



# How do lenders price energy-efficiency loans? Evidence from consumer credit in France

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*A Toxa – 21 June 2018*

# Home Energy Retrofits, e.g., France

- Major potential for energy savings
  - Building sector: 40% final energy use, 25% CO<sub>2</sub> emissions
  - Low stock turnover (1%/yr) → energy retrofit is crucial
  - French target: 500,000 annual home retrofits
- Financing issue
  - Average investment cost: 9,978€ [5,500€-25,500€]
  - 20-40% of retrofits involve credit (75% in automobile)
  - Resulting annual borrowing needs: 1-2 billion euros

For retrofits to deliver,  
*it is important that credit markets function well*

# What's the Efficient Price of Energy Retrofit Loans?


$$IR_{energy\ efficiency} < IR_{conventional}$$

**Unless** energy efficiency fails to deliver due to **information asymmetries** (Fowlie et al., 2015; Giraudet et al., 2018)

$$IR_{retrofit} = IR_{automobile}$$

**Unless** project used as a **screening device** of unobservable borrowers' characteristics.

*Assuming retrofit borrower are more likely to be homeowners, hence wealthier, the effect is ambiguous:*

$IR_{retrofit} > IR_{automobile}$   *Higher WTP prevails (assuming away collateral)*

$IR_{retrofit} < IR_{automobile}$   *Lower risk prevails*

# Empirical Tests of Efficient Pricing

- Kaza et al. (Cityscape, 2014)
  - Residential mortgages in the US
  - ENERGY STAR buildings associated with lower default and prepayment rates
- An and Pivo (Real Estate Econ., 2018)
  - Commercial mortgages in the US
  - Same finding + better loan terms when buildings certified at loan origination
- **Together suggest efficient pricing, BUT...**
  - Selection issue: no control for borrower characteristics
  - One source of variation only: green versus non-green
  - Plus: focus on new constructions, relatively less important for CO<sub>2</sub>

# Our Approach

- We test for efficient pricing using **two** sources of variation in **unsecured** consumer credit
- We use a novel dataset of **posted** interest rates that is immune from **sorting bias**
- *We find evidence of **inefficient** pricing*
  - *Worse terms for retrofits than for autos*
  - *Even worse terms for green than conventional retrofits*
  - *Results are robust but vary over the sample period*

# A Panel of Scraped Data on Unsecured Credit

Objet du prêt **Prêt Personnel Travaux** Résultats de votre simulation :

Montant souhaité  €

**SIMULEZ**

Montant : **15 000 €**

1 500 €  75 000 €

Mensualité : **145,91 €**

145,91 €  1 289,27 €

Durée : **144 mois**

12 mois  144 mois

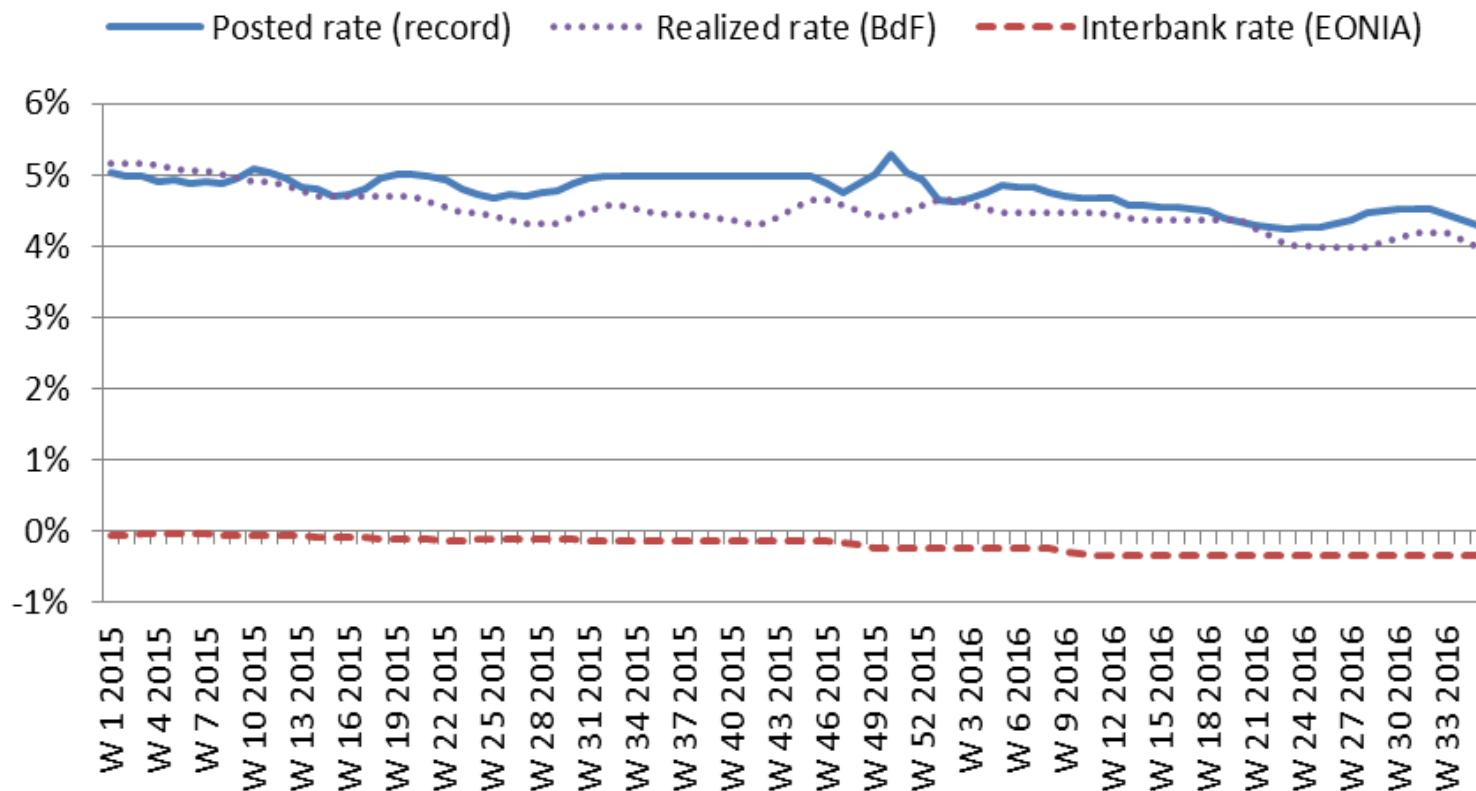
Montant du crédit :	<input type="text" value="15 000"/> €
<b>Montant de la mensualité :</b>	<b>145,91 €</b>
Durée de remboursement :	<input type="text" value="144"/> mois
Taux débiteur fixe :	<input type="text" value="5,940"/> %
<b>TAEG fixe :</b>	<b>6,10 %</b>
<b>Montant total dû :</b>	<b>21 011,46 €</b>
(Hors assurance facultative) dont frais de dossier :	<input type="text" value="0,00"/> €
Coût de l'assurance ADI  :	<input type="text" value="9,37"/> €/

