be perceived as less likely to default, hence be charged a lower interest rate. This effect, which we refer to as the "risk channel," is specific to loans. This leads us to consider an amended version of Hypothesis 2:

Hypothesis 2': *Renovation projects carry lower interest rates than do vehicle projects.*

Rejection of Hypothesis 2' can be interpreted as dominance of the WTP channel over the risk channel, while failure to reject it conveys the opposite. From a welfare perspective, the WTP channel has more detrimental consequences, since it may drive some borrowers out of the market.

3 Data

3.1 Collection

Our dataset consists of a panel of interest rates retrieved from online credit simulators. Most credit institutions in France make such simulators available to prospective borrowers. A simulator typically makes queries about the amount, duration and designation of the desired loan, from which it returns loan terms, characterized by the fixed nominal interest rate, possibly some fees, and the annual percentage yield (*taux annuel effectif global*), which expresses the yearly cost of the loan. Importantly, simulators do not make queries about the applicant's characteristics. The resulting loan-term data are therefore plausibly immune from sorting bias based on applicants' characteristics observed to the lender.

We designed a web-scraping robot that ran such simulators on a weekly basis and assembled a panel dataset of simulated loan terms. We surveyed all credit institutions which, to our knowledge, offered online simulators for household unsecured credit in France during the observation period. This includes 15 institutions which are either the main retailer or some credit subsidiaries of the six main French banking groups, altogether covering 88% of issued household loans (Table 1). We operated the robot for two years, from January 2015 to October 2016, which produced 93 weeks of data. Each week, for a given institution offering a given designation, the robot ran the simulator 108 times, combining 12 different amounts – ranging from 5,000€ to 32,500€, with a step of 2,500€ – and 9 different maturities – ranging from 12 to 108 months, with a step of 12. The data thus produced are 4-tuples of institution, designation, amount and maturity.

[4] Anecdotal evidence moreover suggests that borrowers are on average seven years older in retrofit loans than in auto loans (Meilleurstaux.com, 2015)

Table 1: Characteristics of the institutions surveyed

Banking Group	Market share	ESCG member	**Institution**	Type of institution
BNP Paribas	11%	**Yes**	**BNP Paribas**	Private bank
			Cetelem	Financial credit establishments
			Cofinoga	Financial credit establishments
			Domofinance	Financial credit establishments
BPCE	8%	**No**	**Caisse d'epargne**	Cooperative bank
Crédit Agricole	10%	**Yes**	**Crédit agricole**	Cooperative bank
			LCL	Private bank
			Sofinco	Financial credit establishments
Crédit Mutuel	48%	**No**	**Cofidis**	Financial credit establishments
			Crédit Mutuel	Cooperative bank
			Financo	Financial credit establishments
			Prêt d'union	Financial credit establishments
La Banque Postale	6%	**No**	**La Banque Postale**	Public bank
Socété Générale	4%	**Yes**	**Franfinance**	Financial credit establishments
			Socété générale	Private bank

Note: Market share estimates were computed by the authors using data from the Banque de France (CEFIT database). The institutions surveyed cover 88% of the market

Several sampling issues made our panel dataset unbalanced. First, the menus of designations are specific to each institution, and the number of options each offers varies from 1 to 21 (median 4; mean 7.5). Overall, we recorded 90 different designations, which we grouped into categories, as we will see in the next section. Second, the available ranges of amount and maturity vary as well across institutions. Yet even though sampling was heterogeneous across institutions, this did not introduce a strong bias, as amounts and maturities are very close once averaged per loan category (Figure 1). The average loan size and maturity over the whole dataset are 16,782€ and 47 months, respectively.[5] Third, some data could not be retrieved for certain institutions on certain weeks. This is due to changes in websites that could not be

[5] To put these numbers in perspective, the typical figures are 11,449€ and 47 months, respectively (Meilleurtaux.com, 2015).

detected early enough to adjust the design of the robot – a challenge common in web scraping (Cavallo and Rigobon, 2016). Overall, our workable panel dataset comprises 240,962 observations.

