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SOME DON'T LIKE IT HOT: BANK DEPOSITORS AND NGO CAMPAIGNS AGAINST FOSSIL BANKS

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Some Don't Like it Hot: Bank Depositors and NGO Campaigns Against Fossil Banks.*

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Abstract

We exploit new data on NGO campaigns that target banks financing fossil fuels to build a measure of banks' environmental reputation. Using rich data on bank deposits and loans with households in France, we find that banks perceived as browner face a lower supply of sight deposits and a lower demand for housing loans. Other dimensions of the ES responsibility of banks seem to matter less. The effect of bank's brown reputation is stronger in counties where average education, income and political support for green parties are higher. It also mostly takes place after a regulatory change that makes it easier for individuals to switch banks. Last, we exploit data on new housing loans to show that banks perceived as greener can charge relatively higher interest rates to their customers.

Keywords: Climate change, Households finance, Fossil banks, Green preferences.

JEL Classification: G21, G51, Q54.

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1 Introduction

"Switching banks won't single-handedly rescue the world, but collective involvement guarantees a significant impact."

— Lucie Pinson, Founder of the NGO Reclaim Finance

While academic research has long shown that individual bank customers care for the financial health of their deposit banks (see, e.g., Martinez Peria and Schmukler, 2001; Iyer et al., 2016 and references therein), little is known about how much depositors also value the Environmental and Social (ES) performance of their bank. In this paper, we provide new evidence suggesting that bank depositors react to NGO campaigns against banks that finance climate-damaging activities, divesting from such banks and switching to competitors.

Since the 2015 Paris Agreement and the associated calls for more responsible private finance, environmental NGOs have increasingly tracked and made public the billions of funds funneled annually by large banks worldwide into fossil fuels companies and projects directly contributing to the global climate warming.[1] Many large banking groups have in recent years joined voluntary alliances, such as the UN Environment Programme Finance Initiative, the FSB's Task Force on Climate-related disclosure or the UN Principles for Responsible Banking. However, activist groups have consistently depicted these pro-climate commitments as not being binding enough and accused banks of largely greenwashing their activities.[2] Meanwhile, environmental NGOs have multiplied calls in the general public for boycotting the banks depicted as *fossil* or *brown* because of their continued support to the fossil energy industry.[3]

We leverage new data on NGO campaigns blaming French brown banks and detailed

[1]A prominent example is the "Banking on Climate Chaos" report published every Spring by a consortium of NGOs led by the Rainforest Alliance Network. According to its 2023 release, the world's 60 largest private banks financed fossil fuels with USD $5.5 trillion over the period from 2016 to 2022.

[2]Such allegations of greenwashing are to some extent confirmed by regulators' investigations and academic research as well. In May 2023, the European Banking Authority published its Progress report on Greenwashing Monitoring and Supervision, concluding that the total number of potential cases of greenwashing increased in the banking sector since 2012. Giannetti et al. (2023) provide recent evidence that euro area banks that communicate more about greening their business also lend more to the most-emitting firms and industries.

[3]An early example is a campaign launched by the French environmental NGO Les amis de la Terre in October 2015 called "My bank pollutes, I change banks!" (cf. https://www.amisdelaterre.org/Ma-banque-pollue-je-change-de-banque/).

information on banks' deposits from, and loans to, households in France over the years 2010 to 2020, to shed light on how retail customers respond to news highlighting that their bank's business contributes to climate warming. We find that, other things equal, banks receive less sight deposits and face a lower demand for housing loans whenever they are perceived as browner because of repeated accusations of financing unsustainable fossil companies or projects.

Identification relies on the assumption that NGO campaigns about banks' role in global climate warming is exogenous to French (local) households' saving and borrowing decisions. This assumption is vindicated for at least two reasons. First, NGOs campaigns regarding large banks and climate change mostly relate to international activities of the corporate and investment banking (CIB) arms of the banking groups (such as the syndicated funding of a pipeline in an African country) and arguably not with variations in the retail banking business of the same groups' retail banking arms in French counties. Second, the French banking system is quite concentrated, with seven large banking groups accounting for the bulk of retail deposit taking and household lending in France. The ES responsibility of these large banking groups has been scrutinized by French NGOs for decades. Recent changes in the market shares of these bank brands in French retail banking, if any, are therefore unlikely to drive the decision of NGOs to start investigating their ES-related wrongdoings, and launch campaigns.

We get extensive information on NGO campaigns from Sigwatch, a European consultancy which monitors the activities of some 11,000 NGOs worldwide and advises targeted companies on how to engage with activism. We focus on campaigns that target the main brands of the seven largest banking groups operating in France for reasons related to climate change, as well as, separately, for other types of ES concerns. We assume that repeated NGO actions progressively increase the awareness of the general public and construct a time-varying index of each bank's (bad) reputation for sustainability based on accumulated negative alerts from NGOs on each type of ES issues. We first document the increasing pressure exerted by NGOs on the main French banking groups since the early 2010s and the strong increase in the number of actions that point at banks' funding of fossil fuel industries. Interestingly, our reputation indexes for funding fossil companies (which we denote below *brown* of *fossil* reputation indexes) exhibits a lot of variance both over time and across bank brands.

We then take advantage of granular banking data from the French central bank, which allows us to monitor households' deposits and loans for each individual bank affiliated to the targeted banking groups, in each of mainland France's 94 *départements* (denoted as counties below for simplicity) with monthly frequency. We match this information on individual banks' business with the banking groups' reputation index for climate (un)sustainability, using both information on banks' parent companies and the specifics of banks' names. Banks' affiliation with their respective group is indeed not always transparent to the man of the street, notably because the group's brand is not necessary apparent in individual bank names. We therefore assume that depositors only connect campaigns against a major banking group with their own local bank when the latter's affiliation is transparent enough. This way of matching NGO campaigns with banks in turn increases the heterogeneity of treatment among the 100 individual banks in our final dataset.

Using this bank-county level data, we run panel regressions of bank deposits on banks' fossil reputation indexes, controlling for local bank presence, as well as local economic activity and unobserved bank and county characteristics using fixed effects. Our estimation results show that banks with a reputation to be brown receive significantly less sight deposits from households. Importantly, banks' reputation for being irresponsible along other dimensions of ES sustainability does not appear to matter much, which suggests that ES-conscious depositors are mostly concerned with their bank's contribution to climate change. The effect is driven by sight deposits, while term deposits, which are more subject to contractual frictions, adjust less. It is stronger in counties where inhabitants are on average more educated and more prone to support green parties. Meanwhile, browner banks also face a lower demand for housing loans.

Further, we exploit a well-publicized policy move in February 2017 that made it much easier and (transaction) cost-free for individuals to move their main checking account from a bank to another bank. This regulatory change, due to the late implementation of an article in the so-called Macron law of August 2015, provides us with a quasi-natural experiment that we use to highlight the main mechanism at play: discontent depositors follow the advice of NGOs and switch banks. Indeed, the negative effect of bank's brown reputation on the supply of sight deposits is much larger after the new regulation entered into force.

Last, for a subsample of the same banks, we observe all individual housing loans granted to households by a representative sample of their local branches throughout the country. We leverage this additional loan-level dataset to investigate whether NGO campaigns denouncing brown banks also have an impact on interest rates on housing loans. Controlling for loan, bank and municipality characteristics, we find evidence of some willingness of households to pay for their environmental values: banks with a browner reputation are constrained to charge somewhat lower rates than their greener competitors in order to retain customers.

Our study fits in the booming literature on climate finance (Giglio et al., 2021) and, more precisely, sustainable banking (De Haas, 2023).

We first contribute to the stream of research that aims at assessing the impact of ESG news on firms and investors. For instance, Krueger (2015) finds that the stock prices of US firms drop in response to negative news related to firms' corporate and social responsibility. Derrien et al. (2022) find that financial analysts downgrade the earning forecasts of firms in response to negative ESG news. Hartzmark and Sussman (2019) show that mutual fund investors react to a new salient ESG label by pouring money into high-sustainability funds and exiting low-sustainability ones. Our contribution is here to build a measure of banks' reputation for irresponsible business based on NGO campaigns and look at the reaction of retail bank depositors.

Since the source of ESG information we consider is campaigns by activist groups, our paper also relates to the literature on boycotts. Koenig and Poncet (2019), who also exploit the Sigwatch database, show that imports of clothes from Bangladesh after the Rana Plaza scandal drop in countries whose firms were directly involved in the collapse of the Rana Plaza building, which suggests that consumers in these countries reacted negatively to NGO campaigns naming their domestic companies and apparel brands. Closer to our study, Homanen (2022) documents a decrease in deposit growth with banks involved in the controversial Dakota Access Pipeline in the US. In a similar vein, Jeung (2022) finds that banks shamed by activist groups because they fund the gun industry experienced a relative decrease in deposit growth after a deadly school shooting in Florida in 2018.

While these papers exploit a unique event in a difference-in-differences setting, we consider the accumulated impact of NGO campaigns on banks' reputation for sustainable business over a decade and evaluate the differential response of bank customers depending on the type of ES issue at stake.

Last, our paper speaks to recent studies that aim to evaluate the ESG preferences of individual investors and their willingness to pay (WTP) for their values. Pastor et al. (2021) and Pedersen et al. (2021) provide a theory explaining why ESG-motivated investors should expect lower returns for their responsible investment. Several papers exploit administrative data and field experiments and/or surveys to elicit the non-pecuniary motives of responsible investors (Anderson and Robinson, 2021; Bauer et al., 2021; Giglio et al., 2023; Heeb et al., 2022; Riedl and Smeets, 2017). Notably, Anderson and Robinson (2021) study how Swedish households reallocate their pension savings into ESG-labelled funds after the 2014 heatwave in Sweden and point out that more environmentally-conscious savers are ready to pay higher fees for such funds. Bauer et al. (2021) also find that a majority of individuals members of a Dutch pension fund support a new, more ambitious engagement policy of the fund with invested companies even when they expect engagement to hurt financial performance. Other studies quantify the WTP in terms of lower expected return for various classes of assets (Barber et al., 2021; Riedl and Smeets, 2017). We contribute to this literature by focusing on unsophisticated retail investors, i.e. individual bank depositors, and by providing new evidence of a (small) WTP for borrowing mortgage loans from banks perceived as greener.

The rest of the paper proceeds as follows. We start by laying out our research hypotheses in section 2. We present the data in section 3. Section 4 details how we build a measure of bank reputation based on NGO campaign alerts. Sections 5 and 6 explain the methodology and display the results of our empirical analyses. Last, section 7 concludes.

2 Research hypotheses

We spell out in this section our research hypotheses. As detailed below, we exploit data on NGO campaigns to construct a measure of French banks' reputation with the general public on various ES issues. In the main part of the study, we focus more specifically on campaigns that denounce the funding of fossil energy (or *brown*) projects and companies by French banking groups. NGO campaigns generally target a general audience, so that a measure of banks' reputation for climate responsibility built on NGO alerts naming and shaming banks is a reasonable proxy of how *brown*, or *fossil*, banks are perceived by individual bank customers. We provide evidence below that the campaigns in our dataset are on average largely echoed in mass media, which vindicates our hypothesis.

We then make the following research hypotheses. First, we assume that climate-motivated bank customers react to the information conveyed by negative NGO campaigns and, to some extent, follow NGOs' advice to boycott fossil banks. Under the assumption that the proportion of such attentive, green depositors is high enough, banks with a reputation to fund fossil projects detrimental to the climate should then face a lower *supply* of deposits. We test this hypothesis by regressing the (log of) outstanding deposits on the negative reputation index of banks.

The effect may depend however on the duration of deposits. Indeed, the contractual terms of longer-term and savings deposits often entail frictions. For instance, keeping the benefit of a relatively high interest rate on an ongoing savings scheme with a bank is not warranted if the savings plan is closed and a similar plan is opened with a new bank. As a consequence, we expect the supply of household term deposits to respond less, or even not, to negative shocks to the reputation of banks for sustainable lending.

Funding the purchase of their home is the main reason why households borrow from banks, and taking a mortgage loan with a bank involves opening a checking account with this bank. Further, when granting a mortgage loan, a loan officer frequently invites the borrower to domicile her regular income (wages) with the bank (although this is not mandatory). For these reasons, we expect the *demand* for housing loans to also vary with banks' reputation for responsible business. We therefore also test this hypothesis by regressing the (log of) outstanding mortgage loans on the negative reputation index of banks.

Climate-conscious bank customers may react along the intensive margin, i.e., reduce the amount of deposits they hold with the brown bank and reallocate some money with other banks, or along the extensive margin (exiting the brown bank altogether). While the intensive margin is limited by the number of depositors owning several accounts, the extensive margin is limited by the transaction costs of switching banks. Accordingly, any regulatory change that may cut these costs should increase households' incentives to switch banks. We test for the role of the extensive margin by using a law in support of increased bank mobility as a quasi-natural experiment.

Last, shifts in the supply of deposits and the demand for loans should also involve price effects: a rise in the interest rate on sight deposits and a drop in the interest rate on housing loans, respectively, for the treated banks. In France, no interest is paid by law on sight deposits. However, we can test further the hypothesis that a bank's bad climate-related reputation entails a lower demand for loans by looking at the interest rate for new housing loans. In equilibrium, brown banks ought to cut somewhat their required rate in order to accommodate the lower demand and retain customers. *Mutatis mutandis*, the interest spread between similar housing loans taken from a a green bank vs a brown bank, if any, should reflect the willingness of conscious individuals to pay for their environmental values.