**IMPRIMER**

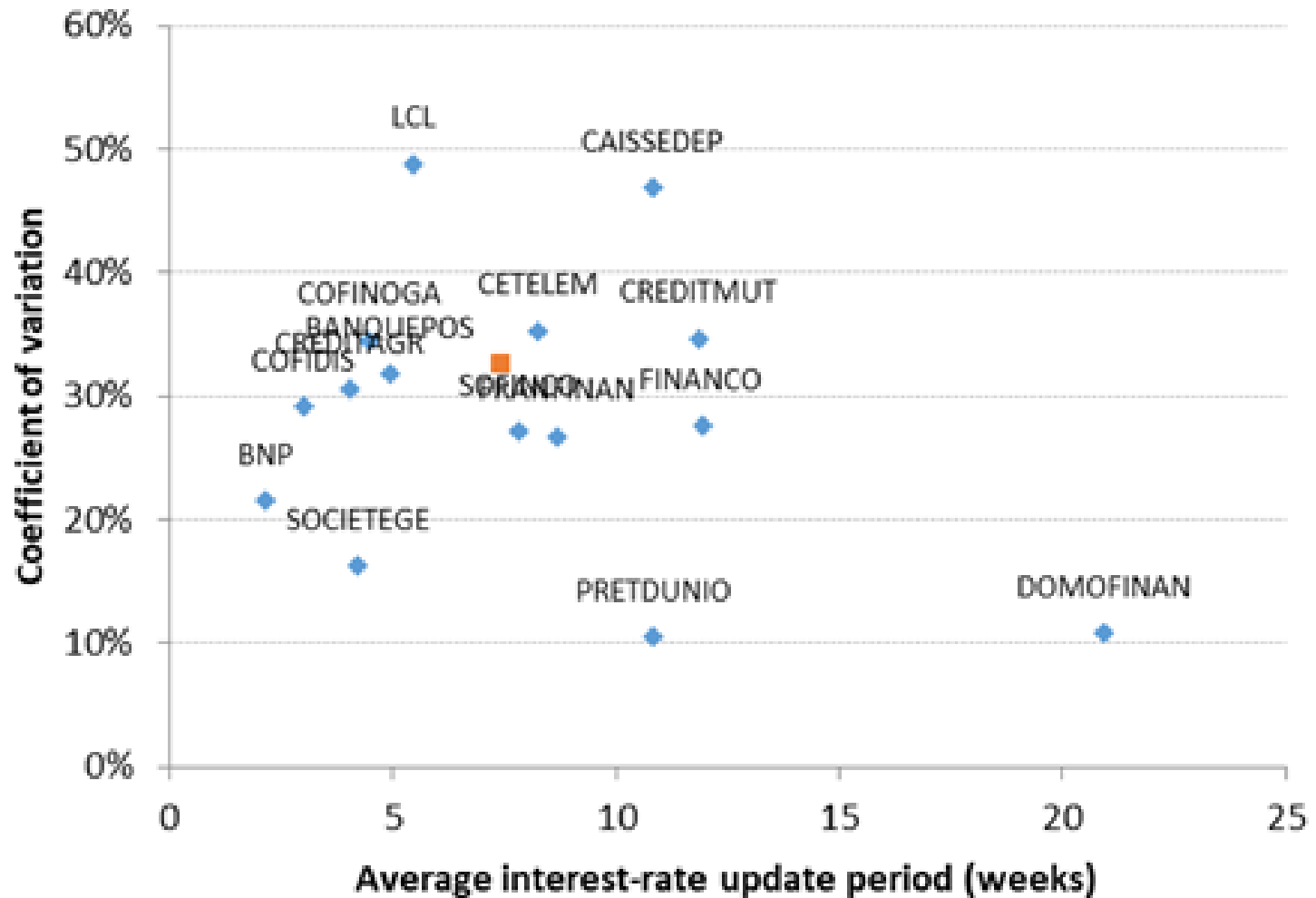
*interest rate*  
=  
*f(amount, maturity, category)*