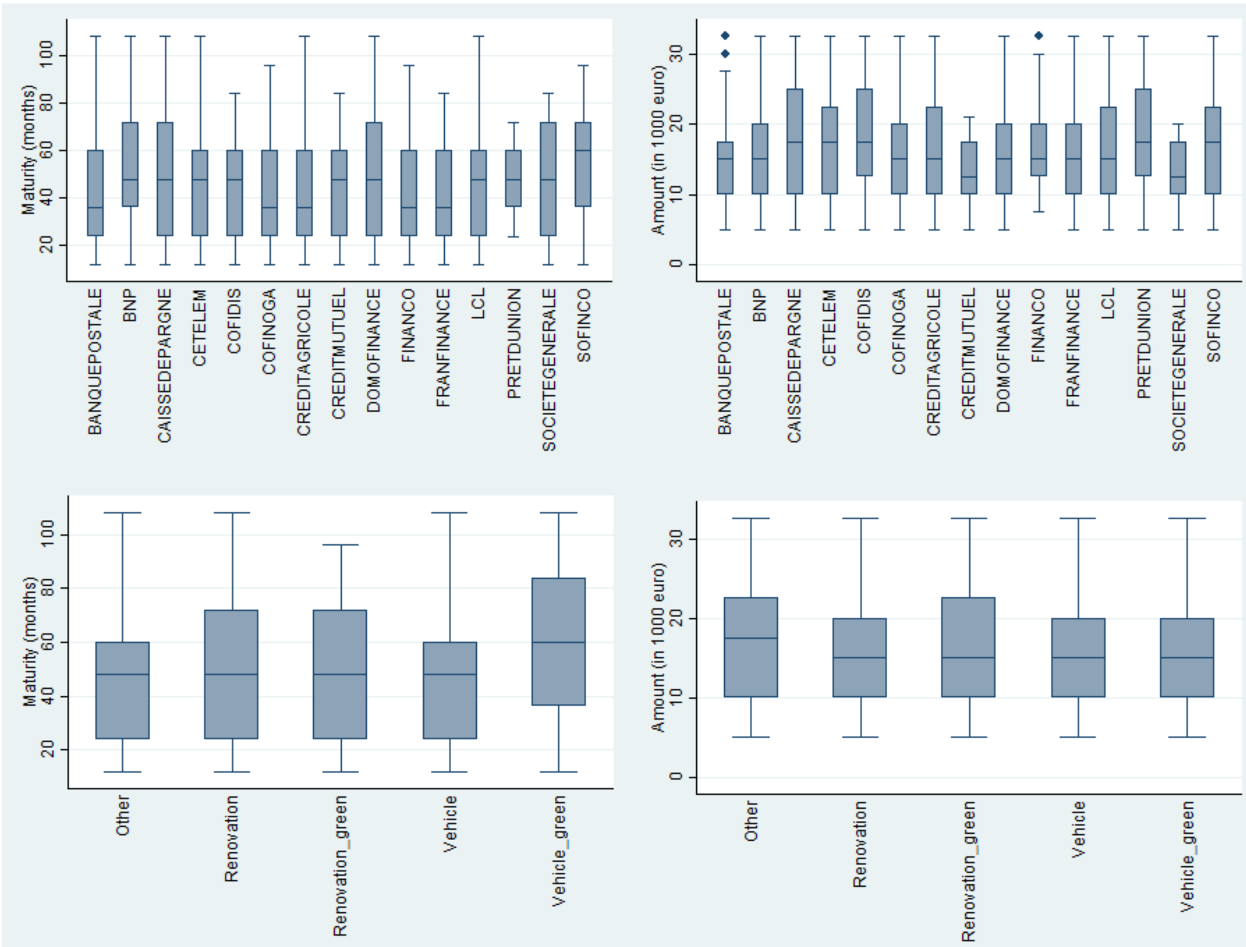

Figure 1: Summary statistics of simulated amounts and maturities

3.2 Loan categorization

The number and labelling of options offered by institutions in their menu of loan designations vary widely. After grouping redundant labels, we still handle 90 distinct designations, which are all variants of vehicle loans, home renovation loans, equipment loans, consumption loans, student loans, health loans and cash loans. These designations are representative of unsecured loans issued in France, 47% of which were dedicated to auto purchase in 2017, 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).

To test the hypotheses stated in Section 2, we group the collected designations into broad categories. Combining the two hypotheses, we are specifically interested in four categories: renovations, green renovations, conventional projects, and green projects. Given the large market share of vehicle projects, we sort this category out of conventional investments. Another motivation for doing so is that one institution makes a distinction between green and conventional vehicles. Our most granular categorization therefore has five items: renovations, green renovations, vehicles, green vehicles, and others. To test the two hypotheses separately, we also consider two more aggregate categorizations: one that groups all green categories on the one hand, all conventional categories on the other; another that groups all renovation categories on the one hand, all vehicle categories on the other. The three workable categorizations are detailed in Table 2. Overall, eleven institutions offer both vehicle and renovation loans; four institutions – Cetelem, Domofinance, Financo and Prêt d'Union – offer both green and conventional retrofits; and one – BNP Paribas – offers both green and conventional vehicles.

Table 2: Categorization of loan designations

Collected entries (90)	2-item categorization	3-item categorization	5-item categorization
Car, motorcycle	Conventional	Auto	Auto
Used car, used vehicle, used boat, used camping car, used trailer, used motorcycle	Conventional	Auto	Auto
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	Conventional	Auto	Auto
Brand new efficient car	Green	Auto	Auto green
Other works, decoration, construction, veranda, indoor/outdoor design	Conventional	Renovation	Renovation
Boiler, wood boiler, electrical heating, water heating, windows, insulation, heat pumps, heating, home improvement	Green	Renovation	Renovation green
Other project, consumption, relocation, wedding, birth, DIY supplies, holidays, event, leisure	Conventional	Other	Other
Health, Family problems	Conventional	Other	Other
Need for money, Need for cash, budget	Conventional	Other	Other
Student loan	Conventional	Other	Other
Electronic device, appliances, Hi-fi, furniture, computer accessories	Conventional	Other	Other

The categorization procedure is crucial. Most collected designation labels are unambiguous and their allocation to the appropriate category is straightforward. This is not quite the case for green and conventional retrofits, which are nevertheless central to our analysis. Making a distinction between the two requires careful interpretation of the labels. Our chosen approach is to allocate to the green retrofit category those retrofit labels that likely reduce the energy consumption of a household. This essentially includes measures on the building envelope and the space and water heating systems. As a robustness check, we subject this categorization to placebo tests and conclude that it is meaningful (see Section 6.2).

3.3 Descriptive statistics

We focus below on the average percentage yield (APY), which represents the monthly price of a loan, including the fees. An obvious concern with our posted data is the accuracy with which they approximate actual data. Comparing the trend of the average interest rate in our dataset, weighted by the market share of the corresponding banking group, to that of issued loans as provided by the Banque de France,[6] we find a positive spread on 73 weeks out of 93 (Figure 2). The mean percentage error over the whole period is 6.0% (mean absolute percentage error: 6.9%; standard error 4.7%), or a 0.3 percentage point. Such a relatively low error lends external validity to our data. Moreover, the fact that the rates on issued loans are almost systematically below posted rates can be interpreted as indirect evidence of the negotiation process lenders and borrowers are known to engage in (see Allen et al., 2014a,b, for evidence from Canada).