3 Data

3.1 NGO campaigns

3.1.1 Presentation and cleaning

Our data on environmental NGO campaigns comes from Sigwatch.[4] Sigwatch is a European consultancy which tracks and collects detailed information on NGO campaigns targeting companies worldwide. This consultancy was founded at the beginning of the 2010s to help companies engage with activist groups and manage their reputation risk. According to their website, Sigwatch covers in 2023 the campaigns of some 11,000 activist groups (NGOs) naming (and often shaming) some 24,000 companies in the world. An NGO campaign is defined as a series of actions and communications by one NGO or a coalition of NGOs, targeting one or several companies in order to achieve a specific goal.

[4] We thank Pamina Koenig (PSE) for sharing the access to this dataset with us.

A campaign may last for several months or even years. Campaign actions are the main milestones of campaigns, i.e. moments when new public protest actions take place, or when new reports are disseminated. They are the most likely to attract public attention.

For each country covered, Sigwatch monitors a list of active NGOs, which they regularly update. They then collect data on campaign actions by browsing the websites of the identified activist organizations.[5] In the dataset provided by Sigwatch, individual observations are better described as company-specific *alerts*. An alert is created for each company named within the frame of a new campaign action. For instance, when a new NGO campaign targets three banks simultaneously for jointly funding a new fossil fuel extraction project, three new alerts are recorded in the dataset, one for of each of the banks. For each alert, detailed information is collected on the participating NGOs (name, home country), the company blamed or, sometimes, praised (name, parent company, country, country of parent etc.), the campaign's details (registration date in Sigwatch's database, internet links, keywords, excerpts of manifestos naming the companies, country of the targeted audience).

Sigwatch also adds qualitative information by coding several proprietary variables: a measure of the NGOs' outreach (NGO power), a sentiment indicator (from very negative to very positive sentiment) and a prominence indicator which measures how exposed the named company is in the campaign. For instance, on 23 March 2018, the French environmental NGO *Les Amis de la Terre* (the French arm of Friends of the Earth International), in association with another French NGO called i-boycott.org, launched a new campaign to denounce the funding by Société Générale (SG) of two contended fossil energy projects: the Rio Grande LNG terminal and the Rio Bravo gas pipeline in Texas.[6] This campaign was registred by Sigwatch on 28 March 2018. Sigwatch rated the campaign against SG as very negative and very prominent, as the call for a "citizen boycott" of the bank was echoed in several newspapers at the time. Interestingly, the webpage of the campaign also mentions BNP Paribas on a more positive note, emphasizing recent commitments by this bank to exit unconventional fossil fuels in response to alleged public pressure. This information translates in Sigwatch's dataset into a second alert within the frame of the

[5]For a general description of the Sigwatch dataset, see Koenig (2017).

[6]For details of the campaign, see: https://www.amisdelaterre.org/stop-rio-grande-lng-une-campagne-citoyenne-de-boycott-vise-societe-generale/.

same campaign (same campaign action identifier), this time naming BNP Paribas. This second alert is associated by Sigwatch with a positive sentiment and an intermediate level of prominence.

For our purpose, we focused on campaigns (i) targeting French banks, (ii) because of some environmental and social (ES) issue, (iii) run by at least one French NGO, (iv) and/or addressing a French audience.[7] We parsed the campaigns' keywords provided by Sigwatch to construct our own dictionary of terms identifying climate change (CC)-related campaigns, vs campaigns related to other environmental (OE) issues and campaigns related to social (S) issues. For instance, keywords such as "coal", "oil", "gas", "shale", "pipeline", "fracking", "drilling", "fossil fuel", "climate change" or "carbon" were used to pick climate change-related campaigns. Among campaigns not related to climate change, keywords such as "battery poultry", "pollution", "rainforest", 'palm oil", "water use", "greenwahsing" were used to pick other environment (OE)-related campaigns. Last, remaining ES campaigns (i.e. after exclusion of a few campaigns related to non ESG topics such as consumer protection), were defined as S. Campaigns we labelled as "social" point at a variety of social or ethical issues, such as human rights abuses, labor rights abuses, tax avoidance and tax havens, complicity in money laundering, support to Israel's policy in the occupied territories, illegitimate debt and poverty, social impact of mining activities, among others.[8]

NGO campaigns targeting banks generally mention the common name of large banking groups, such as *BNP Paribas* or *Crédit Agricole*, i.e. banking brands which are well known to retail customers, some of which may however not be the ultimate parent company. We identified nine banking brands in the cleaned campaigns dataset: Banque Populaire-Caisses d'Epargne (BPCE), BNP Paribas (BNP), Crédit Agricole (CA), Crédit Coopératif (CCoop), Crédit Lyonnais (LCL), Crédit Mutuel-CIC (CM-CIC), HSBC, La Banque Postale (LBP), and Société Générale (SG). We then matched individual campaign alerts with these bank brands. For instance, an alert naming BNP Paribas Wealth Management was identified as an alert pointing at the BNP brand. We are interested here

[7] We include HSBC France, formerly *Crédit Commercial de France*, among French banks because of its large branch network in metropolitan France.

[8] We double-checked that our CC, OE and S labels were indeed consistent with all keywords provided by Sigwatch to describe campaign contents, as well as, when still available, the online content of the campaigns.

in campaigns that aim to arise the awareness of the general public. Campaigns pointing at the asset management arms of large French banking groups without mentioning the brand of the parent bank were therefore considered irrelevant and dropped, because these financial institutions are unknown to most individual bank customers.[9]

3.1.2 Descriptive statistics

Our cleaned dataset of relevant NGO campaigns naming French bank brands includes 361 negative and 79 positive distinct alerts over the period 2010-2020. Among alerts with a negative sentiment, 244 relate to climate change issues (68%), 46 to other environmental issues (13%) and 71 to so-called social issues (19%).

Figures 1 and 2 provide an overview of this data. Figure 1 shows the yearly number of ES-related alerts targeting French banks, sorted by their main issue type (CC, OE, S). Two main facts emerge. First, the pressure exerted by NGOs on French banks for ES motives increased by a factor 8 over the period, with less than 15 alerts in 2010 against more than 110 alerts in 2020. Second, while OE and S issues dominated in the early 2010s, climate change-related alerts gained momentum over the decade and overwhelm other concerns in recent years.

Figure 2 focuses then on CC-related alerts and plots the number of negative vs positive alerts naming French bank brands each month. Negative alerts dominate throughout, but interestingly both the number of bad and good news increased over recent years (2019-2020). This witnesses first an increased monitoring of banks' climate-related policy by French NGOs, echoing the increasing concerns of the general public. The rise in positive news may also point at increased efforts and commitments made by banks in response to public and regulatory pressure and most often after the 2015 Paris Agreement, such as pledges to join coalitions for climate (like UNEP-FI's principles for responsible banking) and to exit the funding of the most damaging activities (such as coal extraction and combustion, arctic oil, or oil extraction from tar sands).

Tables 1 to 4 shed light on who are the most active NGOs and who are the most targeted bank brands. We analyze separately negative and positive alerts. Some campaigns are

[9] Cases in point are Natixis and Amundi, two large asset management firms which are respectively subsidiaries of BPCE and CA.

run by a coallition of NGOs. In such cases, we consider here only the NGO ordered first by Sigwatch.[10] As shown in Table 1, *Amis de la Terre* comes out as the most active NGO in denouncing ES misbehavior by French banks, with 59% of negative alerts on all ES issues and almost 70% of alerts on climate change-related issues. Together, only four NGOs (*Amis de la Terre*, Oxfam, ATTAC and Reclaim Finance) account for some 87% of all negative CC alerts targeting French banks. Meanwhile, *Amis de la Terre* and Reclaim Finance, a recent spin-off of the former, account for more than 77% of positive alerts of the issue.

As regards targeted banks, BNP Paribas comes out as the most blamed bank when considering all ES issues, with a third of all negative alerts over 2010-2020. When looking only at climate change-related issues however, BNP and SG rank ex aequo, with both 31% of negative alerts. CA then comes second with 22% of negative alerts. Interestingly, BNP also rank first when considering positive CC-related alerts, which suggests some reputation gains of the bank's publicized efforts to green its business in recent years.

3.2 Bank data

Our main variables of interest are (i) volumes of outstanding households deposits issued and housing loans held by French banks in each county (in French: *département*) of mainland France and (ii) interest rates of new housing loans granted by a large sample of French bank branches.

We obtain bank-county-level information on deposits and loans in France over the years 2010-2020 from CEFIT, a proprietary dataset of the Banque de France. Specifically, CEFIT provides us with details of the outstanding volumes of deposits issued and loans granted to non-financial customers by individual credit institutions in each of the 94 counties of mainland France. Credit institutions (hereafter, banks) are identified by a unique number (*Code d'identification bancaire*, CIB). We focus on deposits issued to resident households, which we sort into sight deposits vs term deposits , and housing loans granted to the resident households, which we sort into standard housing loans vs regu-

[10] Sigwatch is not explicit about the rationale behind this ordering. However, manual checks for some visible campaigns suggest that the "first" NGO indeed plays a leading role in the campaign, or at least in its French part.

lated housing loans (e.g. lending schemes with capped interest rates or public subsidies targeting poorer households, such as "zero-interest-loans"). Deposits and loans amounts are observed with monthly frequency. We focus on credit institutions which belong to one of the seven largest banking groups operating in France.[11] These groups account for more than 95% of outstanding household deposits throughout the period. Some smaller credit institutions only report to CEFIT with quarterly frequency. We drop these smaller banks and focus on the subsample within major groups which report with monthly frequency. We compute monthly rates of growth of deposits and loans and winsorize them at the first and 99th percentiles. We then drop observations of level variables corresponding to outlier growth rates in order to mitigate the impact of possible reporting breaks (associated, e.g., with local bank mergers). We are left with an unbalanced regression sample of 100 individual banks affiliated to one of the seven major banking groups of the country, and 122,368 bank-county-month-level observations over January 2011 to November 2020.[12]

We obtain geo-localized, loan-level data on newly issued housing loans in France over the years 2013-2020 from MCONTRAN, another proprietary dataset of the Banque de France. More precisely, MCONTRAN collects the details of all new loans to non-financial customers granted by a representative sample of branches of resident banks in the first month of each quarter. Banks report a unique loan identifier and all relevant characteristics of the loan: amount granted, interest rate, maturity at issuance, type of loan, type of collateral if any, identifier and municipality (ZIP-code) of the issuing bank branch etc. We focus on regular (i.e., non-regulated), fixed-rate housing loans with resident households in mainland France.[13] We exclude bridge loans and renegotiated loans, as well as loans with missing total amount, interest rate or initial maturity. For consistency across our evaluation exercises, we restrict the sample to banks for which we also observe county-level information on outstanding deposits and loans volumes from CEFIT. *La Banque*

[11] These banking groups are six major banking groups headquartered in France (BNP, BPCE, *Crédit Agricole*, *Crédit Mutuel-CIC*, *Banque Postale*, *Société Générale*) and the French subsidiary group of HSBC group (HSBC France, formerly CCF).

[12] Note that since our indexes of banks' ES reputation builds on NGO alerts lagged by up to 12 months (see section 4 below for details), we lose the first year of observations. The final regression sample therefore starts in 2011 instead of 2010.

[13] The French mortgage loan market is dominated by fixed-rate loans. According to the French supervisory authority (ACPR), 99.2% of new housing loans issued to French residents were fixed-rate loans, while fixed-rate loans accounted for 97.7% of outstanding amounts as of December 2022 (cf. ACPR, 2023, Le financement de l'habitat en 2022, Analyses et Synthèses, No. 151).

Postale, the French post bank, reports all its housing loans to MCONTRAN as if they were issued by one unique branch, a hub located in Paris, although customers actually deal with the loan officer in their local post office. Since we use in our regressions local controls that relate to the ZIP code of the municipality where the issuing bank branch is actually located, we further exclude loan observations reported by the French post bank. Last, we drop municipalities with less than 10 different loan observations over the period. We also drop municipalities which do not host at least three bank branches throughout. Our final sample is a quarterly dataset of 246,657 individual loans for housing purchase, issued by the local branches of 77 individual banks and located in 1,070 municipalities across 93 counties between the second quarter of 2013 and the last quarter of 2020. Figure A1 in the Appendix shows the map of municipalities included in our final sample, their average number of bank branches and the total number of loans issued by these branches over the period that we observe in our cleaned dataset. The figure confirms that our final selection of municipalities is spread out across the whole country and representative of all regions.

We then construct bank-related controls using various additional sources. Firstly, we use Banque de France's *Fichier des implantations bancaires* (FIB) to construct local measures of bank size and competition in retail banking markets. The FIB dataset monitors the population of active bank branches of all banks in France, including their postal address, with monthly frequency. For each bank, we first compute the (log) number of branches in each county as a proxy for the size of the bank's local network and therefore the size of its local business. We use this variable as our main bank-county-level control in regressions explaining the level of deposits or loans. We then also compute the (log) number of bank branches within each municipality (ZIP-code) and the share of branches of each local bank in a ZIP-code at quarter's end. We use these two variables as proxies for the degree of retail banking competition in each ZIP-code and for the market power of each bank within a ZIP-code. We include them as controls in our regressions explaining the level of housing loan interest rates across banks and ZIP-codes.