- **240,962 simulations** (a.k.a. observations)
  - 15 credit institutions surveyed, covering near totality of the market
  - Data retrieved every week, for 2015-2016 (93 weeks)
  - For each week-institution-category tuple,  $11 \times 8 = 88$  simulations
- Crucially: **no credit score** or other borrower characteristics queried

# External Validity: Posted vs. Realized Rates

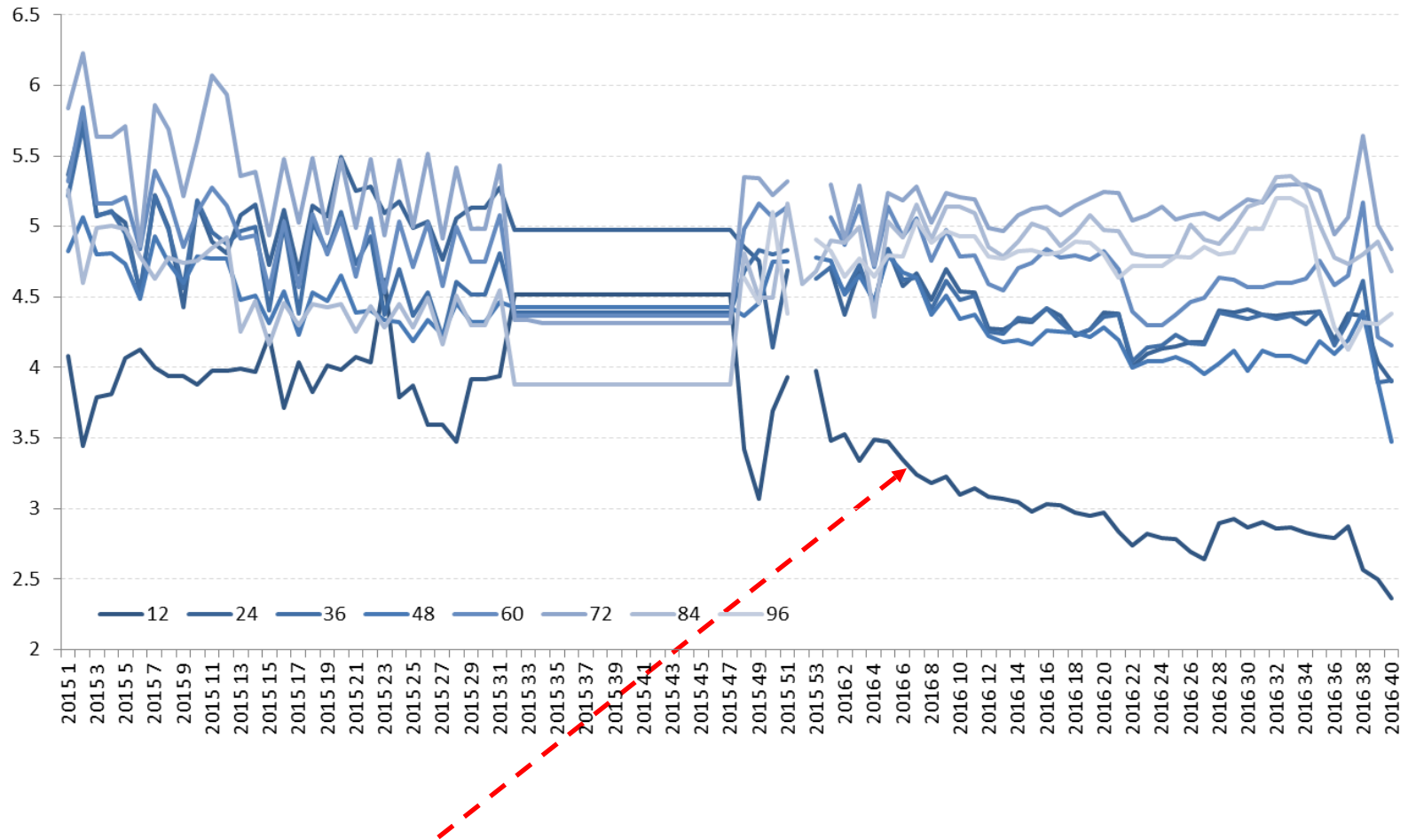


# Price Dispersion in Time and Space





# Time Series, by Maturity



**12-month loans substantially cheaper from early 2016 on**

Effect coincides with an increase in deposits of 154 billion euro between 2015 and 2016 (ACPR annual report, 2016). Role of Quantitative Easing?