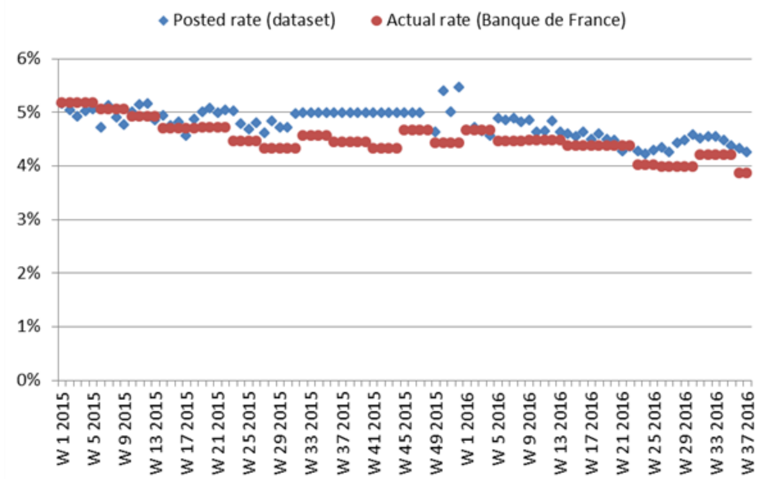

Figure 2: Comparison between posted and actual interest rates

The interest rates posted by credit institutions exhibit some dispersion across space and time. On average, the surveyed institutions update their interest rates every seven weeks and exhibit a coefficient of variation on interest rate of 33% (Figure 3, red square). As we will see later in regressions, dispersion is further substantiated by strong variations in average interest rates across banks. This indicates that despite operating in a highly competitive market (Europe Economics, 2009), institutions adopt heterogeneous pricing strategies, probably driven by differences in their borrower portfolio.

[6] http://webstat.banque-france.fr/fr/browseChart.do?node=5385583&sortByView454=468&SERIES_KEY=MIR1.M.FR.B.A2B.A.R.A.2254U6.EUR.N&SERIES_KEY=MIR1.M.FR.B.A2B.A.R.A.2250U6.EUR.N

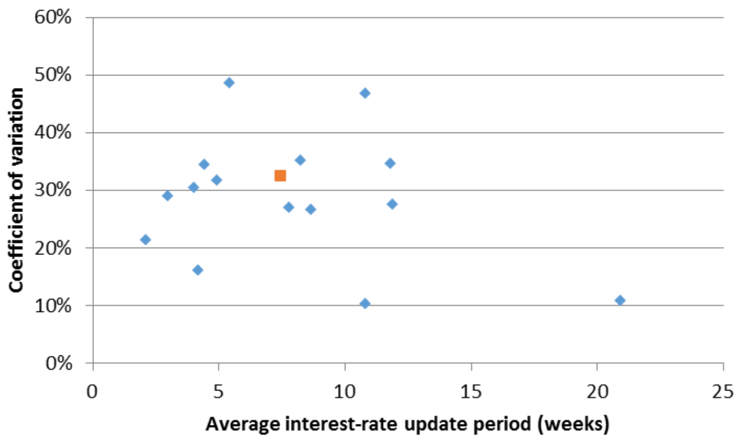

Figure 3: Dispersion of average interest rates across space and time, by institution

A glimpse into the time series of weighted averages of interest rate suggests that some clear, yet unstable, differences exist between categories (Figure 4). The two green categories tend to be associated with lower interest rates. In particular, the average interest rate on green vehicles – which we recall are offered by BNP Paribas only – drops significantly early in 2016.

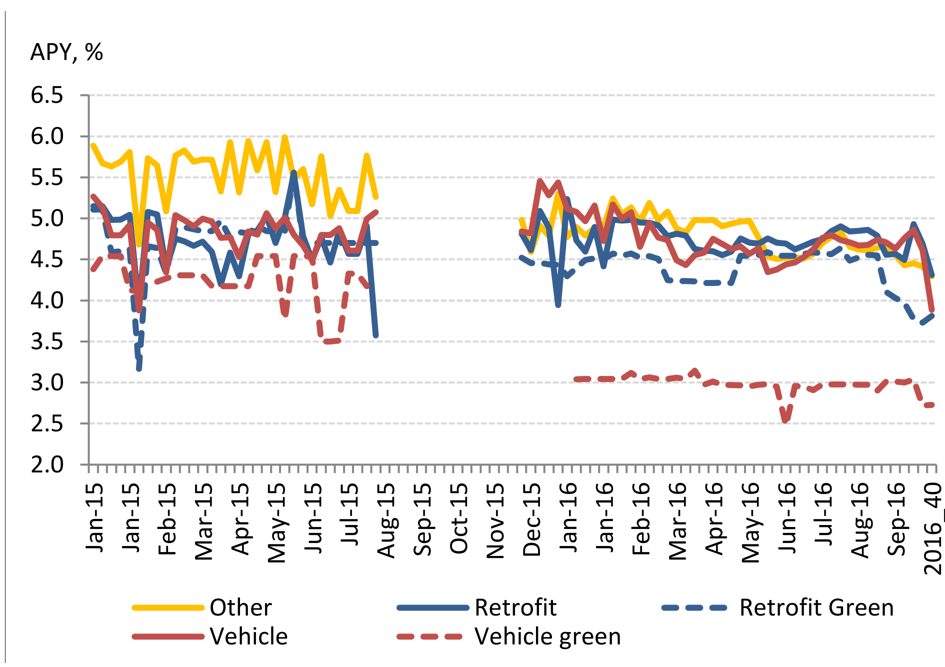

Figure 4: Time series of average spread (in percentage points), by category

Another glimpse suggests that the interest rates averaged by maturity co-move to a large extent (Figure 5). Yet 12-month loans exhibit a peculiar pattern, with an interest rate decreasing more markedly than that of other maturities from early 2016 onwards. This coincides with an increase in deposits of 154 billion euros between 2015 and 2016 induced by quantitative easing by the European Central Bank (ACPR, 2016).

It is likely that banks offered particularly low interest rates on short-term loans to recycle these vast amounts of cash money.