Secondly, we exploit non-consolidated balance sheet and income statement information from the SURFI database of the French bank supervisory authority (ACPR) to construct additional bank-level controls with either monthly or quarterly frequency. For all variables, we consider information related to the France-based business of available credit institutions (excluding branches located abroad or in French overseas territories). SURFI is structured in a variety of sub-datasets, or "reporting forms". The first sub-dataset used, M-SITMENS, provides simplified balance sheet items with a monthly frequency for a subsample of banks. We use this data to construct monthly measures of bank size (log of total assets), leverage (capital and reserves to assets) and reliance on retail deposits (debt to non-financial customers to assets), which we include in our regressions explaining deposits and loan volumes.

We also use two other sub-datasets with quarterly frequency but with a broader coverage, SITUATION and CPTE-RESU.[14] We use this data to construct quarterly measures of bank size (log of total assets), leverage (capital and reserves to assets), asset liquidity (cash and interbank assets to assets), business model (credit to non-financial customers to assets) as well as non-performing loans (loan losses and provisions to credit to non-financial customers), which we include in our regressions explaining the interest rate of new housing loans.

3.3 Other data

Socio-demographic data. We use Census data from 2008 to measure age and education at the city-level (ZIP code).[15] The dataset comprises information on educational attainment, categorized into 7 levels, of individuals aged 16 and over, who were not enrolled in school. It is segmented by gender and age group. We use this data to compute the share of adults with college education or higher education attainment, at both the city and county (*départements*) levels as of 2008. We also leverage fiscal data from *Impot sur le Revenu des Communes de France* (IRCOM) to measure income per capita.[16] The data provides a snapshot of taxation from the previous year as of December 31 of the current year, as well as information on the number of tax households and the total amounts of salaries, wages, or pensions for each region, department, or commune. We use this data to compute the average income per household at both the city and county levels as of

[14] Income statements (CPTE-RESU) are semi-annual. We assume that accounting flows are constant over the two consecutive quarters of each semester to compute quarterly equivalent statements.

[15] Data from INSEE available here.

[16] Data is available here.

2010. Last, we sort counties and cities into quartiles of the the respective distributions of these measures of educational attainment and average income. Figure A3 in the appendix show the geographical distributions of these variables.

Green votes. We recover data on votes for green parties at the 2009 and 2014 European elections in France from the website of the French Ministry of Interior affairs.[17] Electoral results (number of electors, voters, and votes for each candidate) are available at both the level of county (*départements*) and *cantons*, the latter being a smaller administrative grouping of a few ZIP-codes which we map into the constituent municipalities. We use election results to gauge the green preferences of people living in the respective *départements* and cities. Elections of MEUP are relevant for our purpose because they are held under the proportional representation system and green parties generally obtain their best scores at these elections as a result. Results are therefore more likely to reveal the pro-climate preferences of inhabitants than the share of green votes at other elections. For each EUP election in each county or city, we identify all candidates standing for green parties (EELV, GE, Cap 21 etc.) and add up the votes they get to compute their total share of expressed votes. As before, we sort counties and cities into quartiles of the respective distributions of green vote shares. Figure A4 in the appendix shows the geographical distribution of green votes across French counties.

4 Measuring banks' sustainability reputation with NGO campaigns

4.1 NGO campaigns and mass media: gauging the impact on bank depositors

We aim to construct a monthly measure of French banks' reputation on sustainability (or ES) issues in the general public, i.e. Main Street bank depositors. Our source of information are NGO campaigns that raise the public's attention to banks' irresponsible business. NGO campaigns can reach the general public through a variety of channels,

[17]Data available here.

including mass media, NGOs' websites and social networks. To vindicate our approach, we therefore first investigate whether the NGO alerts selected from the Sigwatch dataset find their way into general interest newspapers or other mass media. We gauge the impact of NGO campaigns on retail bank customers by web-scrapping a broad selection of French information websites for corresponding mass media releases.[18] For each NGO campaign alert in our dataset, our Python algorithm launches a Google query using the respective NGO and bank names, as well as selected keywords from the alert's content, and then returns the URL and titles of newspapers articles meeting these criteria within a time window of 10 days before and one month after the recorded alert date. We manually drop irrelevant hits (false positive) that are not related to climate change.

Overall, we identify some mass media coverage for about a half of all negative, climate change-related, NGO campaign alerts over 2010-2020. When some media coverage is identified, the median alert benefits from two releases, while the top 10% of media-covered campaign alerts are echoed by four media websites or more. Figure 3 shows the share of negative, CC-related, alerts with media coverage through time. Media coverage fluctuated over the decade, reaching first a high in 2015, the year of the Paris Agreement, then regaining momentum towards the end of the sample period with about two thirds of alerts being echoed in newspaper articles or other mass media. In spite of possible shortcomings of our search algorithm, which may miss relevant newspaper articles, this suggests that the NGO alerts in our dataset are likely to reach a broad audience among French bank customers.

4.2 Sustainability Reputation Indexes

4.2.1 Methodology

In this section, we detail how we use NGO campaigns to construct our index of banks' reputation for irresponsible business. In the following presentation, we focus on climate change-related NGO alerts, but we proceed similarly for each type of ES alerts (CC, OE, S and all ES). Since we have no basis for assuming that bank depositors pay an equal

[18] We include the websites of all nation-wide daily newspapers, the first 19 daily regional newspapers, all weekly general interest or economics-related magazines, and major TV and radio broadcasts. See the complete list in the appendix.

attention to negative and positive news, and therefore do not know how they may combine them, we deal with negative and positive alerts separately, using the same methodology. We therefore construct a Sustainability Reputation Index (SRI) reflecting negative CC-related alerts (negative SRI on CC issues, in short "negative CC SRI") and another one that reflects positive CC-related alerts ("positive SRI"). For simplicity, we focus below on how we construct the negative CC SRI. For each negative CC-related alert, we use the qualitative information provided by Sigwatch to compute an alert-specific impact score AIS_{nbd}:

$$AIS_{nbd} = S_{nbd} \times P_{nbd} \times N_{nbd}$$

where n denotes the NGO (or coallition of partner NGOs) running the campaign, b denotes the targeted bank brand, d the date of release of the alert. S_{nbd} is the absolute value of the (negative) sentiment qualifying the alert, scaled to one. P_{nbd} is the prominence of the bank's brand in the alert, also scaled to one. Last, N_{nbd} denotes the scaled "power" (outreach) of the most powerful of the NGOs participating in the campaign. Concretely, an alert is supposed to have a maximal impact (score equal to one) when the associated sentiment is very negative (sentiment of -2), the prominence of the bank brand in the release is very high (4, i.e., the bank is named in the headline of the campaign) and at least one of the participating NGOs is viewed by Sigwatch as very powerful (NGO power of 2.75).

For each bank brand, we then sum over all alerts' impact scores within a month and take the square root of this sum. We denote the resulting bank-month variable MRS_{bt} (for Monthly Reputation Score):

$$MRS_{bt} = \sqrt{\sum_{d \epsilon t} AIS_{nbd}}$$

Applying a concave function to the sum of alerts' scores is intended to account for a decreasing marginal impact of news on the perception of a bank's responsibility by depositors: in other words, the first article blaming SG for funding a controversial gas terminal is supposed to raise the awareness of customers by more than the 10th article accusing

SG of fueling climate change in the same month.[19]

Last, we assume that people remember NGO campaigns they hear about for some time, but not for ever. Therefore, a bank's (bad) sustainability reputation builds up with time as bad news accumulate, but the memory of past campaigns is less salient than the reaction to recent ones. More precisely, we define our monthly, bank sustainability reputation index (SRI) as:

$$SRI_{bt} = \sum_{\tau=0}^{12} exp(-\tau.\theta).MRS_{b,t-\tau}$$

where the decay parameter $\theta = ln(2)/6$, so that the memory of past NGO campaign alerts halves after six months. This shortcut amounts to assuming that 50% of the targeted audience forgets about these news after 6 months (75% after 12 months, 100% after more than one year).[20]

Figure 4 shows the resulting bad reputation index for climate change issues $SRI(CC)^{-}_{bt}$ (or *brown reputation index* for brevity) of the seven main bank brands (BPCE, BNP, CA, CM-CIC, HSBC, LBP, SG). Importantly for the empirical relevance of our exercise, the figure witnesses a lot of variation, both within banks and across banks.

4.2.2 From bank brands to individual banks

We build reputation indexes on ES issues for the major bank brands in France. However, we observe deposits and loans, as well as individual housing loans for individual banks, not bank brands. We explain in this section how we match bank brands with individual credit institutions.

The nine brands identified in the Sigwatch dataset belong to the seven largest banking groups operating in France. We therefore restrict our sample to the 100 individual credit institutions that are affiliated with these banking groups and report to CEFIT. We then

[19] In a similar vein, Ardia et al. (2022), who construct a daily index of media climate change concern (MCCC) based on articles in US newspapers, also apply a square root function to their daily sum of individual alerts in order to "capture the fact that increased media attention always increases climate change concerns, but at a decreasing rate".

[20] We checked that our main results are robust to alternative calibrations of this time-decay parameter, see below. As an example, Figure A5 in the appendix displays alternative measures of the brown reputation index of one major bank when we vary this calibrated parameter.

match these individual institutions with their group's main brand whenever the brand is transparent in the bank's name. Otherwise, we assume that the bank's name is its own brand in the eye of customers.

The rationale for this procedure is that retail depositors know big bank brands but are unlikely to be aware that their bank belongs to a criticized banking group when the bank's affiliation is not transparent in its name. For instance, *Crédit Agricole Ile-de-France*, a cooperative regional bank, obviously belongs to *Crédit Agricole* (or CA) group. The affiliation is transparent to all depositors, even unsophisticated ones. When customers of this bank read negative news about some climate-damaging business of CA, they therefore must feel involved.

In contrast, *Crédit du Nord* is a small banking group, mostly present in Northern France, which belongs to the larger *Société Générale* (SG) group. Until 2022, the visual identity of *Crédit du Nord* made no reference to SG group and *Crédit du Nord* enjoyed a large degree of operational autonomy. We therefore assume that its customers would not identify themselves as customers of SG group, and we associate *Crédit du Nord* with its own, specific brand. Similarly, customers of *Banque de Savoie*, a small local capitalist bank, are unlikely to see themselves as customers of its parent company, BPCE group, mostly known for its large network of regional cooperative banks and local savings banks. We therefore associate *Banque de Savoie* with its own, specific brand and not with BPCE. We end up having 23 different brands for the 100 banks in our regression sample. Only the nine largest bank brands show up in NGO alerts covered by Sigwatch. The 14 banks associated with the 14 remaining brands are therefore never affected by NGO campaigns.

5 Fossil banks and their customers: Empirical analysis

5.1 Methodology

We aim to evaluate whether NGO campaigns affect households' supply of deposits with "brown" or "fossil" banks, blamed for "banking on climate change". We are also interested in assessing the impact of brown banks' bad reputation on households' demand for housing loans. As explained above, NGO campaigns are arguably exogenous to local developments in banks' deposits from and loans to French households.

Using monthly data on households deposits and loans at the bank-county level, we estimate the following empirical model:

$$\begin{aligned} ln(Y_{bct}) = \;& \beta^- \times SRI^-_{bt} + \beta^+ \times SRI^+_{bt} + \gamma \times ln(BB_{bct}) \\ & +\theta \times Z_{b,t-1} + \delta_b + \delta_{ct} + u_{bct} \end{aligned} \quad (1)$$

where Y_{bct} is the outstanding amount at time t of deposits issued (or loans granted) by bank b to customers in county (*département) c*. The main independent variable of interest is our index of banks' reputation regarding their negative contribution to climate change (SRI^-_{bt}). According to our hypotheses, we expect coefficient β^- to be negative. Note here that SRI^-_{bt} is defined at the level of a bank brand, which reflects in general the name of the consolidating parent bank. Within a banking group, some banks are affected by the reputation index of the group's brand and some are not because their affiliation to the group is not obvious to retail customers.

In this baseline regression, we control for the banks' *positive* reputation index regarding climate change issues (SRI^+_{bt}), the number of bank b's branches in county c, and for a set of (lagged) monthly bank-level balance sheet variables stacked in $Z_{b,t-1}$. We include in Z the (log) total assets of the bank, its leverage and its reliance on retail deposits for funding. Last, we control for bank fixed effects δ_b and for county-time fixed effects δ_{ct}. The former absorb all invariant unobserved bank characteristics (including for instance the bank type, i.e. cooperative vs commercial bank). The latter account for unobserved time-varying local and macroeconomic factors (such as the level of local economic activity, house prices, or the monetary policy stance) that may impinge on the local supply of retail deposits and the local demand for housing loans.[21] In all regressions, we cluster standard errors at the level of individual banks, which is the dimension of treatment. The standard deviations of coefficient estimates are therefore adjusted to account for both possible

[21] In other words, identification takes place within county and time: within a county in a given month, we compare deposits with two banks that differ by the level of their brown reputation, other things being kept equal.

auto-correlation in the time series of deposits (or loans) within bank-county cells and for possible correlation of shocks at each date within a bank across counties (such as a nation-wide advertisement campaign).