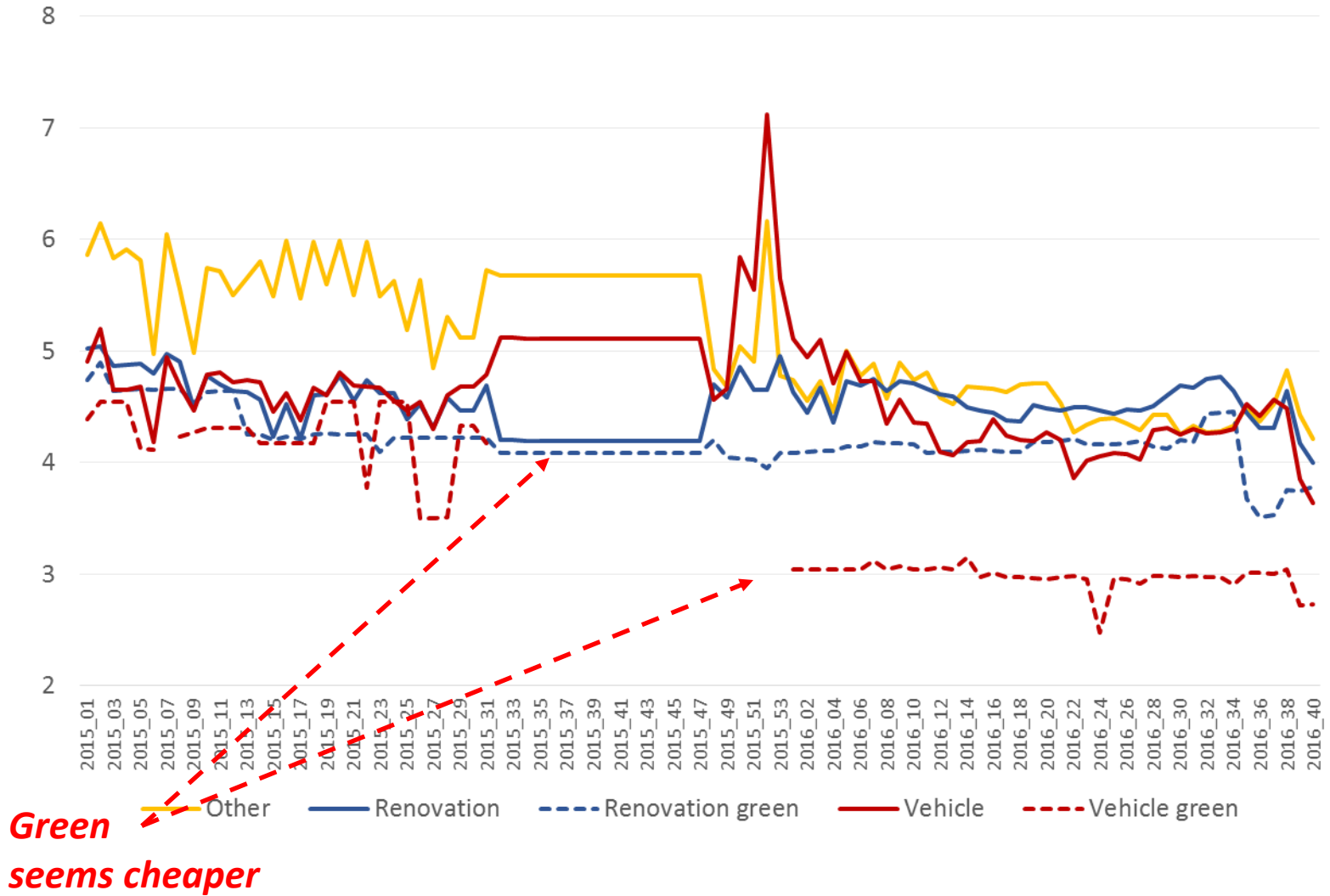
# Categorization of Loan Purposes

Collected entries (90)	Categorization 1	Categorization 2	Categorization 3
Car, motorcycle	Conventional	Vehicle	Vehicle
Used car, used vehicle, used boat, used camping car, used trailer, used motorcycle	Conventional	Vehicle	Vehicle
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	Vehicle	Vehicle
Brand new efficient car	Green	Vehicle	Vehicle_efficient
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_efficient
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