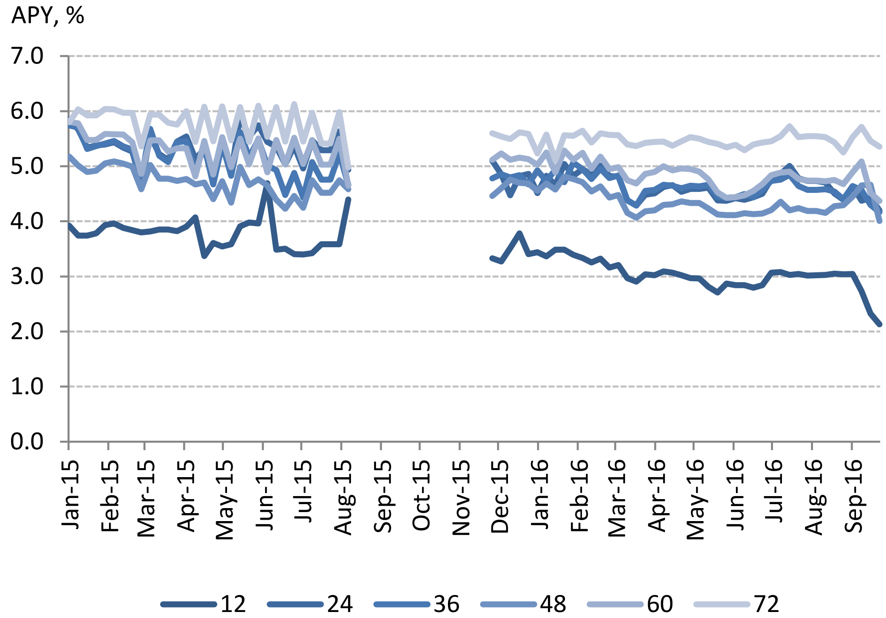

Figure 5: Time series of average spread (in percentage point), by maturity

Figure 6 sheds light on the interaction between these phenomena through the market yield curve , which illustrates how interest rates vary with maturities. We constructed the yield curves for each category using the Nelson-Siegel-Svensson model (Nelson and Siegel, 1987) and estimated them at one point in 2015 and a year after.

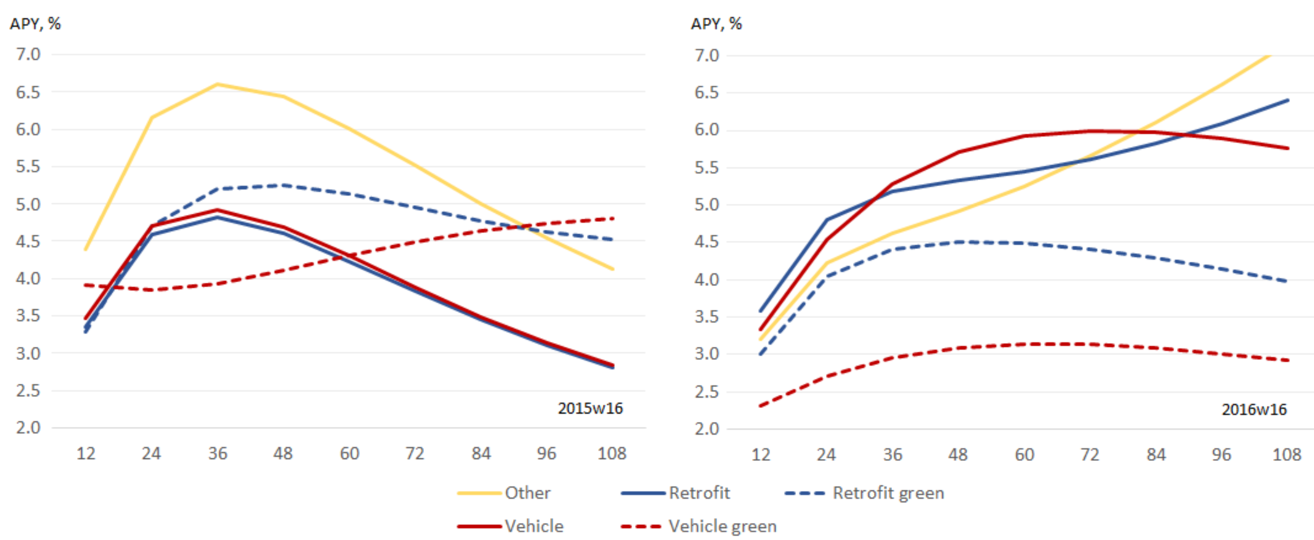

Figure 6: Empirical yield curves at two points in time, by category

We observe that all categories (except green vehicles) exhibited a bell-shaped curve in 2015, with a negative slope for high maturities. In 2016, expectations went back to normal, with a more usual positive slope for conventional categories. The two green categories however underwent a downward shift, which suggests recognition of the lower risk associated with green projects.

These observations call for a separate analysis of interest rates across maturities (12-month versus higher maturities) and over time (2015 versus 2016).

4 Econometric model

Our goal is to make inference on how credit institutions perceive the risks associated with different loan designations. We consider the spread s between the posted interest rate i (measured as the APY) in our dataset and the spot yield of the government bond b of the same maturity:[7]

$$s_{kamtc} = i_{kamtc} - b_{mt},$$

where $k \in \{1, \ldots, 15\}$ denotes the credit institution, $a \in \{5000, 7500, \ldots, 32500\}$ the amount simulated in euros, $m \in \{12, 24, \ldots, 108\}$ the maturity of the loan in months, c one category within one of the three retained categorization and t the week on which the loan was simulated. Regressing the spread instead of using government bonds to explain the interest rate allows us to address potential endogeneity problems between the two. It moreover allows us to focus on the bank margin, which is the part of the interest rate most affected by loan designations. Note that, as government bonds carried negative yields over the period, the spread is generally larger than the associated interest rate.

We consider a parsimonious model that expresses the spread as a linear combination of the following determinants:

$$s_{kamct} = \alpha_0 + \alpha_1 L_{am} + \alpha_2 I_k + \alpha_3 T_t I_k + \beta_c D_c + \varepsilon_{kamct},$$

where L_{am} is a vector of loan characteristics, including the duration of the loan, its square, and the amount borrowed, I_k is a vector of institution fixed effects, T_t a vector of time fixed effects and D_c a vector of project categories. Through the institution fixed effect, we assume that different lenders adopt different pricing strategies, depending on their client portfolio, size or capitalization. The product $T_t I_k$ captures institutions' individual responses to changes in the macroeconomic and financial environment. The associated coefficient α_3 can be interpreted as the additional effect of a particular institution for a particular loan category with respect to the average effect of that institution α_2 and the average effect of that loan category β_c.[8]

[7] For the French government bond yields, we use the data on the observed yields for tradable maturities and inferred rates for nontradable maturities, as given by the ECB (Source: ECB, Data Source in SDW: Government bond, nominal, all issuers whose rating is triple A - Svensson model - continuous compounding - yield error minimization - Yield curve spot rate - Euro, provided by ECB).

