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CLIMATE-CONSCIOUS BANK CUSTOMERS

Formerly circulated under the title "Some Don't Like It Hot: Bank Depositors and NGO Campaigns Against Brown Banks"

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Climate-Conscious Bank Customers*

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Abstract

We study how retail depositors behave when their bank is publicly accused of contributing to climate change by funding fossil fuel companies. Using data on environmental NGO campaigns targeting French banks between 2010 and 2020, we construct a time-varying index of each bank's "brown" reputation. We combine this measure with granular data on household deposits to assess how such reputational shocks affect deposit demand. Sight deposits decline following negative publicity, and the effect becomes significantly stronger after a 2017 reform that removed transaction costs for switching checking accounts between banks. Last, using a large sample of new mortgage loans, we also show that browner banks face a relatively lower demand for housing loans and adjust by offering slightly lower loan rates. The results suggest that depositors act on their environmental preferences when frictions affecting bank mobility are low enough.

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

JEL Classification: G21, G51, Q54.

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1 Introduction

Do households respond to allegations that their bank contributes to climate change? Prior research shows that individual bank customers care about the financial soundness of their deposit banks (see, e.g., Martinez Peria and Schmukler, 2001; Iyer et al., 2016), but much less is known about how non-pecuniary motives, specifically environmental concerns, shape where households hold their money. This question has become increasingly relevant as public scrutiny and pressure on banks to align with climate goals have intensified, especially after COP21.[1]

In this paper, we document that retail depositors withdraw funds from banks publicly accused by non-governmental organizations (NGOs) of financing fossil fuels, and that this response is stronger when switching costs are low. We use novel data on NGO campaigns targeting French banks to construct a *Brown Reputation Index* (BRI) that captures the intensity and visibility of each bank's climate-related controversies over time. We combine this index with detailed administrative data on household deposits from 2010 to 2020 to study how depositors respond to reputational shocks revealing that their bank contributes to climate change.

Three institutional features make France a useful laboratory for this analysis. First, France has an active and visible NGO sector that has long monitored and publicized banks' financing of fossil-fuel companies. Beyond naming and shaming, these NGOs have repeatedly called on customers to boycott *brown* banks that continue to finance fossil energy, and their campaigns are regularly amplified by the mass media.[2] Second, in February 2017, a regulatory reform (Article 43 LCACE) eliminated the administrative burden of switching current accounts by requiring the new bank to handle—at no cost to the customer—all paperwork needed to transfer a checking account. This quasi-natural experiment sharply reduced switching frictions that may prevent depositors from aligning their bank choices with their environmental preferences. Finally, deposit-rate competition in France is limited: checking accounts generally bear no interest, and the bulk of household savings is held in state-regulated products offering the same tax-free yield at every bank. This institutional feature allows us to isolate non-pecuniary motives, such as environmental concerns, as potential drivers of deposit flows.

Identification relies on the assumption that the timing and intensity of NGO campaigns about French banks' role in global warming are exogenous to French households' local bank choices.

[1] A prominent example is the "Banking on Climate Chaos" report published annually by a consortium of NGOs led by the Rainforest Alliance Network. Its 2023 release estimates that the world's 60 largest private banks financed fossil fuels by USD $5.5 trillion between 2016 and 2022.

[2] An early example is the 2015 campaign by the French NGO *Les Amis de la Terre*, "My bank pollutes, I change banks!" (link).

This assumption is plausible for two reasons. First, campaigns that point at fossil energy funding commonly relate to the corporate and investment banking activities of large banking groups—such as syndicated loans or project finance for fossil-fuel undertakings in the USA, see Figure 1 for an example—rather than their domestic retail operations. These CIB activities respond to global corporate lending opportunities and arguably not to small changes in the domestic retail banking business. As a result, the timing of campaigns is unlikely to be driven by new developments in the domestic deposit market shares of banks in France. Second, the French banking sector is highly concentrated, with a small number of large, visible, banking groups accounting for the majority of household deposits with quite stable domestic retail market shares over our period of study. Shocks in retail market shares are therefore unlikely to explain which banks are targeted by NGOs or when new campaigns occur.