Table 5 presents descriptive statistics for the dependent and independent variables used in these regressions.

5.2 NGO campaigns targeting "fossil" banks and the supply of sight deposits

5.2.1 Main results

Table 6 reports our findings when the dependent variable in equation 1 is the volume of households' sight deposits and the main independent variable is the bank's CC-related negative reputation index. Columns (1) an (2) control for bank and county-time fixed effects, while columns (3) to (5) include time-varying bank controls. The supply of households' sight deposits decreases significantly when negative NGO campaigns weigh down on the reputation of the bank: the coefficient of SRI^- is negative and significant at the 1 percent level. Interestingly, the impact of NGO campaigns on bank depositors seems to be asymmetric: the coefficient on the positive reputation index is much smaller than the coefficient of the negative one, and never significant.

In column (3), we control for the number of branches of each bank in each county, which we observe at monthly frequency. We use this variable as a proxy for the bank's local demand for household deposits (or local bank "size"). Controlling for changes in local bank size increases the estimated negative effect of banks' brown reputation. In other words, omitting this control induces an attenuation bias. This makes sense since the largest French bank groups, and notably the two brands the most targeted by French NGO campaigns for contributing to global warming, have closed a large number of their local branches in the last decade against the backdrop of the rise of online banking.

For a sub-sample of banks, we can measure monthly bank-level, balance sheet indicators that are often used as covariates when explaining deposit collection, and lending by banks. Adding these controls (column 4) does not change qualitatively our findings. Interestingly, when combined with our measure of local bank size (the number of branches of the bank in the county), the significance of these controls vanishes (column 5). This in turn vindicates the choice of this local bank size measure as a relevant time-varying bank-level control.

In the baseline, we control for unobservable bank characteristics using bank-level fixed effects. For robustness, we tried an alternative specification and included bank-county-level fixed effects among controls instead. This amounts to a more standard "within" panel regression, where identification is achieved within a bank-county pair using only the variations through time of deposits and bank reputation indexes and controlling for unobserved, time-varying county-level factors. Table 7 presents the results. The estimates of the main coefficient of interest, β^{-}, are almost unchanged and still highly significant.[22]

Last, these baseline results are also robust to changes in the specification of the reputation index, notably the rate at which people are assumed to forget about past news. Table 8 shows how estimation results in column (3) of Table 6 change when the time-decay parameter θ is set to reflect alternative assumptions regarding the persistence of the monthly scores (MRS_{bt}). For the sake of comparability across columns, the main variables of interest ($SRI(CC)^{-}_{bt}$ and $SRI(CC)^{+}_{bt}$) are here standardized. The first column shows the results under no persistence of the monthly reputation scores. Subsequent columns show the results when 50% of past news are forgotten after, respectively, 1, 3, 6 (the baseline) and 9 months.

The estimated effect of negative campaigns against brown banks is economically significant. On average, a bank hit by NGO campaign alerts that push its climate change-related SRI up by one standard deviation (0.87) faces a relative drop in households' sight deposits by 3.5% (using the estimate in column 3 of the table). In euros, this translates into an average decrease in sight deposits at the bank-county level by some 9 million euros.

5.2.2 Depositors are mostly concerned about climate change

We focus in the baseline above on the impact on deposit supply of NGO campaigns that denounce fossil energy funding by brown banks. However, NGO also blame banks

[22] In such a saturated specification, fixed effects explain almost all the variance of the dependent variables. Interestingly however, the within-R^2 of the regressions are still non-negligible, in the range of 2.5% to 13% depending on specifications.

for funding projects which raise other types of ES concerns (e.g., human right abuses). Which ES issue do bank depositors value most? To answer this question, we run the same regression as in column (3) of table 6 above, but this time replacing the climate change-related negative SRI with the bad reputation indexes related to the other ES issues.

Table 9 reports the results of these alternative specifications. As shown in columns (2) and (3), we find no evidence that depositors react much to NGO campaigns blaming their bank for reasons related to other environmental (OE) or social (S) issues. Although estimated coefficients are negative, they remain far from significance, even when we consider all types of alerts together (column 5). We conclude that the overall negative reaction of bank depositors to banks' bad ES reputation (column 4) is actually mostly driven by the reaction to news related to climate change. In other words, depositors really "don't like it hot".[23]

5.3 Extensions

5.3.1 NGO campaigns, term deposits and housing loans

We now look at the response of term deposits and loans for house purchase to a heightened CC-related negative reputation index. Table 10 presents the results. The first column repeats the baseline result for comparison purpose. The hypothesis that sight deposits respond more than term deposits is vindicated by the data (column 2), as the coefficient on term deposits is twice smaller and only significant at the 10% level.

We also find evidence suggesting that while depositors decrease their supply of deposits to brown banks, they also cut their demand for housing loans. The effect is again large and both statistically and economically significant. Whenever the negative CC-related SRI of a bank is higher by one standard deviation, the volume of housing loans borrowed from this bank decreases by close to 6%.footnoteFor robustness, table A4 in the appendix confirms that estimation results in the alternative within-county-bank specification are identical.

[23]For robustness, table A3 in the appendix shows that estimation results in the alternative within-county-bank specification are almost unchanged.

5.3.2 Heterogeneous effects of households characteristics and bank competition

In this section, we test whether the impact of negative NGO campaigns denouncing brown banks is larger among more climate-conscious, or greener, investors. We do not observe individual bank customers and even less their political preferences. However, electoral studies suggest that electors who vote for green parties, arguably climate-motivated customers, are on average more educated, and to some extent, more urban and well off. To confirm this in our data, table A2 in the appendix shows the pairwise correlations between (quartiles of) average levels of education, income, bank competition (here a proxy for city size) and green vote across French counties at the end of the 2000 decade. The correlation coefficients of income, bank competition and college education with green vote are 0.44, 0.55 and 0.77 respectively.

We therefore take advantage of observing bank deposit volumes at the level of counties and exploit heterogeneity in county-level demographics and electoral outcomes. For this purpose, we augment our empirical model in equation 1 and include in the regression additional variables which we interact with the bank's reputation index for climate damaging business. These variables account for geographical heterogeneity in key dimensions of households' characteristics: the share of households with college education, income, and the share of green votes in the elections of MEP. All these variables are measured before the beginning of our sample as explained in the data section above.

Table 11 shows our findings. Each column investigates in turn one dimension of heterogeneity. To account for possible non-linearities, we include interactions of the negative climate change-related SRI with dummies for counties in the third and in the last quarter of the distribution of the respective households characteristic. We cluster here standard errors at the bank-county level since we assume that it is now the relevant dimension of treatment.[24] Although our proxies for the green motivation of depositors are arguably imprecise, we find some suggestive evidence of a stronger impact of NGO campaigns on deposits held in the wealthiest, most educated and politically greenest counties, compared with counties below the median in each dimension.

[24]Results still hold at the 10% level if we cluster standard errors at the bank level instead. For details, please see Table A6 in the appendix.

Last, we test for the role of bank competition. We sort counties into bank competition quartiles based on the Herfindahl index of households' bank deposits in each county as of 2010.[25] Results are presented in the last column of table 11. The coefficient of the interaction between the negative CC-related SRI and a dummy for counties with the highest level of bank competition (fourth quartile) is negative and of similar size as the coefficients of other interacted terms in the previous columns. This result comforts the intuition that switching banks is easier in a more competitive banking environment.

5.4 Exploring the margins

More than a third of French depositors hold more than one bank account.[26] Discontent depositors aware of the ES wrongdoings of one of their banks may choose to reduce their supply of deposits to the "fossil" bank and rebalance their savings towards other banks (intensive margins), or to exit the brown bank and switch all their money to another bank (extensive margin). While several prominent NGO campaigns explicitly urge customers of brown banks to change banks, which margin prevails is unclear so far.

To shed more light on this, we exploit a policy move which dropped the costs of changing banks for individuals in France to almost zero. Changing banks indeed entails substantial transaction costs for the depositor, who must *a priori* take care of the continuity of all regular payments and transfers (such as rents, tax payments, various subscriptions etc) associated with her bank account. A provision of the so-called "Macron law" of 6 August 2015 (article 43), which entered into force on 6 February 2017, requires the new bank to take in charge all this paperwork on behalf of the individual customer switching banks.[27] Moving sight deposits across banks then became much easier after this date and newspapers accounted at the time for a visible impact of this regulation on customers' behavior as soon as one month after its implementation.[28] However, the law does not mandate the new bank to do the paperwork when customers choose to close and move

[25] Figure A2 in the appendix shows the geography of bank competition across counties.
[26] According to the 2022 issue of the survey conducted by the French Banking Federation and Ifop, 37% of French depositors are clients of two or more banks.
[27] Cf. law 2015-990 of August 6, 2015: *Loi pour la croissance, l'activité et l'égalité des chances économiques*.
[28] For instance, France's reference daily newspaper, *Le Monde*, reports on March 7, 2017, about the "promising start of the Macron law" (see here).

their term and savings deposits instead. The Macron law then provides us with both a natural experiment and a plausible placebo.

To investigate which margin matters most, we interact banks' negative reputation index with a dummy variable for the quarters posterior to the implementation of the policy ($Post$):

$$
\begin{aligned}
ln(Y_{bct}) = \quad & \beta^{-} \times SRI^{-}_{bt} + \beta^{-}_{Post} \times SRI^{-}_{bt} \times \text{Post} && (2)\\
& +\beta^{+} \times SRI^{+}_{bt} + \gamma \times ln(BB_{bct}) && (3)\\
& +\theta \times Z_{b,t-1} + \delta_b + \delta_{ct} + u_{bct}
\end{aligned}
$$

Table 12 presents the results. In columns (1-4) of the table, the dependent variable is the volume of sight deposits. The negative effect of NGO alerts denouncing brown banks is much larger after the new law than before and strongly significant. In columns (5-6), we show the results when the dependent variable is the volume of term deposits instead, our placebo variable in the perspective of the 2017 Macron law. As expected, the reaction of term deposits to negative NGO campaigns is not significantly affected by the law. Overall, this evidence suggests that the extensive margin plays an important role in shaping the total response of customers' deposits to NGO campaigns.[29]

However, looking at figure 3, one may be concerned that the change induced by the 2017 regulation coincides with a period of better coverage of NGO campaigns by French mass media. To alleviate this concern, we limit the sample in column (4) to two years when the media coverage of NGO campaigns against brown banks in France was similarly high: 2015 (before the policy change) and 2017 (thereafter). We find confirmation that banks' brown reputation mostly affects the supply of households sight deposits when it is possible for individuals to switch banks at no administrative cost.

Last, figure 5 shows estimates of the main coefficient of interest (β^{-}_{Post}) in a dynamic specification of equation (2), where the brown reputation index of the bank is interacted with year dummies instead of the $Post$ step variable. The equation is estimated over a

[29] Again, results are almost unchanged in the alternative within-county-bank specification, as shown by Table A5 in the appendix.

window of three years before and after the change in regulation. As the figure shows, the negative impact of banks' brown reputation on deposits increases significantly on impact, i.e., in the first year of the new policy regime.

6 Willingness-to-pay for greener banking: evidence from housing loans

6.1 Methodology

In this section, we exploit loan-level information on new housing loans granted by banks and investigate whether NGO campaigns targeting brown banks impinge on the level of housing loan interest rates. We observe loans in the first month of each quarter for a sub-sample of the previous population of banks over 2013 to 2020. We estimate the following empirical model:

$$\begin{aligned} r_{ibmt} = \quad & \beta^{-} \times SRI^{-}_{bt} + \beta^{+} \times SRI^{+}_{bt} \\ & + \gamma \times X_i + \zeta \times Q_{mt} + \theta \times Z_{bmt} \\ & + \delta_b + \delta_{ct} + u_{ibmt} \end{aligned} \tag{4}$$

where r_{ibmt} is the (fixed) interest rate of loan i issued at time t by bank b in municipality (ZIP code) m. The main independent variable of interest is bank b's bad reputation index regarding its negative contribution to climate change (SRI^{-}_{bt}). According to our hypotheses, we again expect coefficient β^{-} to be negative.

In equation (4) we first control for the main characteristics X_i of the new loan i: its initial maturity, the initial loan amount, and a dummy for the use of collateral (usually a mortgage). Second, we also control for relevant dimensions of the municipality of the lending bank branch, which we assume to also be the municipality where the borrowing household dwells. In the vector Q_{mt} we stack the time-varying number of bank branches in the same ZIP code (a proxy for municipality-level bank competition), as well as invariant characteristics of the city's population (dummies for quartiles of income and of the share of adults with college education before the sample period). Third, Z_{bmt} includes a time-varying measure of the bank's local market share (the share of bank b' branches in the total number of bank branches located in m), as well as standard (lagged) bank-level controls (asset size, asset liquidity, leverage, the share of customer credit in total assets and the proportion of non-performing customer loans). Last, as before, we also control for bank-level fixed effects and county-time fixed effects. Standard errors are clustered at the bank level.

Table 13 presents descriptive statistics for the dependent and independent variables used in these regressions.