[8] The institution and institution*time fixed effects allow us to deal with the cross-institution correlation and the autocorrelation of the error terms. This increases the precision of our estimates. One would also like to cluster errors

The coefficients β_c associated with loan categories are our main estimates of interest. We subject them to t-tests in order to assess the hypotheses stated in Section 2, which we statistically reformulate as follows:

H_a: $\beta_1^{green} < \beta_1^{conventional}$

H_b : $\beta_1^{retrofit} \leq \beta_1^{vehicle}$

We test H_a with the two-item categorization, H_b with the three-item categorization and examine the interaction of the two hypotheses with the five-item categorization. To ensure representativeness of our loan sample, we assign weights to our observations proportional to the share of the corresponding banking group in the French market for personal consumer credit (Table 1). We further assign uniform weights to all subsidiaries within a banking group.

by designation or institution to account for intra-institution correlation. Yet that would be equivalent to assuming no correlation between the clusters, which, given the high degree of competition in the banking market, we consider a restrictive hypothesis. Moreover, a robust estimation would require many more clusters – typically 40 to 50 (Angrist and Pischke, 2009).

5 Estimation results

5.1 General effect of loan designation

We estimate three variants of the model with ordinary least squares (OLS): model 1 uses the two-item categorization; model 2 uses the three-item categorization; model 3 uses the five-item categorization (Table 3). As expected, the spread is positively related to the duration, though at a slightly decreasing rate. An additional year increases the spread by about 0.4 percentage point. In contrast, the amount has a very small, negative effect on the spread.

Table 3: OLS estimates of the baseline regression

Dependent variable:	Model 1	Model 2	Model 3
spread APY (in percentage points)	2 categories	3 categories	5 categories
Constant (Other)	4.50***	4.51***	4.51***
	(-39.66)	(-39.6)	(-39.58)
Duration (month)	0.03***	0.03***	0.03***
	(-41.17)	(-41.13)	(-41.01)
Duration^2	-0.00***	-0.00***	-0.00***
	(-20.92)	(-21.01)	(-20.86)
Amount (10,000€)	-0.02***	-0.02***	-0.02***
	(-45.83)	(-45.81)	(-45.76)
Green dummy	-0.02**		
	(-2.97)		
Renovation		0.03**	0.02*
		(-2.66)	(-2.07)
Vehicle		-0.04***	-0.03*
		(-3.35)	(-2.55)
Renovation green			0.04***
			(-3.76)
Vehicle green			-0.50***
			(-33.56)
Institution dummy	YES	YES	YES
Institution dummy*Time dummy	YES	YES	YES
N	240,962	240,962	240,962
R-sq	0.414	0.415	0.415
adj. R-sq	0.412	0.412	0.413

t-statistics in parentheses

* p<0.05, ** p<0.01, *** p<0.001

The comparison of projects dummies across models suggests that green projects are priced below conventional projects (model 1) and that vehicle projects are priced below renovation projects (model 2). These results are statistically significant at conventional levels and confirmed by t-tests (Table 4), but small in magnitude. Interacting the two dimensions in model 3, we see that the former result does not apply to renovations and is in fact driven by the strong discount observed on green vehicles, which we recall is attributable to one institution. Again, these results are statistically significant and confirmed by t-tests.

The observed differences in marginal prices for vehicles and home renovation suggest that discrimination is at play: faced with ex ante hidden information about borrower characteristics, lenders use the loan purpose as a screening device. The polarity we obtain suggests that the WTP channel prevails over the risk channel. Our result thereby adds to the scare literature seeking evidence of information asymmetries in consumer credit (Zinman, 2014). It is in particular close to the finding of Allen et al. (2014a,b) that lenders price mortgages in a way consistent with discrimination based on unobserved bargaining power of borrowers.

Table 4: Statistical tests on the baseline regression

Hypotheses tests	Hypothesis	Model 1 2 categories	Model 2 3 categories	Model 3 5 categories
H0: β_green=0				
H1: β_green≠0	**H_a**			
t-stat value		-2.97		
p-value		0.00		
Reject H0?		yes		
H0: β_renovation<β_vehicle				
H1: β_renovation>β_vehicle	**H_a**			
t-stat value			8.05	
p-value			0.00	
Reject H0?			yes	
H0: β_renovation_gr<β_renovation				
H1: β_renovation_gr>β_renovation	**H_a**			
t-stat value				2.66
p-value				0.00
Reject H0?				yes
H0: β_vehicle_gr<β_vehicle				
H1: β_vehicle_gr>β_vehicle	**H_a**			
t-stat value				-35
p-value				0.00
Reject H0?				no

Moreover, our results suggest that home energy efficiency is subject to a double energy efficiency gap: the first because renovation projects carry relatively high interest rates, the second because within this category, the green attribute further increases the interest rate.

5.2 Effects by year of sample

Motivated by the changes observed in the time series by categories (Figure 4) and changes in the yield curve (Figure 6), we estimate the different models on year subsamples (Table 5). The coefficients associated with duration indicate a steeper yield curve in 2016. The green discount observed over the period is only effective in 2016; conversely, in 2015, green projects carry a higher interest rate (model 1). Likewise, the ranking observed over the period between renovation and vehicle projects only applies to 2016 and is reversed in 2015 (model 2). The change in the merit order of the five categories observed in 2016 is consistent with an interaction between these two shifts (model 3). Again, all results are statistically significant and confirmed by t-tests. This leads us to the conclusion that the double energy efficiency gap observed over the period is not consistent: in 2015, only its first dimension applies, whereas in 2016, only its second dimension applies. In other words, the market seems to increasingly recognize the lower risk associated with green projects, but charges increasingly higher interest rates for renovation projects than for vehicles.