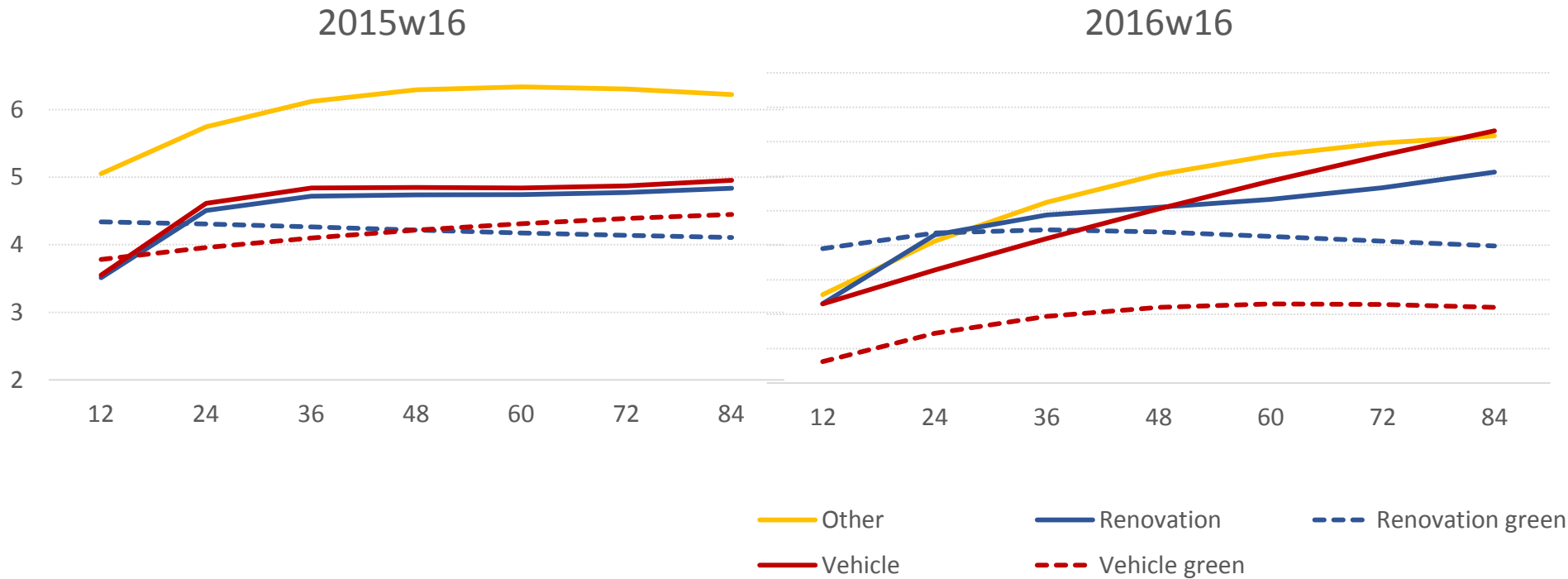
Out of 15 credit institutions...

- 11 distinguish between renovation and vehicle
- 4 distinguish between green and conventional renovation
- 1 distinguishes between green and conventional autos

# Time Series, by Purpose



# Yield Curves (rate vs. maturity)



# Simplest Econometric Model

*l*: lender  
*c*: category  
*y*: yield  
*t*: time

$$s_{lyct} = \beta_0 + \beta_1 L_y + \beta_2 P_c + \underbrace{\gamma_l + \gamma_l \cdot \mu_t}_{\text{FE capturing conjuncture and variation by institution (Khwaja & Mian, 2008)}} + \varepsilon_{lyct}$$

*Interest rate minus gvt  
bond of same maturity*

*Loan characteristics*

**Project dummy**

*FE capturing conjuncture and  
variation by institution  
(Khwaja & Mian, 2008)*

## Efficient pricing hypotheses

- H1:  $\beta_2^{green} \leq \beta_2^{conventional}$
- H2:  $\beta_2^{retrofit} = \beta_2^{automobile}$

# Estimation Results

Dependent variable spread	Model 1	Model 2	Model 3
	Two categories	Three categories	Five categories
_cons	4.455*** (46.23)	4.576*** (47.50)	4.574*** (47.51)
duration	0.0384*** (93.15)	0.0382*** (92.87)	0.0382*** (92.76)
duration2	-0.000261*** (-64.06)	-0.000259*** (-63.34)	-0.000258*** (-63.11)
amount	-0.0249*** (-74.05)	-0.0249*** (-74.24)	-0.0249*** (-74.16)
cst_GREEN	-0.00731 (-0.96)		
Retrofit		-0.122*** (-16.65)	-0.136*** (-17.88)
Vehicle		-0.172*** (-26.43)	-0.162*** (-24.78)
Retrofit green			-0.0842*** (-8.68)
Vehicle green			-0.588*** (-22.89)
Institution dummy	YES	YES	YES
Institution dummy x Time dummy	YES	YES	YES
N	240962	240962	240962
R-sq	0.386	0.388	0.389
R-sq adj	0.384	0.386	0.386

*(Small) green premium*

*Screening?*

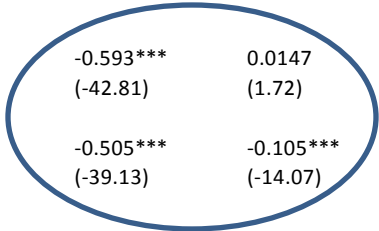
*Green discount*

t-statistics in parentheses

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

# Estimation on Year Subsamples

Dependent variable	Two categories		Three categories		Five categories	
	2015	2016	2015	2016	2015	2016
_cons	5.035*** (54.67)	5.799*** (25.06)	5.448*** (59.67)	5.851*** (25.29)	5.448*** (59.72)	5.843*** (25.29)
duration	0.0253*** (31.67)	0.0492*** (101.21)	0.0246*** (31.21)	0.0496*** (102.00)	0.0247*** (31.44)	0.0493*** (101.57)
duration2	-0.000247*** (-28.79)	-0.000330*** (-70.20)	-0.000236*** (-27.89)	-0.000334*** (-71.04)	-0.000238*** (-28.11)	-0.000331*** (-70.42)
amount	-0.0307*** (-33.67)	-0.0240*** (-66.31)	-0.0299*** (-33.27)	-0.0240*** (-66.41)	-0.0299*** (-33.29)	-0.0239*** (-66.29)
cst_GREEN	0.0681*** (5.47)	-0.0467*** (-4.96)				
Retrofit			-0.593*** (-42.81)	0.0147 (1.72)	-0.616*** (-43.89)	0.0146 (1.63)
Vehicle			-0.505*** (-39.13)	-0.105*** (-14.07)	-0.501*** (-38.69)	-0.0885*** (-11.78)
Retrofit green					-0.481*** (-26.89)	0.000613 (0.05)
Vehicle green					-0.426*** (-11.63)	-0.866*** (-25.11)
Institution dummy	YES	YES	YES	YES	YES	YES
Institution dummy x Time dL	YES	YES	YES	YES	YES	YES
N	69695	171267	69695	171267	69695	171267
R-sq	0.448	0.380	0.464	0.381	0.464	0.383
R-sq adj	0.444	0.378	0.460	0.379	0.460	0.381