6.2 Results

Table 14 presents estimation results for alternative specifications. In all regressions, we include loan-level controls and fixed effects. In column (2), we add city-level controls. In columns (3-5), we also include bank-specific controls. In the last column, we restrict the sample to loans issued in larger cities with more than 20 local bank branches throughout, i.e. more competitive local bank markets. The coefficient of the negative reputation index is negative and strongly significant: banks' brown reputation is associated with lower interest rates on new housing loans. This negative effect holds whenever we control for all loan, city and bank characteristics. Combined with our previous result of a lower volume of outstanding housing loans for browner banks, this confirms that bank customers tend to reduce their demand of new housing loans when banks are perceived as climate killers. Last, this price effect is significantly larger in (larger) cities where there are more bank branches and competition between bank brands on the local mortgage loan market is therefore more intense.

The size of the estimated effect of NGO campaigns on the interest rate of new housing loans is arguably small: when the CC-related negative reputation index of the lender is higher by one standard deviation (0.89 in this sample), the offered interest rate is lower by close to 2 basis points (bp), to be compared with an average interest rate of 2.58%. Note however that this small spread (a few basis points) has the same magnitude as the difference between the yields of comparable green and conventional bonds (the so-called *greenium*) in the 2010s, cf. for instance Zerbib (2019) and Flammer (2021) for recent estimates. It also compares well to the interest rate spread of some 7.5 bp which US banks charge on mortgage in areas threatened by sea-level rise (sea-level rise premium), as estimated by Nguyen et al. (2022).

A growing literature aims at measuring the willingness-to-pay (WTP) of environmentally-minded, or more generally ES-conscious investors. The available evidence suggests that such investors purchase green stocks or fund shares although they expect lower returns for their pro-social investments, therefore confirming that ES-conscious investors value the "warm glow" of doing good beyond financial performance. Our results are the first to shed light on the WTP of retail bank borrowers: other things equal, banks perceived as greener face a relatively higher demand for housing loans and can therefore charge slightly higher interest rates.

7 Conclusion

We provide compelling evidence on the growing influence of sustainability considerations in shaping financial decisions of households. Bank customers, especially in counties with higher education levels and pro-environmental sentiments, significantly react to NGO campaigns spotlighting banks' contributions to climate change. Depositors actively withdraw their deposits from banks perceived as environmentally irresponsible and seek for greener alternatives. Additionally, we document that these campaigns impact the demand for housing loans, with a direct effect on interest rates. These findings contribute to the literature in sustainable finance by shedding light on retail customers' responsiveness to banks' environmental reputation. It aligns with previous work documenting the impact of environmental, social, and governance (ESG) factors on financial decision-making by individuals but complements it by focusing on the market for bank deposits and studying the influence of NGO campaigns.

The implications are substantial for both banks and NGOs. First, it underscores the need for financial institutions to adopt genuine sustainable practices and transparently communicate their commitment to environmental responsibility. As public awareness and demand for green finance continue to rise, banks navigating this changing landscape will likely find themselves better positioned to attract and retain conscientious customers, while avoiding climate-related bank runs. For NGOs and their funders, it also means that well-designed, impactful press campaigns that make depositors aware of the impact of their financial decisions are an effective way of reinforcing public action in the fight against climate change.

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Table 1: Negative alerts targeting French banks: breakdown by NGO and ES topic.

NGO Name	CC issue					
	No		Yes		Total	
	No	Col %	No	Col %	No	Col %
Action Non-violente COP21	1	0.9	0	0.0	1	0.3
Amis de la Terre	43	36.8	170	69.7	213	59.0
Attac France	19	16.2	9	3.7	28	7.8
BankTrack	0	0.0	2	0.8	2	0.6
Bizi	3	2.6	0	0.0	3	0.8
Extinction Rebellion	0	0.0	1	0.4	1	0.3
FIDH	1	0.9	0	0.0	1	0.3
Facing Finance	0	0.0	1	0.4	1	0.3
FairFin	2	1.7	0	0.0	2	0.6
Fondation 30 Millions d'Amis	7	6.0	0	0.0	7	1.9
France Libertes	0	0.0	1	0.4	1	0.3
Friends of the Earth	4	3.4	4	1.6	8	2.2
Global Witness	3	2.6	0	0.0	3	0.8
Greepeace	6	5.1	9	3.7	15	4.2
LDH	6	5.1	0	0.0	6	1.7
Notre Affaire A Tous	0	0.0	3	1.2	3	0.8
Observatoire des Multinationales	2	1.7	3	1.2	5	1.4
Oxfam	0	0.0	23	9.4	23	6.4
Pax	1	0.9	0	0.0	1	0.3
Rainforest Network Alliance	0	0.0	2	0.8	2	0.6
Reclaim Finance	0	0.0	11	4.5	11	3.0
Secours Catholique	5	4.3	0	0.0	5	1.4
Sherpa	3	2.6	3	1.2	6	1.7
SumOfUs	3	2.6	0	0.0	3	0.8
Tax Justice Network TJN	3	2.6	0	0.0	3	0.8
Transparency International France	1	0.9	0	0.0	1	0.3
UFC Que Choisir	1	0.9	0	0.0	1	0.3
Western Sahara Resource Watch	3	2.6	0	0.0	3	0.8
Youth For Climate France	0	0.0	2	0.8	2	0.6
Total	117	100.0	244	100.0	361	100.0

Note. Period: 2010-2020. All ESG issues and breakdowns. Only campaigns by French-based NGOs and/or targeting France. Source: Sigwatch, authors' computations.

Table 2: Positive alerts targeting French banks: breakdown by NGO and ES topic.

NGO Name	**CC issue**					
	No		**Yes**		**Total**	
	No	Col %	No	Col %	No	Col %
Amis de la Terre	7	63.6	43	63.2	50	63.3
BankTrack	0	0.0	3	4.4	3	3.8
FairFin	1	9.1	0	0.0	1	1.3
Friends of the Earth	0	0.0	1	1.5	1	1.3
Global Witness	0	0.0	2	2.9	2	2.5
Greepeace	2	18.2	4	5.9	6	7.6
Human Rights Watch HRW	1	9.1	0	0.0	1	1.3
Rainforest Network Alliance	0	0.0	4	5.9	4	5.1
Reclaim Finance	0	0.0	9	13.2	9	11.4
Sierra Club U.S.A.	0	0.0	2	2.9	2	2.5
Total	11	100.0	68	100.0	79	100.0

Note. Period: 2010-2020. All ESG issues and breakdowns. Only campaigns by French-based NGOs and/or targeting France. Source: Sigwatch, authors' computations.

Table 3: Negative alerts targeting French banks: breakdown by bank brand and ES topic.

	Total				Proportion			
	All ES	CC	Other E	S	All ES	CC	Other E	S
Bank brand								
BPCE	24	17	4	3	0.07	0.07	0.09	0.04
CA	70	53	8	9	0.19	0.22	0.17	0.13
CM-CIC	13	10	1	2	0.04	0.04	0.02	0.03
SocGen	98	75	12	11	0.27	0.31	0.26	0.15
BNP	124	75	13	36	0.34	0.31	0.28	0.51
HSBC	23	8	6	9	0.06	0.03	0.13	0.13
LBP	6	5	1	0	0.02	0.02	0.02	0.00
Cred. Coop	1	0	1	0	0.00	0.00	0.02	0.00
LCL	2	1	0	1	0.01	0.00	0.00	0.01
Total	361	244	46	71	1.00	1.00	1.00	1.00

Note. Period: 2010-2020. All ESG issues and breakdowns. Only campaigns by French-based NGOs and/or targeting France. Source: Sigwatch, authors' computations.

Table 4: Positive alerts targeting French banks: breakdown by bank brand and ES topic.

	Total				Proportion			
	All ES	CC	Other E	S	All ES	CC	Other E	S
Bank brand								
CA	23	20	2	1	0.29	0.29	0.29	0.25
CM-CIC	11	11	0	0	0.14	0.16	0.00	0.00
SocGen	6	5	0	1	0.08	0.07	0.00	0.25
BNP	28	23	4	1	0.35	0.34	0.57	0.25
HSBC	2	1	0	1	0.03	0.01	0.00	0.25
LBP	7	7	0	0	0.09	0.10	0.00	0.00
Cred. Coop	2	1	1	0	0.03	0.01	0.14	0.00
Total	79	68	7	4	1.00	1.00	1.00	1.00

Note. Period: 2010-2020. All ESG issues and breakdowns. Only campaigns by French-based NGOs and/or targeting France. Source: Sigwatch, authors' computations.

Table 5: Bank-county-level regression sample: descriptive statistics

	Mean	Std.Dev.	p10	p25	Median	p75	p90	Nb.Obs.
Sight deposits (thds)	253521.88	402551.93	13339.00	42836.00	122849.00	302626.50	656251.00	122368
Sight deposits (log)	11.55	1.51	9.50	10.67	11.72	12.62	13.39	122368
Term deposits (log)	12.05	1.61	9.85	11.04	12.21	13.31	14.01	122365
All deposits (log)	12.55	1.57	10.40	11.59	12.72	13.75	14.43	122484
Housing loans (thds)	668225.86	1.01e+06	31905.00	85971.00	277114.00	831315.00	1.78e+06	122362
Housing loans (log)	12.43	1.55	10.37	11.36	12.53	13.63	14.39	122362
Regul. hous. loans (log)	9.83	2.02	7.03	8.86	10.10	11.23	12.05	118919
All housing loans (log)	12.53	1.56	10.43	11.46	12.63	13.74	14.48	122376
Sight deposits (dlog)	0.01	0.03	-0.03	-0.01	0.01	0.02	0.04	123619
Neg. ES SRI	0.80	1.13	0.00	0.00	0.27	1.14	2.62	127154
Pos. ES SRI	0.15	0.40	0.00	0.00	0.00	0.00	0.58	127154
Neg. CC SRI	0.55	0.87	0.00	0.00	0.00	0.85	1.92	127154
Pos. CC SRI	0.13	0.39	0.00	0.00	0.00	0.00	0.48	127154
Nb branches (log)	2.39	1.37	0.00	1.39	2.48	3.43	4.08	110720
Assets(-1) (log)	25.15	1.87	22.93	23.56	25.47	26.41	27.77	95452
Capital/Ass.(-1)	0.04	0.02	0.02	0.02	0.02	0.05	0.07	95447
Non-bank dep./Ass.(-1)	0.49	0.24	0.13	0.16	0.61	0.68	0.74	95447
Share green vote	13.86	5.47	7.91	9.29	12.62	18.21	22.02	127154
Share college educ.	0.22	0.07	0.16	0.18	0.20	0.24	0.28	127154
Income per hhld. (log)	3.13	0.15	2.98	3.03	3.09	3.18	3.27	127154
HHI deposits (pp)	1.25	0.58	0.53	0.83	1.19	1.68	2.04	127154

Note. Bank-county-level sample. Period: 2011-2020. Deposits and loans in euro thds.

Table 6: Banks' brown reputation and the supply of sight deposits: baseline.

	(1)	(2)	(3)	(4)	(5)
Negative CC SRI	-0.033***	-0.033***	-0.040***	-0.020***	-0.030**
	[0.010]	[0.010]	[0.013]	[0.007]	[0.013]
Positive CC SRI		0.008	0.017	-0.007	0.043
		[0.019]	[0.018]	[0.026]	[0.043]
Nb branches (log)			0.953***		0.925***
			[0.054]		[0.053]
Assets(-1) (log)				0.146***	0.057
				[0.050]	[0.083]
Capital/Ass.(-1)				-2.209**	-0.230
				[0.928]	[1.228]
Non-bank dep./Ass.(-1)				0.805***	0.551*
				[0.239]	[0.315]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122368	122368	106119	91324	76525
Clusters	100	100	99	59	58
R2	0.772	0.772	0.937	0.816	0.949

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 7: Banks' brown reputation and the supply of sight deposits: within bank-county specification.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.035***	-0.035***	-0.042***	-0.023***	-0.029***
	[0.011]	[0.011]	[0.010]	[0.007]	[0.009]
Positive CC		0.009	0.011	0.007	0.016
		[0.016]	[0.017]	[0.018]	[0.025]
Nb branches (log)			0.210**		0.122*
			[0.102]		[0.062]
Assets(-1) (log)				0.141***	0.114**
				[0.052]	[0.046]
Capital/Ass.(-1)				-2.412*	-2.120*
				[1.257]	[1.231]
Non-bank dep./Ass.(-1)				0.837***	0.596***
				[0.239]	[0.214]
Bank-County FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122368	122368	106119	91252	76453
Clusters	100	100	99	58	57
R2 Within	0.025	0.026	0.076	0.136	0.109

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 8: Banks' brown reputation and the supply of sight deposits: varying the persistence of the public's awareness.

	(1)	(2)	(3)	(4)	(5)
	No mem.	HL: 1m	HL: 3m	HL: 6m	HL: 9m
Negative CC SRI (stdd)	-0.007***	-0.015***	-0.029***	-0.035***	-0.037***
	[0.002]	[0.004]	[0.009]	[0.012]	[0.012]
Positive CC SRI (stdd)	0.005	0.007	0.007	0.007	0.006
	[0.004]	[0.006]	[0.007]	[0.007]	[0.007]
Nb branches (log)	0.953***	0.953***	0.953***	0.953***	0.953***
	[0.054]	[0.054]	[0.054]	[0.054]	[0.054]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	106119	106119	106119	106119	106119
Clusters	99	99	99	99	99
R2	0.937	0.937	0.937	0.937	0.937

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. Both variables are here standardized. In column (1), no persistence is assumed. In column (2) to (5), the time-decay parameter is adjusted so that the half-life of news is 1, 3, 6 (baseline) and 9 months respectively. In all cases, we assume that all information older than 12 months is forgotten. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 9: Banks' negative reputation regarding climate change vs other ES issues: impact on sight deposits.