Table 5: Evolution of the effects

Dependent variable:	Model 1: 2 categories		Model 2: 3 categories		Model 3: 5 categories	
Spread (in percentage points)	2015	2016	2015	2016	2015	2016
Constant (Other)	4.86***	5.88***	5.13***	5.80***	5.13***	5.79***
	(44.70)	(28.59)	(46.35)	(27.67)	(46.29)	(27.6)
Duration (month)	0.028***	0.04***	0.02***	0.04***	0.03***	0.04***
	(20.34)	(43.16)	(19.49)	(43.77)	(19.59)	(43.49)
Duration^2	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***	-0.00***
	(-16.60)	(-21.98)	(-15.43)	(-22.93)	(-15.51)	(-22.62)
Amount (10,000€)	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(-16.32)	(-42.85)	(-16.19)	(-42.94)	(-16.19)	(-42.86)
Green dummy	0.06***	-0.06***				
	(8.78)	(-8.55)				
Renovation			-0.45***	0.19***	-0.47***	0.20***
			(-21.12)	(15.95)	(-21.82)	(16.08)
Vehicle			-0.30***	0.03*	-0.29***	0.05***
			(-13.65)	(2.45)	(-13.32)	(3.54)
Renovation green					-0.32***	0.13***
					(-15.20)	(11.14)
Vehicle green					-0.27***	-0.78***
					(-12.10)	(-43.88)
Institution dummy	YES	YES	YES	YES	YES	YES
Institution dummy*Time dummy	YES	YES	YES	YES	YES	YES
N	69,695	171,267	69,695	171,267	69,695	171,267
R-sq	0.481	0.403	0.488	0.404	0.489	0.406
adj. R-sq	0.476	0.401	0.484	0.402	0.485	0.404

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

A table similar to Table 4 could be presented for these results (as well as for the rest reported in this paper). To save space, we omit it here. However, since the standard errors of the estimates are very small, the differences between the estimated coefficients are always statistically significant, so the validity of the hypotheses can be verified simply by comparing the values of the corresponding coefficients.

Regarding the prevalence of WTP effect versus risk effect, higher rates for vehicles in 2015 advocate for the dominance of the risk effect; however, the relation flips over in 2016, with vehicle loans becoming relatively more affordable.

5.3 Effects by loan maturity

Motivated by the changes observed in the time series by maturities (Figure 5), we estimate model 3 on duration subsamples, considering separately 12-month loans and loans with longer duration (Table 6). The ranking of categories for 12-month loans conforms that observed at the aggregate level. When considering loans with longer duration, this ranking changes in one important respect: green renovations are charged low interest rates only seconded by green vehicles. In other words, lenders seem to perceive green retrofits as riskier investments when financed by a short-term loan than when financed by a long-term loan. Further regressions on both year and maturity subsamples suggest that this phenomenon essentially occurred in 2016.

Table 6: Comparison of short-term and long-term effects

Dependent variable:	Duration		
Spread (in percentage terms)	12 months	>12 month	all
Constant (Other)	2.85***	5.31***	4.51***
	(-51.02)	(-123.82)	(-39.58)
Duration (month)		-0.02***	0.03***
		(-14.37)	(-41.01)
Duration^2		0.00***	-0.00***
		(-18.83)	(-20.86)
Amount (10,000€)	-0.02***	-0.02***	-0.02***
	(-17.56)	(-43.78)	(-45.76)
Renovation	0.08***	-0.03*	0.02*
	(-3.83)	(-2.29)	(-2.07)
Renovation green	0.31***	-0.06***	0.04***
	(-13.2)	(-5.60)	(-3.76)
Vehicle	0.08**	-0.05***	-0.03*
	(-3.12)	(-4.32)	(-2.55)
Vehicle green	0.05**	-0.56***	-0.50***
	(-1.84)	(-37.02)	(-33.56)
Institution dummy	YES	YES	YES
Institution dummy*Time dummy	YES	YES	YES
N	34,135	206,827	240,962
R-sq	0.662	0.469	0.415

adj. R-sq	0.652	0.466	0.413

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

5.4 Effects by lending institution

We run an alternative specification of model 3 with an additional interaction term $D_c I_k$ meant to capture the idiosyncratic way in which institutions price the risk associated with loan designations, as compared to the market. The results are displayed in Table 7. Generally speaking, Cofidis, Credit Mutuel, Société Générale et Cofinoga post the highest interest rates while LCL, BNP, Caisse d'Epargne and Cetelem post the lowest rates (column 1). The specific way in which an institution values a project category is given by the sum of the institution coefficient in the first column, the project category coefficient in the first row and the appropriate coefficient in the institution-category matrix. Thus estimated, the institutions' pricing strategies appear highly heterogeneous. In particular, among the institutions making a distinction between green and conventional renovations, Domofinance, Financo and Prêt d'union offer lower interest rates for the former, while Cetelem adopts the opposite strategy.

Table 7: Effects by loan type and lenders

		Loan type FE			
	Institution FE	Renovation	Renovation Green	Vehicle	Vehicle Green
		-0.32***	-0.00	-0.41***	-0.77***
		Supplementary Loan*Institution FE			
BNP	-0.81***	0.33***		-0.21**	
CAISSE D'EPARGNE	-1.09***	1.66***		2.13***	
CETELEM	-0.98***	0.58***	0.44***	0.08	
COFIDIS	2.07***	0.24**		0.44***	
COFINOGA	0.45**	-0.30**		-0.14	
CREDIT AGRICOLE	-0.06	0.39***		0.21*	
CREDIT MUTUEL	0.82***	-3.28***		-0.52***	
DOMOFINANCE	-0.46***	-0.34***	-0.59***		
FINANCO	-0.05	-0.09	-0.55***	-0.37***	
FRANFINANCE	-0.87***	0.46***			
LCL	-2.81***			1.30***	
PRET D'UNION	-0.35**			0.41***	
SOCIETE GENERALE	0.52**				
SOFINCO	-0.51**	1.48***			

We then exploit the fact that three banking groups – BNP Paribas, Crédit agricole, Société générale – are members the Environmental and Social Corporate Governance (ESCG) group to see if such a commitment has an impact on their pricing behaviour. We run model 3 on two subsamples respectively gathering ESCG members and non-members. The regressions are little informative as to whether the pricing of green projects varies between the two groups, as the former is the only one that makes a distinction between green and conventional vehicles, yet it makes no distinction between green and conventional renovations. Interestingly, however, the regressions suggest that the two groups adopt opposite pricing strategies with respect to Hypothesis 2 (Table 8). Specifically, ESCG institutions charge higher interest rates for renovations than for vehicles. Moreover, it is noteworthy that non-ESCG institutions charge lower interest rates for green renovations than for conventional ones.