*twist*

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

# Robustness: Control Variables

*Instead of using lender\*time dummies, we control for*

- *macro factors*
- *financial factors*

Dependent variable	Model				
	(1)	(2)	(3)	(4)	(5)
Spread APY					
intercept	4.449*** (28.34)	3.757*** (24.33)	4.305*** (29.63)	4.020*** (28.67)	1.612*** (7.83)
<i>Loan characteristics</i>					
duration	0.100*** (68.68)	0.0985*** (69.00)	0.102*** (81.34)	0.102*** (86.67)	0.103*** (87.01)
duration <sup>2</sup>	-0.002*** (-50.16)	-0.002*** (-51.36)	-0.002*** (-63.24)	-0.002*** (-67.60)	-0.002*** (-67.97)
duration <sup>3</sup>	0.000*** (39.03)	0.000*** (41.88)	0.000*** (54.35)	0.000*** (58.18)	0.000*** (58.57)
amount	-0.020*** (-50.70)	-0.020*** (-52.52)	-0.025*** (-74.11)	-0.025*** (-77.62)	-0.025*** (-77.26)
<i>Macroeconomic factors</i>					
ir_1y	-0.343*** (-14.53)	-0.155*** (-6.68)	-0.219*** (-10.48)	-0.266*** (-13.47)	-0.380*** (-16.63)
hicp	-0.234*** (-43.02)	-0.241*** (-45.29)	-0.201*** (-42.51)	-0.203*** (-45.91)	-0.229*** (-45.09)
u	-0.082*** (-5.79)	-0.002 (-0.17)	-0.069*** (-5.43)	-0.030* (-2.52)	-0.027* (-2.25)
<i>Financial factors</i>					
CAC40_spread	0.022 (1.78)	0.096*** (8.05)	0.103*** (9.64)	0.092*** (9.17)	0.079*** (7.75)
ciss_stress	-2.918*** (-12.80)	-3.069*** (-13.75)	-1.599*** (-8.11)	-1.314*** (-7.11)	-1.075*** (-5.75)
yc_slope	-0.388*** (-21.74)	-0.413*** (-23.61)	-0.407*** (-26.38)	-0.417*** (-28.78)	-0.406*** (-28.03)
<i>Indicator variables</i>					
loan type		X	X	X	X
lender			X	X	X
loan type*lender				X	X
loan type*fuel price (S95)					X
time dummy					
N	240962	240962	240962	240962	240962
R-sq	0.088	0.121	0.321	0.404	0.405
R-sq adj.	0.088	0.121	0.321	0.404	0.405

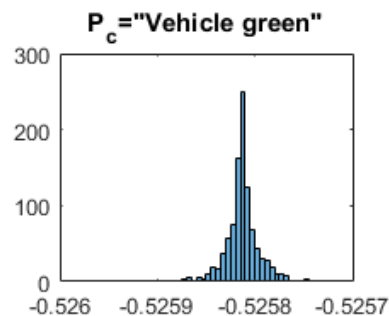
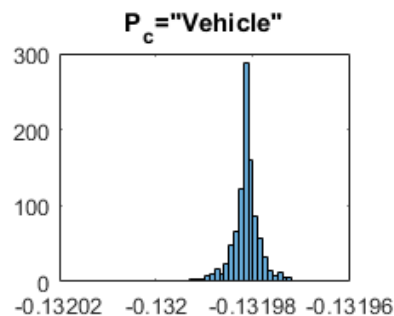
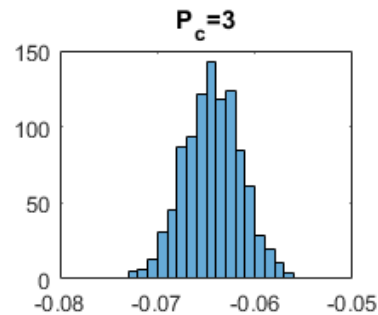
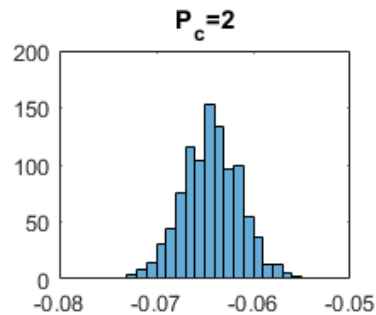
Previously obtained results continue to hold