	(1)	(2)	(3)	(4)	(5)
Negative CC SRI	-0.040***				-0.042***
	[0.013]				[0.014]
Negative OE SRI		-0.023			-0.042
		[0.020]			[0.028]
Negative S SRI			-0.025		-0.019
			[0.018]		[0.019]
Negative ES SRI				-0.043***	
				[0.014]	
Positive ES SRI				0.027*	0.025
				[0.015]	[0.016]
Nb branches (log)	0.953***	0.953***	0.953***	0.953***	0.953***
	[0.054]	[0.054]	[0.054]	[0.054]	[0.054]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	106119	106119	106119	106119	106119
Clusters	99	99	99	99	99
R2	0.937	0.937	0.937	0.937	0.937

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *Negative OE*, *Negative S* and *Negative ES*) is the negative reputation index (SRI) of the bank brand because of CC (resp. OE, S or ES) issues. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 10: NGO campaigns against brown banks on the supply of sight vs term deposits and the demand for housing loans.

	(1) Sight dep.	(2) Term dep.	(3) All dep.	(4) Hous. loan	(5) Regul hl.	(6) All hl.
Neg. CC SRI	-0.040***	-0.020*	-0.024**	-0.064***	-0.107***	-0.069***
	[0.013]	[0.012]	[0.011]	[0.019]	[0.028]	[0.019]
Pos. CC SRI	0.017	0.027	0.019	-0.022	0.096	-0.022
	[0.018]	[0.022]	[0.019]	[0.020]	[0.062]	[0.021]
Nb branches (log)	0.953***	0.956***	0.957***	0.874***	0.924***	0.876***
	[0.054]	[0.053]	[0.054]	[0.050]	[0.058]	[0.050]
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	106119	106045	106149	106188	102664	106198
Clusters	99	99	99	99	99	99
R2	0.937	0.948	0.941	0.943	0.939	0.945

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of, or loans to, households as indicated in columns' titles. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 11: The role of household characteristics.

	College	Income	Green vote	Bk Compet.
	(1)	(2)	(3)	(4)
Negative CC	-0.020*	-0.017	-0.021**	-0.018*
	[0.011]	[0.010]	[0.011]	[0.011]
Neg. CC × Z Q3	-0.028	-0.036*	-0.027	-0.030
	[0.024]	[0.022]	[0.023]	[0.022]
Neg. CC × Z Q4	-0.050**	-0.053**	-0.046*	-0.051**
	[0.023]	[0.023]	[0.023]	[0.022]
Pos. CC SRI	0.018***	0.018***	0.018***	0.018***
	[0.006]	[0.006]	[0.006]	[0.006]
Nb branches (log)	0.954***	0.954***	0.954***	0.954***
	[0.029]	[0.028]	[0.029]	[0.028]
Bank FE	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes
Obs.	106119	106119	106119	106119
Clusters	965	965	965	965
R2	0.937	0.937	0.937	0.937

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of, or loans to, households as indicated in columns' titles. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB)-county level.

Table 12: Mechanism: impact of the 2017 *Macron reform* on bank mobility.

	Sight dep.				Term dep.	
	(1)	(2)	(3)	(4)	(5)	(6)
				2015+2017		
Negative CC	-0.040***	-0.014	-0.006	-0.017	0.007	0.018*
	[0.013]	[0.009]	[0.010]	[0.012]	[0.009]	[0.010]
Neg. CC × Post		-0.040**	-0.039*	-0.021**	-0.040	-0.044
		[0.017]	[0.022]	[0.009]	[0.026]	[0.036]
Pos. CC SRI	0.017	0.018	0.048	0.011	0.028	0.034
	[0.018]	[0.017]	[0.038]	[0.011]	[0.021]	[0.042]
Nb branches (log)	0.953***	0.953***	0.925***	0.957***	0.956***	0.930***
	[0.054]	[0.054]	[0.053]	[0.055]	[0.053]	[0.050]
Assets(-1) (log)			0.049			0.220***
			[0.083]			[0.078]
Capital/Ass.(-1)			-0.619			-0.458
			[1.020]			[1.341]
Non-bank dep./Ass.(-1)			0.568*			0.538*
			[0.306]			[0.302]
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	106119	106119	76525	21885	106045	76374
Clusters	99	99	58	98	99	58
R2	0.937	0.937	0.949	0.940	0.948	0.958

Note. Bank-county-level sample. Period: 2011-2020, except col. 4: 2015 and 2017 only. Dep. variable: log sight deposits (col. 1 to 4), or term deposits (col. 5-6) of households as indicated in columns' titles. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 13: Loan-level sample: descriptive statistics

	Mean	Std.Dev.	p10	p25	Median	p75	p90	Nb.Obs.
Loan rate (TEG)	2.58	0.76	1.76	2.01	2.39	3.04	3.75	246657
Maturity (months)	207.94	75.19	109.00	145.00	216.00	276.00	300.00	246657
Loan amount (EUR thd)	134.62	116.52	30.00	61.81	110.00	174.39	254.93	246657
Loan amount (log)	11.48	0.88	10.31	11.03	11.61	12.07	12.45	246657
Collateralized	0.40	0.49	0.00	0.00	0.00	1.00	1.00	246657
Local bank branches	48.86	79.18	5.00	8.00	17.00	62.00	123.00	245734
Local bank branches (log)	3.09	1.23	1.61	2.08	2.83	4.13	4.81	245734
Share local branches	0.15	0.10	0.05	0.09	0.12	0.20	0.29	245734
Negative CC SRI	0.91	0.89	0.00	0.00	0.75	1.51	2.26	238057
Positive CC SRI	0.31	0.61	0.00	0.00	0.00	0.33	1.49	238057
Share college education (2008)	0.29	0.13	0.16	0.20	0.25	0.35	0.48	242038
Income per hhld (2010)	27.81	12.92	19.68	21.39	23.84	28.40	41.34	242038
Green vote (2009)	0.22	0.05	0.16	0.18	0.21	0.24	0.28	242038
Education Q4	0.58	0.49	0.00	0.00	1.00	1.00	1.00	242038
Income Q4.	0.28	0.45	0.00	0.00	0.00	1.00	1.00	242038
Green vote Q4	0.59	0.49	0.00	0.00	1.00	1.00	1.00	242038
Assets(-1) (log)	24.91	1.47	23.40	23.72	24.44	25.80	27.66	223853
Liquid assets/Ass. (-1)	0.16	0.08	0.06	0.10	0.15	0.21	0.26	223853
Capital/Ass.(-1)	0.07	0.04	0.02	0.02	0.07	0.10	0.11	223853
Cust. credit/Ass.(-1)	0.58	0.23	0.13	0.42	0.69	0.72	0.76	223853
Net NNP / Cust.cred. (-1)	-0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00	212093

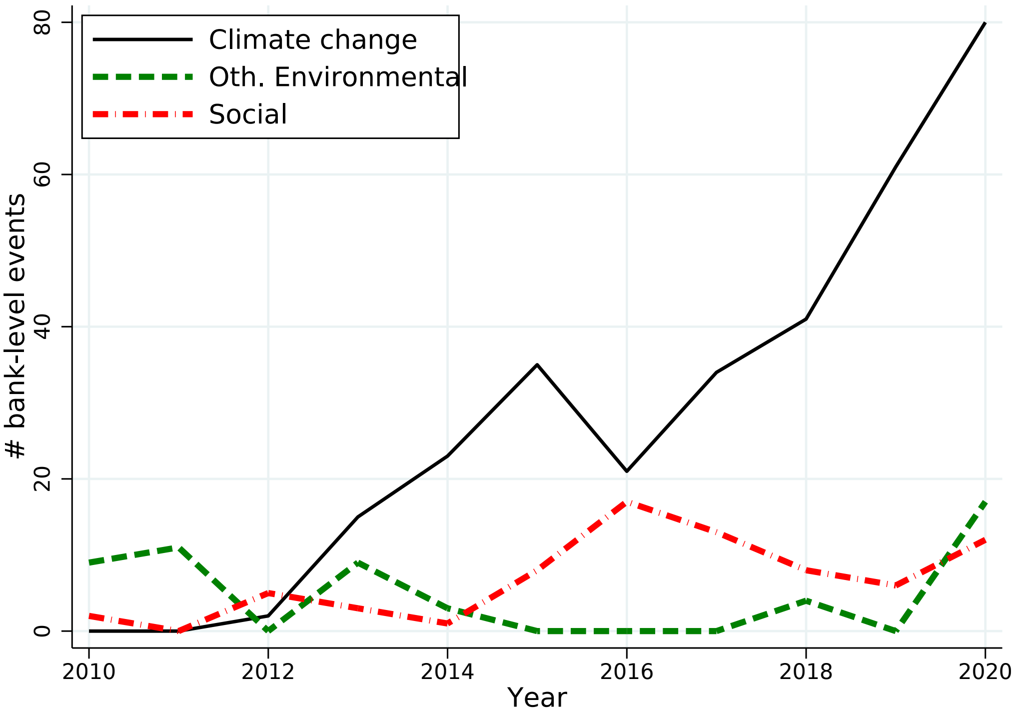
Note. Loan-level sample. Period: 2013-2020. Dep. variable: housing loan rate (TEG).

Table 14: Banks customers' climate change concerns and interest rates on new housing loans.

	(1)	(2)	(3)	(4)	(5)
Negative CC SRI	-0.020***	-0.019***	-0.019***	-0.020***	-0.029***
	[0.006]	[0.006]	[0.006]	[0.007]	[0.008]
Positive CC SRI	0.000	0.000	0.000	0.003	-0.005
	[0.007]	[0.007]	[0.007]	[0.007]	[0.010]
Maturity (months)	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Loan amount (log)	-0.076***	-0.074***	-0.074***	-0.077***	-0.074***
	[0.014]	[0.014]	[0.014]	[0.014]	[0.015]
Collateralized	-0.015*	-0.014*	-0.015*	-0.002	0.006
	[0.009]	[0.009]	[0.009]	[0.008]	[0.008]
Local bank branches (log)		-0.018***	-0.019***	-0.020***	-0.024***
		[0.003]	[0.003]	[0.003]	[0.007]
Income Q3		-0.013**	-0.012**	-0.012*	-0.015
		[0.005]	[0.005]	[0.006]	[0.014]
Income Q4.		-0.040***	-0.040***	-0.040***	-0.065***
		[0.007]	[0.007]	[0.007]	[0.023]
Education Q3		-0.022***	-0.023***	-0.023***	-0.102**
		[0.007]	[0.008]	[0.007]	[0.041]
Education Q4		-0.043***	-0.043***	-0.044***	-0.121***
		[0.008]	[0.008]	[0.008]	[0.040]
Share local branches			-0.063*	-0.056	-0.063
			[0.032]	[0.034]	[0.067]
Assets(-1) (log)				0.031	-0.024
				[0.091]	[0.070]
Liquid assets/Ass. (-1)				-0.328*	-0.367*
				[0.185]	[0.185]
Capital/Ass.(-1)				-2.058**	-2.980**
				[1.012]	[1.128]
Cust. credit/Ass.(-1)				0.725**	0.999***
				[0.292]	[0.316]
Net NNP / Cust.cred. (-1)				6.014	6.137
				[12.376]	[14.359]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	238036	232636	232636	198720	87745
Clusters	76	75	75	75	73
R2	0.756	0.757	0.757	0.777	0.787

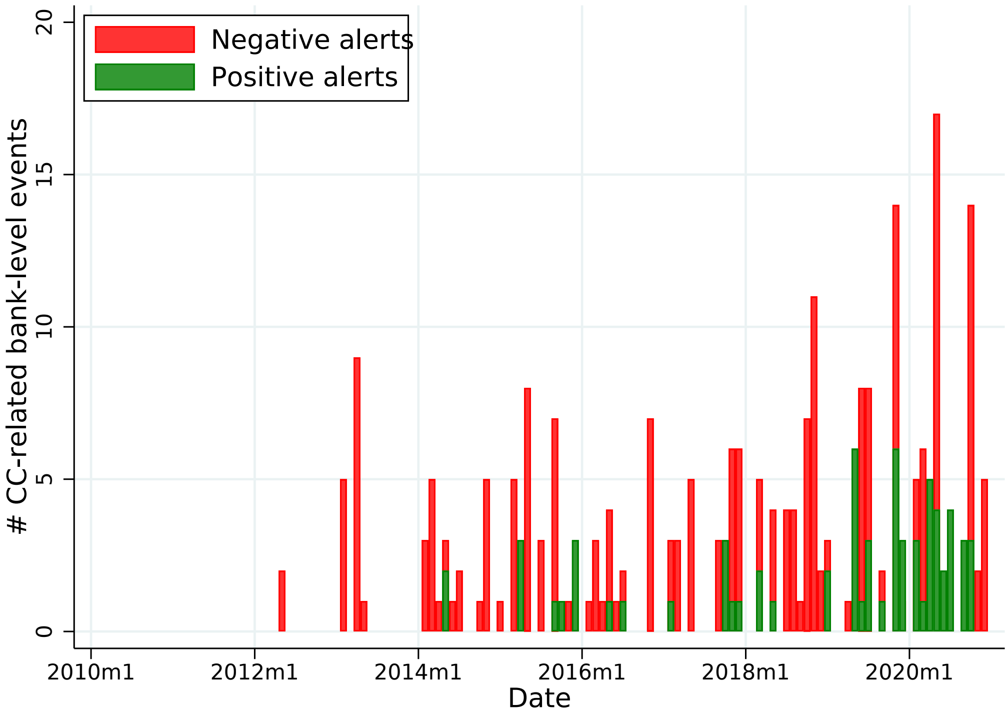
Note. Loan-level sample. Period: 2013-2020. Dep. variable: interest rate of new housing loans, including fees (*TEG*). *Local bank branches* is the total number of bank branches in the county, a measure of local bank competition. *Share bank branches* is the ratio of the bank's branches to the total number of all bank branches in the same ZIP-code, a measure of the bank's local market shares. SE clustered at the bank (CIB) level.