Table 8: Effect of ESCG status

Dependent variable	ESCG status	
Spread (in percentage terms)	no ESCG	ESCG
Constant (Other)	4.09***	4.44***
	(70.69)	(41.71)
Duration (month)	0.04***	0.03***
	(38.47)	(26.04)
Duration^2	-0.00***	-0.00***
	(-21.83)	(-18.81)
Amount (10,000€)	-0.02***	-0.01***
	(-33.25)	(-13.24)
Dummy Retrofit	-0.21***	0.08**
	(-15.73)	(3.28)
Dummy Retrofit Green	-0.63***	
	(-51.05)	
Dummy Vehicle	-0.17***	-0.35***
	(-12.80)	(-14.83)
Dummy Vehicle Green		-1.61***
		(-64.28)
Time fixed effects	YES	YES
N	215,859	25,103
R-sq	0.123	0.412
R-sq adj	0.122	0.409

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

6 Robustness checks

6.1 Macroeconomic and financial controls

We substitute a set of macroeconomic and financial variables for time fixed effects and examine how it affects the values of the estimated coefficients of loan categories. We estimate the following model:

$$s_{kamct} = \alpha_0 + \alpha_1 L_{am} + \alpha_2 I_k + \alpha_3^M M_t + \alpha_3^F F_t + \beta_c D_c + \varepsilon_{kamct},$$

where M_t is a vector of macroeconomic variables, F_t a vector of financial variables, and all other variables are those defined in the previous model. Macroeconomic controls include: the inflation rate, as measured by the harmonized index of consumer prices; the unemployment rate, which approximates the phase of the business cycle; the interest rate on one-year government bonds in the Euro area, which captures the quantitative easing in which the European Central Bank (ECB) engaged during the period. Financial controls include: the spread between the return on the CAC40 index and the interest rate on one-year government bonds, which approximates the volatility of the stock market; the stress index provided by the ECB, which approximates the volatility in the bond market;[9] and investors' expectations, as measured by the slope of the yield difference between ten-year and one-year government bonds.

These substitutions do not qualitatively affect the results of the baseline model and preserve the ranking between the interest rates associated with different project categories (Table 9). Macroeconomic and financial factors explain a very modest part of the variation of the spread, which is consistent with previous findings (Gambacorta, 2008). Unemployment stands out at the only added control with a statistically significant effect. Its negative sign could be explained by a depressed demand, to which lenders respond with lower interest rates. Another explanation could be that unemployment insurance offered by lenders during the negotiation process can mitigate risks (Hsu et al., 2012). Despite being non-significant, estimates for the other variables have the expected polarity. Quantitative easing has a positive effect, suggesting that institutions benefited from a loosening of the monetary policy, possibly at the expense of consumers. Inflation too has a positive effect, suggesting that cost pass-through is affected by some market power. Higher risks in the equity market, as approximated by the two volatility indices, increase the spread, suggesting that lenders transfer part of the portfolio risks to their clients. The impact of the yield curve slope is positive, suggesting that optimistic expectations are associated with a higher demand for consumer loans.

[9] 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 9: Effect of macroeconomic and financial controls

Dependent variable APY spread (in percentage points)	Baseline model with controls for			
	Baseline model	Macro factors	Financial factors	Macro and financial factors
Constant (Other)	4.51***	6.79***	-5.22	-5.13
	(-39.58)	(-6.94)	(-0.00)	(-0.00)
Duration (month)	0.03***	0.03***	0.03***	0.03***
	(-41.01)	(-41.02)	(-41.01)	(-41.02)
Duration^2	-0.00***	-0.00***	-0.00***	-0.00***
	(-20.86)	(-20.86)	(-20.86)	(-20.86)
Amount (10,000€)	-0.02***	-0.02***	-0.02***	-0.02***
	(-45.76)	(-45.75)	(-45.76)	(-45.75)
Dummy Retrofit	0.02*	0.02*	0.02*	0.02*
	(-2.07)	(-1.88)	(-2.07)	(-1.88)
Dummy Retrofit Green	0.04***	0.04***	0.04***	0.04***
	(-3.76)	(-3.63)	(-3.76)	(-3.63)
Dummy Vehicle	-0.03*	-0.03**	-0.03*	-0.03**
	(-2.55)	(-2.83)	(-2.55)	(-2.83)
Dummy Vehicle Green	-0.50***	-0.50***	-0.50***	-0.50***
	(-33.56)	(-33.78)	(-33.56)	(-33.78)
One-year bonds		11.33		-1.27
		(0.34)		(-1.23)
Price index		0.20		-0.03
		(0.97)		(-0.68)
Unemployment		-0.11***		-0.11***
		(-6.29)		(-6.29)
CAC40			1.87	2.17
			(-0.65)	(0.65)
Stress index			15.84	17.02
			(1.03)	(-0.65)
Yield curve slope			0.69	-0.07
			(0.49)	(-0.39)
N	240,962	240,962	240,962	240,962
R-sq	0.415	0.416	0.415	0.416
adj. R-sq	0.413	0.413	0.413	0.413

t statistics in parentheses
* p<0.05. ** p<0.01. *** p<0.001

6.2 Placebo tests

As stated in Section 3.2, we build our own categorization of the 90 distinct designations recorded by the robot. While most designations labels are clear enough to be categorized in a straightforward manner, green-renovation labels are subject to interpretation. We conduct two placebo tests to examine the relevance of our categorization in general, and that of the green-renovation category in particular.