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



# Robustness: Placebo tests on Renovation

After 1000 tests



$$H_0: \beta_1^{Renovation1} = \beta_1^{Renovation2}$$

$$H_1: \beta_1^{Renovation1} \neq \beta_1^{Renovation2}$$

F(1,239939) 0.16  
 Prob>F 0.6901  
**H0 not rejected**

$$H_0: \beta_1^{Renovation} = \beta_1^{Renovation_{green}}$$

$$H_1: \beta_1^{Renovation} \neq \beta_1^{Renovation_{green}}$$

F(1,239939) 17.74  
 Prob>F 0.0000  
**H0 rejected**

$$H_0: \beta_1^{Renovation} = -0,06 \ \& \ \beta_1^{Renovation_{green}} = -0,06$$

$$H_1: \beta_1^{Renovation} \neq -0,06 \ \& \ \beta_1^{Renovation_{green}} \neq -0,06$$

F(1,239939) 9.03  
 Prob>F 0.0001  
**H0 rejected**

# CONCLUSION: Efficient loan pricing? Not quite.

$IR_{energy\ efficiency} < IR_{conventional} ???$

➔ **Yes** for automobiles (1 bank)

➔ **No** for retrofits (4 banks)

$IR_{retrofit} = IR_{automobile} ???$

➔ **No.** Automobile overall cheaper, though not initially (11 banks)

⇒

Interacting the two effects:  
*Energy-retrofit loans subject to **double energy-efficiency gap**???*

# Further research

## ➤ Extensions

- 12-month puzzle needs further investigation
- Control for lending institutions' characteristics
- A theory of project-based discrimination in loan pricing

## ➤ Policy implications

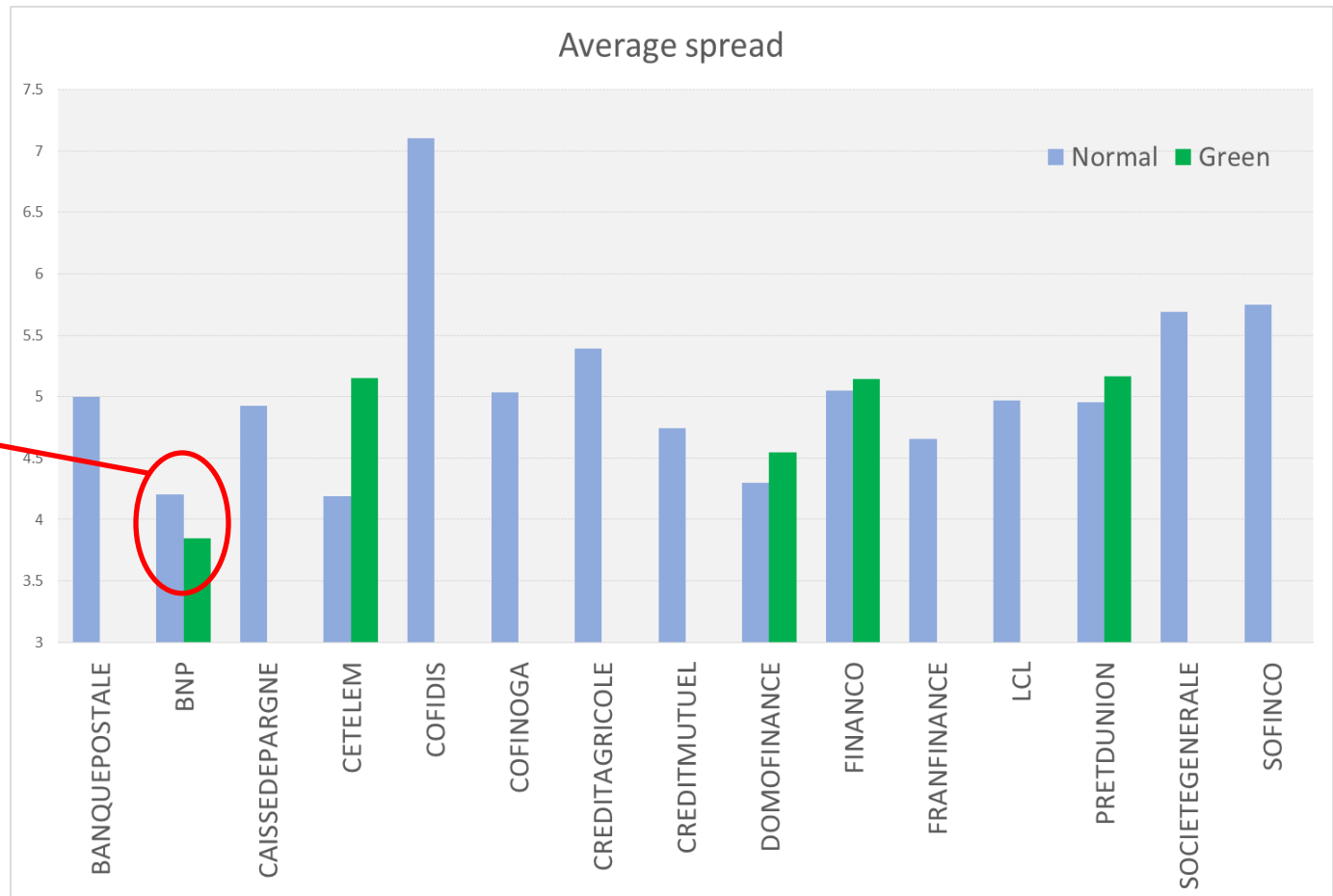
- Public cost of zero-interest loans inflated?
- Linked credit: e.g., Domofinance (Iossa and Palumbo, 2004)