Figure 1: NGO campaign alerts on ES issues by type.



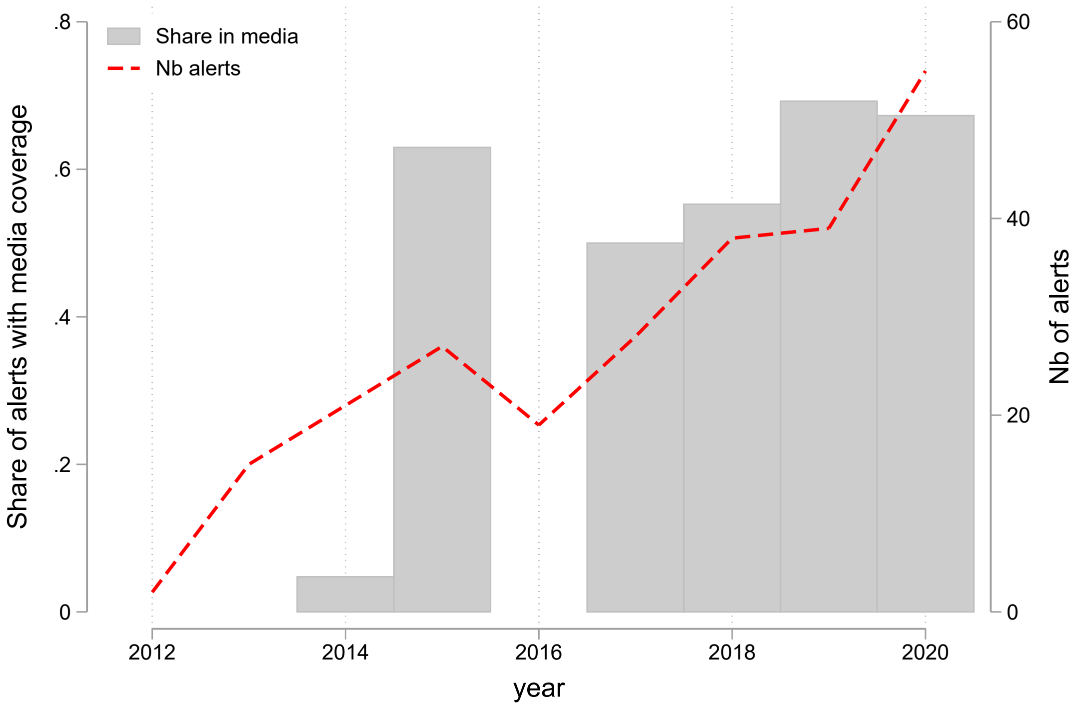
Note. Period: 2010-2020. All negative and positive NGO campaign alerts pointing at French banks (bank brands). An alert is defined by a campaign event and the name of the targeted bank. Source: Sigwatch, authors' computations.

Figure 2: NGO campaign alerts on climate change-related issues.



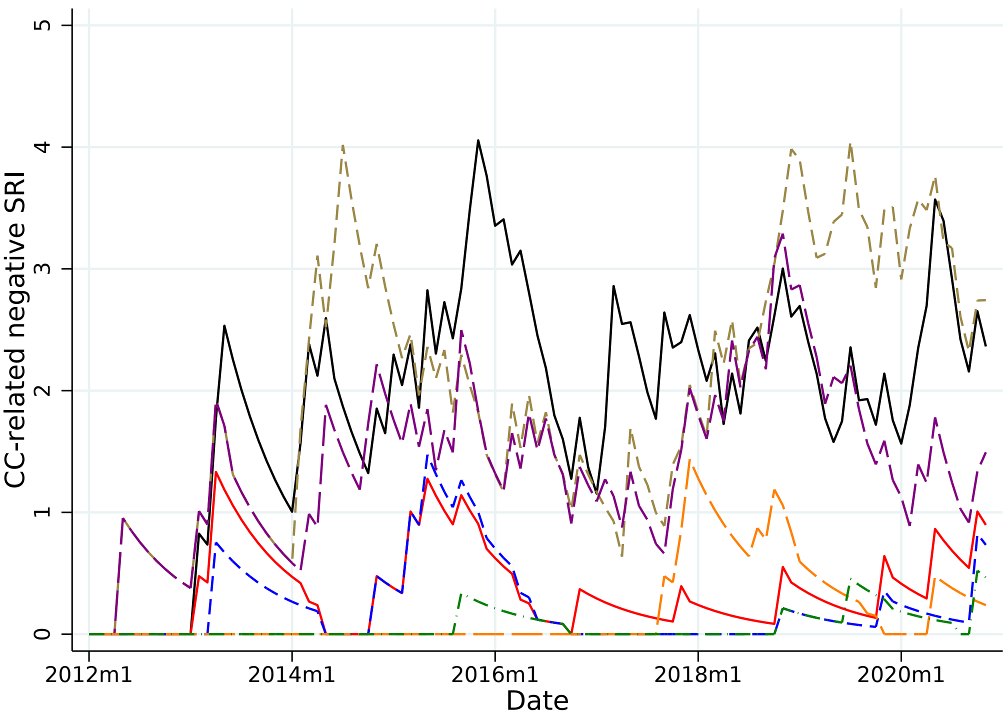
Note. Period: 2010-2020. All negative and positive NGO campaign alerts pointing at French banks (bank brands). An alert is defined by a campaign event and the name of the targeted bank. Source: Sigwatch, authors' computations.

Figure 3: Negative alerts on climate change: mass media coverage.



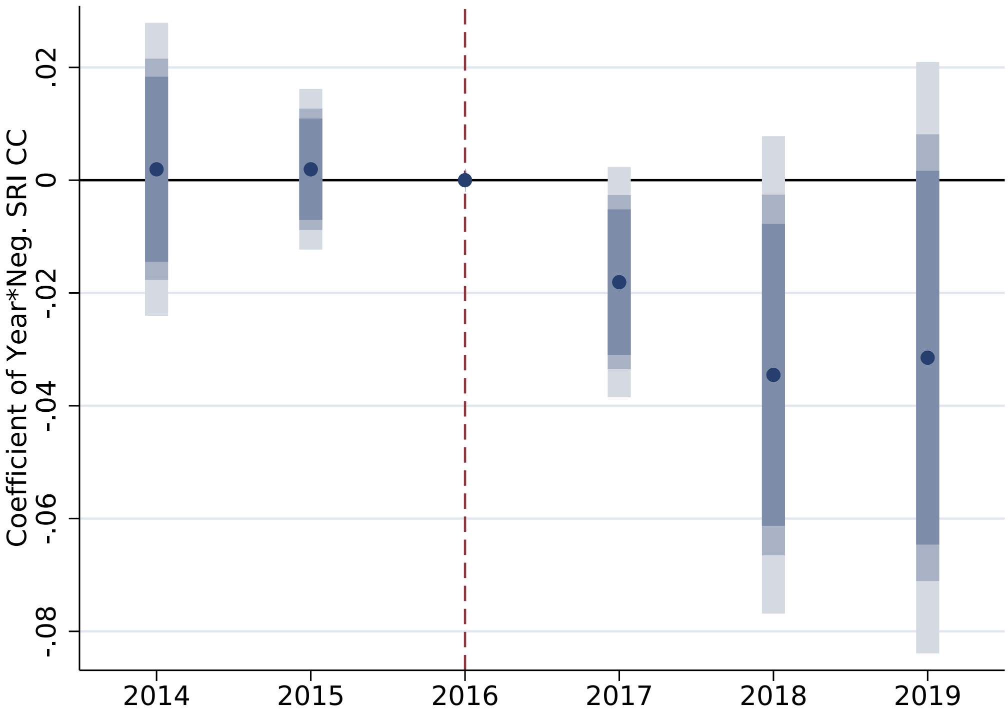
Note. The figure shows the share of NGO alerts about fossil banks for which we can identify some media coverage on the websites of all national and major regional French daily and weekly newspapers, as well as French TV and radio broadcasts. Period: 2010-2020. Sample: negative NGO campaign alerts blaming French banks (bank brands) on CC issues. An alert is defined by a campaign event and the name of the targeted bank. Source: Sigwatch, authors' computations.

Figure 4: Banks' bad reputation index on climate change-related issues: overview.



Note. Only negative NGO campaigns targeting the bank brand. Source: Sigwatch, authors' computations.

Figure 5: Banks' brown reputation and the 2017 law on bank mobility: dynamic specification.



Note. Bank-county-level sample. Period: 2014-2019. Dep. variable: log sight deposits of households. The figure shows the estimated coefficients of the negative CC reputation index interacted with year dummies. Bars: confidence intervals at 90, 95 and 99% plotted in increasingly lighter shades of grey.

A Appendix

Table A1: Evaluating the media coverage of NGO alerts: list of mass media outlets used for the web-scraping exercise.

Nation-wide daily newspapers
www.lemonde.fr
www.liberation.fr
www.lesechos.fr
www.lopinion.fr
www.lefigaro.fr
www.humanite.fr
www.latribune.fr
www.20minutes.fr
Regional newspapers
www.ouestfrance.fr
www.sudouest.fr
www.leparisien.fr
www.lavoixdunord.fr
www.ledauphine.com
www.letelegramme.fr
www.leprogres.fr
www.lanouvellerepublique.fr
www.lamontagne.fr
www.ladepeche.fr
www.dna.fr
www.estrepublicain.fr
www.midilibre.fr
www.laprovence.com
www.republicain-lorrain.fr
www.nicematin.com
www.ouest-france.fr/le-courrier-de-l-ouest
www.lunion.fr
www.lardennais.fr.
Weekly newspapers and information websites

www.marianne.net
www.lexpress.fr
www.lepoint.fr
www.nouvelobs.com
www.huffingtonpost.fr
www.slate.fr
www.challenges.fr
www.la-croix.com
lexpansion.lexpress.fr
www.jeuneafrique.com
lentreprise.lexpress.fr
www.capital.fr
investir.lesechos.fr.
Radio and TV broadcasts
www.france24.com
www.actu.fr
www.franceinfo.fr
information.tv5monde.com
www.europe1.fr
www.rtl.fr
korii.slate.fr
www.rfi.fr
france3-regions.francetvinfo.fr
www.franceculture.fr
www.francetvinfo.fr.

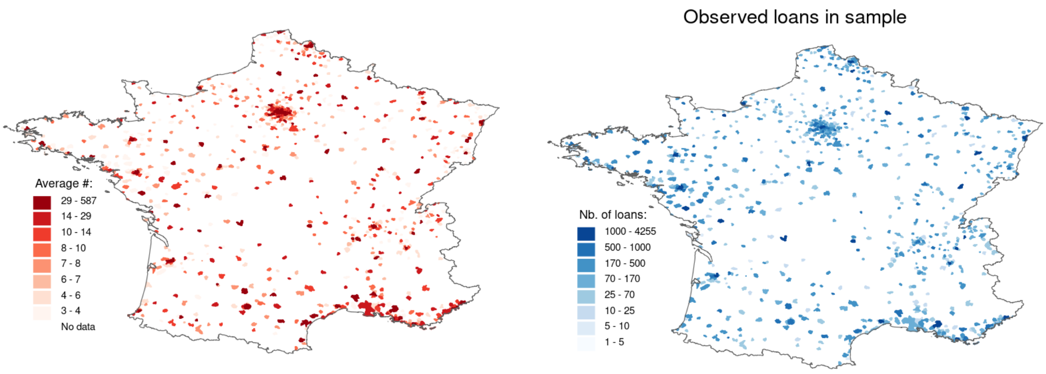
Table A2: Socio-demographic variables, green vote and bank competition in French counties: correlation matrix

	Educ.	Inc.	Green	Comp.
Education	1.00			
Income	0.74	1.00		
Green vote	0.77	0.55	1.00	
Bank comp.	0.65	0.60	0.44	1.00

Note. This table shows the correlation matrix of (quartiles of) the following four variables measured at the county level: the share of adults with college education or higher in 2008, the average income per household in 2010, the share of green vote in expressed votes in the 2009 European Parliament elections, bank competition for deposits in 2010 (based on the HHI of deposits across banks within a county).

Figure A1: Geography of bank branches and granted housing loans, loan-level sample.