We collect detailed information on NGO campaigns from Sigwatch, a European consultancy that monitors the activities of more than 11,000 NGOs worldwide and advises targeted companies on how to engage with environmental and social activism. When it comes to banks in France, NGOs have mostly targeted the main, mot popular brands of the largest banking groups operating in this country. We focus here on campaigns that blame the seven largest banking groups for reasons related to climate change, such as the financing of fossil-fuel companies.[3] We assume that repeated NGO actions succeed in raising public awareness but that attention to past campaigns fades over time.[4] Accordingly, our *Brown Reputation Index* (BRI) varies at the bank $\times$ month level with both (i) the accumulation of negative campaigns over a rolling window of one year and (ii) depositors' fading memory of past events.[5] We document a steady rise in NGO pressure on major French banks since the early 2010s, together with a sharp increase in climate-related actions denouncing their funding of fossil-fuel industries. The resulting BRI displays substantial variation both over time and across bank brands. To gauge the visibility of these campaigns, we further use a web-scraping algorithm to trace their diffusion through traditional and social media (focusing here on X, formerly Twitter). Around 70% of campaigns are covered in at least one major media outlet or echoed on social media, suggesting that NGO actions reach a wide audience and are likely to shape public perceptions of banks' environmental conduct.

We then exploit granular administrative data from the Banque de France, which record house-

[3]Credit institutions belonging to these banking groups account for some 95% of household bank deposits in mainland France.

[4]This assumption is inspired by psychological approaches such as Malmendier and Nagel (2016, 2011), among others.

[5]For robustness, we also construct alternative version of the index that assume a better or worse memory of past news.

holds' deposits for some 100 individual banks affiliated with the seven targeted banking groups, across the 94 counties (*départements*) of mainland France, at a monthly frequency. We match each bank's deposit data with the BRI of its corresponding brand, using information on parent companies and the naming conventions of individual institutions. This setup allows us to examine how variation in banks' reputational exposure to climate-related campaigns translates into changes in household deposit flows across space and over time.

Our main empirical specification is a panel regression of households' sight deposits, at the individual bank $\times$ county $\times$ month level, on banks' *Brown Reputation Index*, controlling for time-varying bank characteristics such as total assets, leverage, reliance on customer deposits for funding, the number of branches of the bank in each county and the interest rate paid on checking account balances. All regressions include bank-county and county-time fixed effects. Bank-county fixed effects absorb time-invariant differences across individual credit institutions, including their average total size and local market share, their business model (e.g., capitalist vs cooperative banks), international scope, and long-standing relationships with NGOs, that could jointly affect both campaign targeting and deposit behavior. County-time fixed effects capture local and nation-wide factors that may influence all banks, locally or at the national scale, such as macroeconomic conditions, and (local or nationwide) changes in the climate awareness of households over the period. For robustness, we also estimate the same specification at the more aggregated level of individual banks, which is the dimension of treatment. However, we argue that the more granular bank-county-level dataset is better suited for our purpose. Indeed, some large bank brands are represented each by only one individual bank with branches all over the country, while others (notably cooperative bank brands), are represented by a network or different regional institutions which have each only a local outreach.[6]

We find that an increase in the *Brown Reputation Index* of a bank is associated with a decline in household deposits at the bank level, but the effect becomes significant only *after* the implementation of the so-called "bank mobility reform" (Article 43 LCACE), when moving checking accounts from one bank to another became cost-free for retail customers. After February 2017, deposit volumes drop by about 2% when a bank's Brown Reputation Index increases by one standard deviation. This pattern suggests that bank switching costs materially constrained the depositors' ability to act on their environmental preferences.

[6]As a consequence, a naive bank-level regression analysis tends to put an excessive weight on the latter brands, ending up comparing mostly blamed vs praised cooperative brands while some large, capitalist, bank brands account for a sizable deposit market share and are among the most criticized by environmental NGOs. As we discuss below, there is no better solution to this issue that to run the analysis at the local level, where each main retail banking brand is as a matter of rule represented by a unique credit institution.

To better isolate this role of switching costs and exploit the exogeneity of the reform with respect to banks' climate policies and performance, we further implement a difference-in-differences approach. Treated banks are defined as those belonging to the three "brownest" national bank brands as of December 2016. We restrict the sample to a symmetric window of 12 months before and 12 months after the reform, limiting exposure to other concurrent shocks. The results corroborate our baseline findings: brown banks experience a decline in household sight deposits of about 2% after the policy change, relative to banks in the control group.

We then examine whether the sensitivity of deposits to NGO campaigns varies across local markets. Notably, we test whether the effect is stronger in counties with higher income, greener political preferences and more competitive local banking markets. We find evidence suggesting that the response of bank customers is more pronounced in richer and "greener" counties. In contrast, we do not find any stronger effect of banks' brown reputation in more competitive counties. However, defining local bank competition for retail deposits at the relatively large level of counties is questionable, and more granular data on deposits held at the municipality level would probably be necessary to make a more definitive answer on this point.