In the first placebo test, we randomly assign each of the 90 designations to one out of five arbitrary categories, following a uniform distribution. We then produce OLS estimates of model 3 with these categories, simply labelled 1 to 5. We repeat this procedure 1,000 times. Figure 7 displays the distribution of estimated coefficients for all categories. Table 10 displays the mean of obtained coefficients and p-values. The table confirms that the coefficients estimated for arbitrary categories are centered around zero. The mean of the p-value is 0.5 and it is uniformly distributed, as it should be under the null hypothesis that the value of each of the coefficients is zero. The results lead us to the conclusion that our five-item categorization is meaningful.

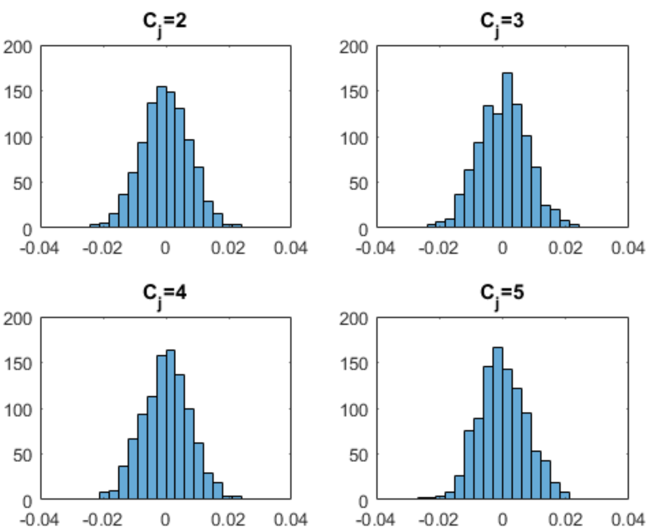

Figure 7: Placebo test on all categories

Table 10: Placebo test on all categories

	Cj=2	Cj=3	Cj=4	Cj=5
Average β1	0.00	0.00	0.00	0.00
Average $\sigma_{\beta 1}$	0.01	0.01	0.01	0.01
Average p-value	0.50	0.50	0.51	0.50

In the second placebo test, we restrict the procedure to those designations which initially fell in either renovation or green renovation categories. We randomly assign those designations to two arbitrary categories while maintaining other designations in their initial category (vehicle, green vehicle and other). We then estimate model 3 and repeat the procedure 1,000 times. The distributions of estimated coefficients appear much narrower for the two vehicle categories than for the two arbitrary renovation categories (Figure 8). The latter are moreover centered around the same value. The mean p-value of 0 indicates that, on average, the null hypothesis on the insignificance of the coefficients is rejected (Table 11). Moreover, the probability distribution of the p-value is not uniform but has a bell shape skewed towards zero, as it should when the null is rejected. This indicates that, irrespective of the green attribute, the retrofit category has a significant impact on the spread. A statistical test fails to reject the null hypothesis that estimated coefficients for the two arbitrary categories are equal (F(1,239939)=0.16; Prob>F=0.6901), as the two placebo categories are now indistinguishable. However, they are different from our baseline estimates obtained with our categorization (F(1,239939)=9.03;Prob>F=0.0001), thus implying that our categorization of conventional and green renovations is also meaningful.

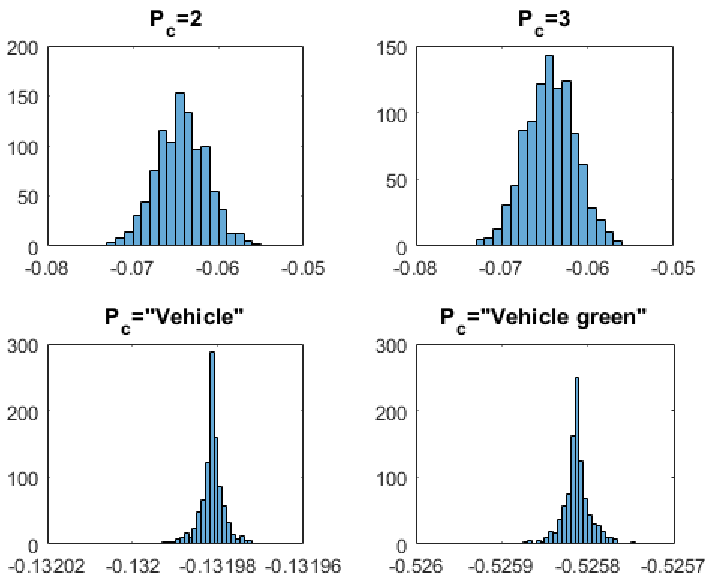

Figure 8: Placebo test on renovation categories

Table 11: Placebo test on renovation categories

	Renovation 1	Renovation 2	Vehicle	Vehicle green
Average β1	0.03	0.03	-0.03	-0.51
Average $\sigma_{\beta 1}$	0.01	0.01	0.01	0.02
Average p-value	0.00	0.00	0.00	0.00

7 Conclusion

We have assembled a unique panel dataset of simulated-loan data to investigate how the interest rate for green projects compares to that of conventional projects on the one hand, how the interest rate for renovations compares to that of vehicles on the other. Regarding the first hypothesis, we found a green discount in 2016, but not in 2015. This result is consistent with the notion that financial agents increasingly value environmental aspects, as recently substantiated by An and Pivo (2018) in the US market for commercial mortgages and Karpf and Mandel (2018) in the US market for municipal bonds. Regarding the second hypothesis, the differences we observe in the interest rates offered for different types of loans is consistent with lenders using loan designation as a screening device for price discrimination of their borrowers. Specifically, our findings suggest dominance of the risk channel in 2015 and dominance of the WTP channel in 2016 in lenders' pricing strategies. Generally speaking, our results are small in magnitude but statistically significant and robust to a variety of specifications. They together suggest that different types of information asymmetries might affect the market for unsecured credit in France, at different points in time. This is particularly true for home energy retrofits, which can be interpreted as a new form of energy efficiency gap.

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