# APPENDIX

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

# Cross-section, by Bank\*Purpose

*Green  
only cheaper  
for autos*



# Tests

Dependent variable spread	Model 1	Model 2	Model 3
	Two categories	Three categories	Five categories
H1: Green premium H1°: $b_{\text{green}} = b_{\text{conv}}$	<b>H1 rejected</b> H1° not rejected t=-0.13	n/a	<b>H1 not rejected</b> H1° rejected F=317.47
H2: Loan type as screening device H2°: $b_{\text{renov}} = b_{\text{auto}}$		<b>H2 not rejected</b> H2° rejected F=192.71	<b>H2 not rejected</b> H2° rejected F=511.58

F correspond to the F-statistics of the Wald test for the corresponding null

# Role of Energy Prices

Dependent variable	Energy price (EP)		
	S95	Electricity	Crude oil futures
spread			
Other*EP	0.615***	-1.622***	-0,000327
Renovation*EP	-0.560***	1.324***	0,000134
Renovation_green*EP	-0.357***	0.401***	-0,000412
Vehicle*EP	-0.383***	-0.226**	0.000615**
Vehicle_green*EP	1.643***	-3.245***	0,000271

*Price discrimination?*

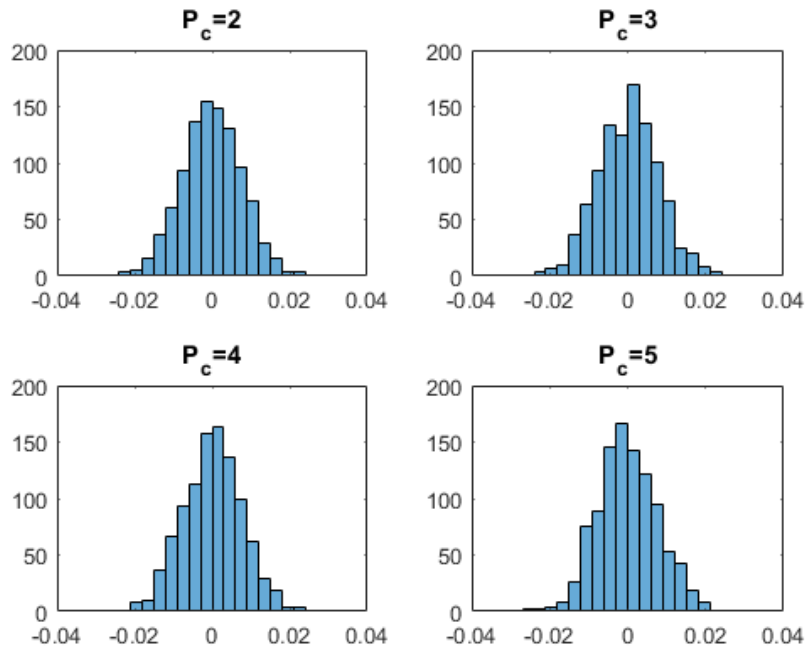
Institution dummies	X	X	X
Institution dummies*time dummies	X	X	X
N	240803	240803	240803
R-sq	0,32	0,32	0,32
R-sq adj	0,32	0,32	0,32

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

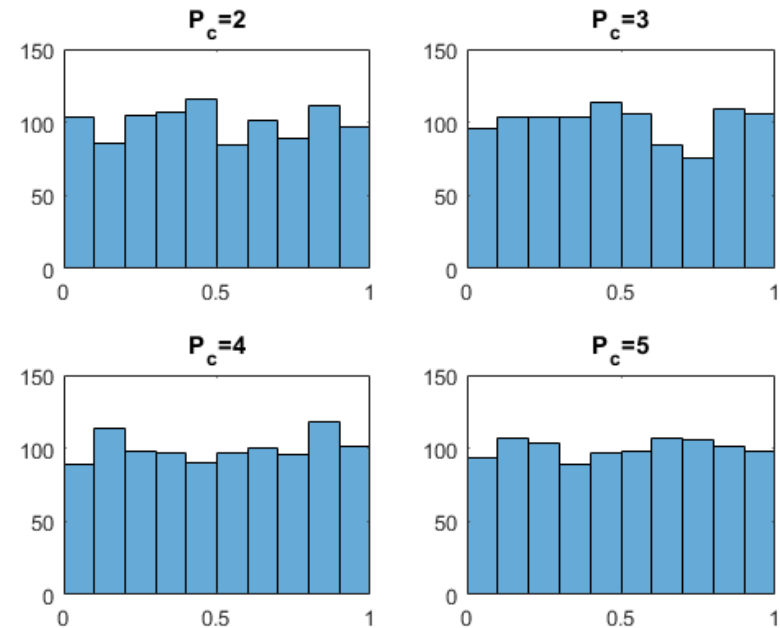


# Robustness: Placebo tests on All Categories

After 1000 tests



Distribution of estimated dummy coefficients



Distribution of p-values of the estimated dummy coefficients