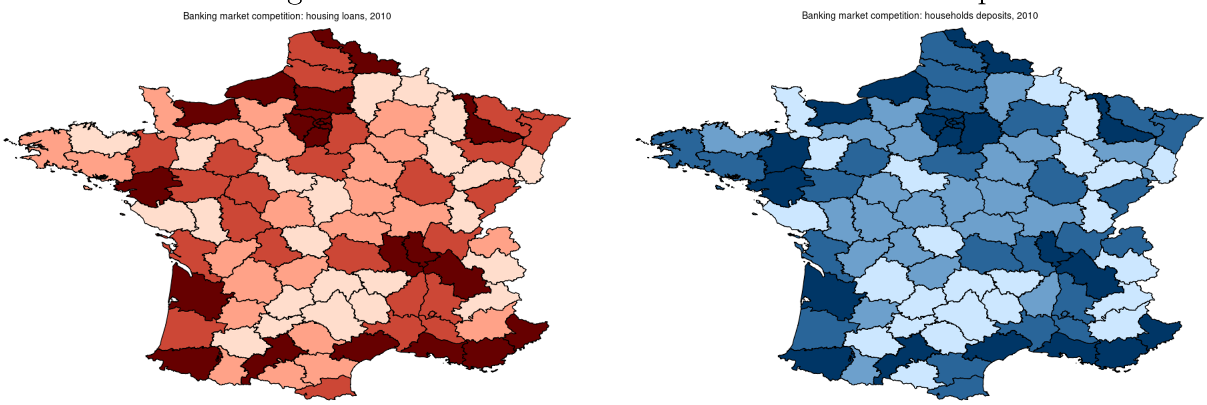
Nb. bank branches (average) Observed loans (total)



Note. Period 2013-2018. Average number of bank branches per municipality (ZIP code) over the period. Total number of new housing loans issued by banks in each municipality over the period.

Figure A2: Bank competition, county-level heterogeneity.

Housing loans Households deposits



Note. Quartiles of the HHI of deposits/housing loans across banks in each county. Darker color: lower HHI, i.e. more competitive local bank market.

Figure A3: Higher education and income, county-level heterogeneity.

College education (2008) | Income per household (2010)

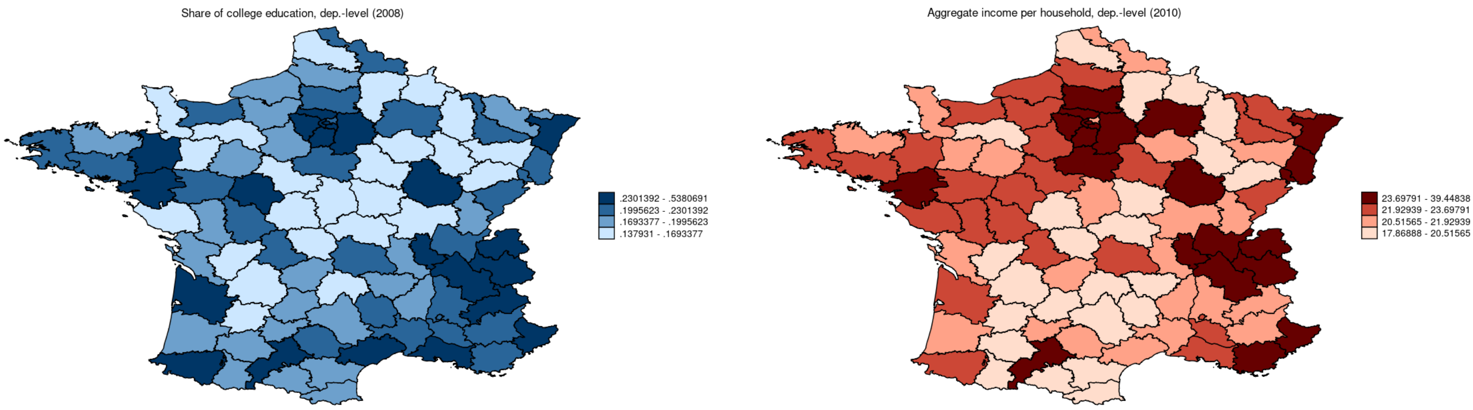


Figure A4: Vote for green parties at the EUP elections, county-level heterogeneity.

2009 | *2014*

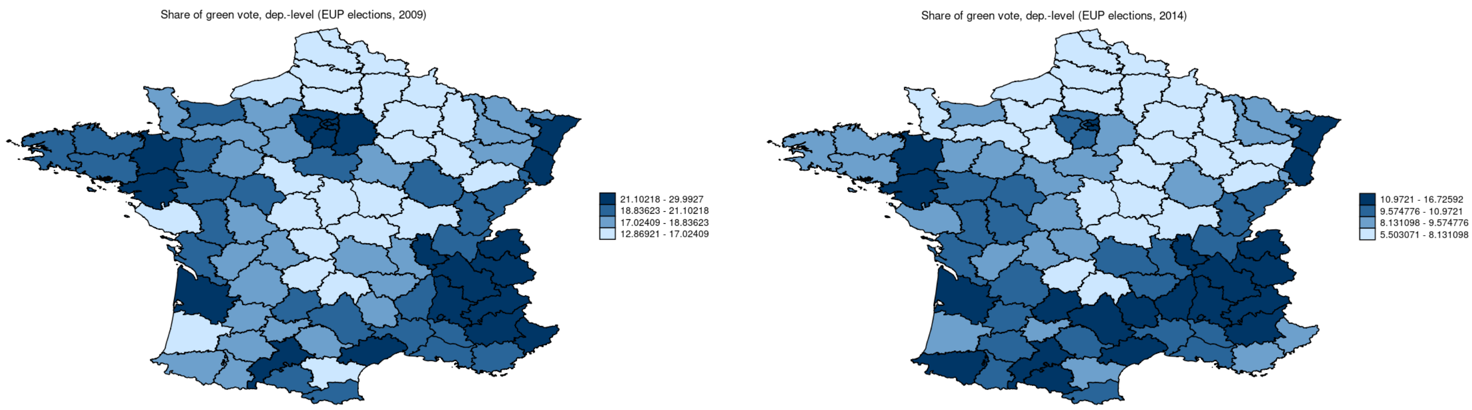
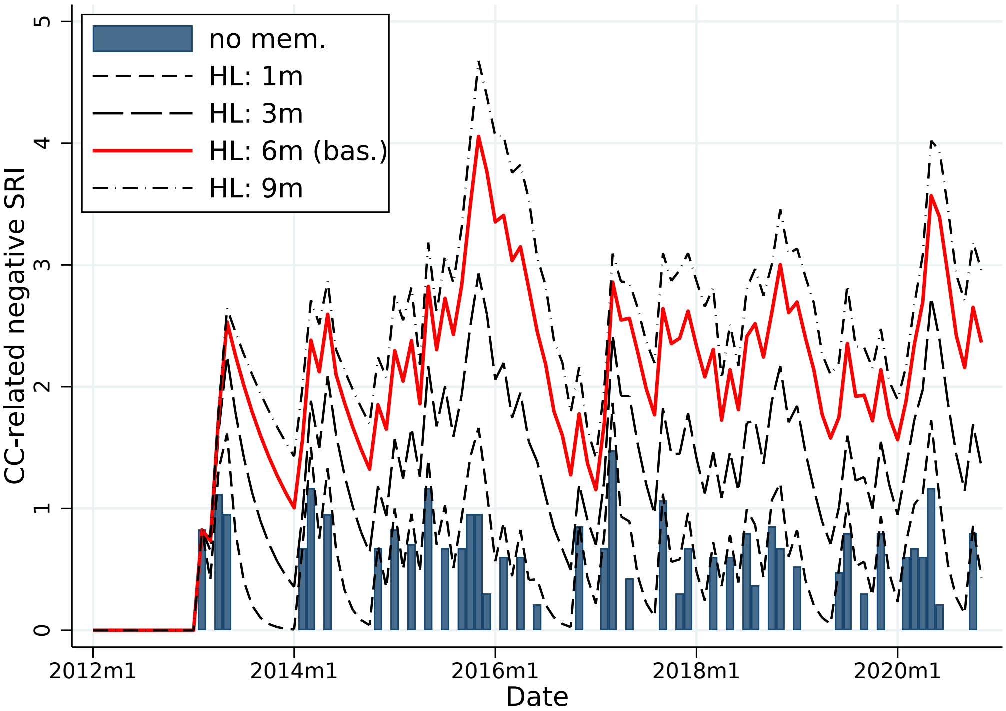


Figure A5: Fossil reputation index: alternative assumptions regarding news persistence in the public's awareness.



Note. The figure shows alternative measures of the fossil (or brown) reputation index of one of the most targeted bank brands, depending on our assumptions regarding how fast people forget about past information. The bars show the fossil monthly reputation score, assuming that people stay aware for only one month. Lines show the computed fossil reputation indexes series when the half-life (HL) of past news is 1, 3, 6 or 9 months. Source: Sigwatch and authors' computations.

Table A3: Banks' negative reputation regarding climate change vs other ES issues: within bank-county specification.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.042***				-0.041***
	[0.010]				[0.010]
Negative OE		0.003			-0.019
		[0.015]			[0.021]
Negative S			-0.043***		-0.029*
			[0.015]		[0.015]
Negative ES				-0.042***	
				[0.010]	
Positive ES				0.017	0.017
				[0.015]	[0.015]
Nb branches (log)	0.209**	0.210*	0.206*	0.216**	0.212**
	[0.102]	[0.108]	[0.105]	[0.102]	[0.103]
Bank-County FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	106119	106119	106119	106119	106119
Clusters	99	99	99	99	99
R2 Within	0.075	0.038	0.046	0.082	0.082

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *Negative OE*, *Negative S* and *Negative ES*) is the negative reputation index (SRI) of the bank brand because of CC (resp. OE, S or ES) issues. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table A4: NGO campaigns against brown banks on the supply of deposits and the demand for housing loans: within bank-county specification.

	(1)	(2)	(3)	(4)	(5)	(6)
	Sight dep.	Term dep.	All dep.	Hous. loan	Regul hl.	All hl.
Neg. CC SRI	-0.042***	-0.021**	-0.025***	-0.064***	-0.106***	-0.069***
	[0.010]	[0.008]	[0.007]	[0.019]	[0.029]	[0.019]
Pos. CC SRI	0.011	0.021	0.013	-0.027	0.095	-0.027
	[0.017]	[0.018]	[0.015]	[0.020]	[0.060]	[0.020]
Nb branches (log)	0.210**	0.288*	0.290*	0.410***	0.138	0.391***
	[0.102]	[0.154]	[0.152]	[0.150]	[0.204]	[0.140]
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	106119	106040	106148	106187	102661	106197
Clusters	99	99	99	99	99	99
R2 Within	0.076	0.085	0.084	0.093	0.039	0.101

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of, or loans to, households as indicated in columns' titles. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table A5: Mechanism: impact of the 2017 *Macron reform* on bank mobility: within bank-county specification.

	Sight dep.			Term dep.		
	(1)	(2)	(3)	(4)	(5)	(6)
Negative CC	-0.042***	-0.022***	-0.011	-0.021**	-0.001	0.013*
	[0.010]	[0.006]	[0.007]	[0.008]	[0.006]	[0.007]
Neg. CC × Post		-0.030***	-0.030***		-0.031*	-0.034
		[0.010]	[0.010]		[0.016]	[0.021]
Pos. ES SRI						
Nb branches (log)	0.210**	0.218**	0.130**	0.288*	0.295*	0.075
	[0.102]	[0.101]	[0.060]	[0.154]	[0.152]	[0.060]
Pos. CC SRI	0.011	0.012	0.020	0.021	0.022	0.005
	[0.017]	[0.016]	[0.022]	[0.018]	[0.017]	[0.022]
Assets(-1) (log)			0.107**			0.282***
			[0.044]			[0.032]
Capital/Ass.(-1)			-2.402**			-2.157**
			[1.172]			[1.013]
Non-bank dep./Ass.(-1)			0.609***			0.581***
			[0.213]			[0.141]
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	106119	106119	76453	106040	106040	76297
Clusters	99	99	57	99	99	57
R2 Within	0.076	0.089	0.125	0.085	0.099	0.189

Note. Bank-county-level sample. Period: 2011-2020, except col. 4: 2015 and 2017 only. Dep. variable: log sight deposits (col. 1 to 4), or term deposits (col. 5-6) of households as indicated in columns' titles. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table A6: The role of household characteristics: bank-level clustering of SE.

	College (1)	Income (2)	Green vote (3)	Bk Compet. (4)
Negative CC	-0.020	-0.017	-0.021	-0.018
	[0.014]	[0.013]	[0.015]	[0.015]
Neg. CC × Z Q3	-0.028	-0.036	-0.027	-0.030
	[0.025]	[0.023]	[0.022]	[0.025]
Neg. CC × Z Q4	-0.050*	-0.053*	-0.046*	-0.051
	[0.028]	[0.027]	[0.025]	[0.032]
Pos. CC SRI	0.018	0.018	0.018	0.018
	[0.018]	[0.018]	[0.017]	[0.018]
Nb branches (log)	0.954***	0.954***	0.954***	0.954***
	[0.054]	[0.053]	[0.054]	[0.053]
Bank FE	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes
Obs.	106119	106119	106119	106119
Clusters	99	99	99	99
R2	0.937	0.937	0.937	0.937

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of, or loans to, households as indicated in columns' titles. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.