Last, for a sub-sample of the same banks, we observe all individual housing loans granted to households in the first month of each quarter by a large sample of local bank branches throughout the country. In an extension to our main analysis, we leverage this additional loan-level dataset to investigate whether NGO campaigns against brown banks also have an impact on households' demand for housing loans. This extension is motivated by the fact that opening a checking account and borrowing for housing purchase are frequently joint decisions. Controlling for loan, bank and municipality characteristics, we then show that banks with a browner reputation charge lower rates than their greener competitors on average. This discount tends to decrease over time, excepted in municipalities where competition in the local market for retail deposits is fiercer, which we measure based on the number of bank branches locally. Since we also find that the volume of mortgage loans decreases with the brown reputation index of a bank, we conclude that browner banks face a lower demand for housing loans. Overall, these additional results also point to the willingness of (at least some) households to pay a (slightly) higher loan rate in order to align their bank choice with their environmental values.

Our study contributes to the rapidly growing literature on climate finance (Giglio et al., 2021) and, more specifically, on sustainable banking (De Haas, 2025; Morse and Sastry, 2024).

We first add to the literature on individual consumers' and investors' non-pecuniary motives and their reactions to ESG-related news (Krueger, 2015; Riedl and Smeets, 2017; Hartzmark and Sussman, 2019; Anderson and Robinson, 2021; Bauer et al., 2021; Heeb et al., 2022; Derrien et al., 2022; Giglio et al., 2023; Crosignani and Le, 2023; Meier et al., 2023). Closest to our work, Choi et al. (2023) show that U.S. banks facing more ESG controversies—measured using RepRisk data—experience deposit declines in counties more exposed to sea-level rise. We differ by focusing on information disseminated by NGOs—major providers of public data about banks' fossil-fuel financing—which directly reach ordinary citizens. Our findings suggest that environmental accountability can extend deep into the financial system, even among unsophisticated and indirect holders of capital.

Second, our paper relates to the literature on NGO activism and boycotts, including campaigns targeting financial institutions. Using Sigwatch data, Koenig and Poncet (2019) show that imports from Bangladesh declined after the Rana Plaza disaster in countries where firms were most blamed by NGOs.[7] Homanen (2022), Jeung (2022) and Dursun De Neef and Ongena (2023) find evidence that U.S. banks publicly shamed for financing controversial projects or industries experienced subsequent deposit losses. Our contribution here is twofold. First, we highlight the role of NGOs as intermediaries of collective climate action: by reducing informational and coordination frictions, repeated campaigns enable households to sanction their banks. Second, we show that the effectiveness of such boycott mechanisms depends critically on the regulatory environment. NGO campaigns can discipline banks only when legal and institutional frameworks—such as reforms that lower switching costs—allow depositors to act on their preferences.

Finally, this study connects to the long-standing literature on deposit-market competition and deposit stickiness.[8] A standard view in the United States and Europe is that banks compete locally for demand deposits by adjusting deposit rates, so that rates tend to be lower in more concentrated markets.[9] France is a special case: most banks do not pay interest on checking accounts, and household savings are largely held in state-regulated products offering the same tax-free yield across banks.[10] French institutions therefore do not compete on deposit rates.[11]

[7]More recently, Brendel et al. (2025) show that NGO campaigns denouncing greenwashing have negative financial effects on targeted firms, while Fioretti et al. (2025) analyze the strategic timing of campaigns around firms' annual general meetings. Last, Akey et al. (2025) show that firms care for their ES reputation and try to repair it after negative publicity is sent to key stakeholders.

[8]See, e.g., Haddad et al. (2023) and Argyle et al. (2025), and the references therein. Degryse et al. (2009), pp. 49–54, provide a useful survey of empirical results across countries.

[9]For a recent debate on the local market power of banks, local versus national rate setting, and the deposit channel of monetary policy in the United States, see Drechsler et al. (2017), Drechsler et al. (2021), and Begenau and Stafford (2023).

[10]See Section 6 for more details.

[11]This is confirmed by our regressions, in which the bank-specific interest rate on checking accounts is never a significant driver of sight-deposit volumes.

Our findings nonetheless suggest that, in this environment, greener banks enjoy a competitive advantage and retain retail customers more effectively than brown competitors, particularly when regulation promotes bank mobility.

The paper proceeds as follows. Section 2 provides institutional background on the Article 43 LCACE reform of February 2017. Section 3 sets out our research hypotheses. Section 4 presents the data. Section 5 describes the construction of the *Brown Reputation Index* based on NGO campaign. Section 6 explains the empirical methodology and presents the main results on household demand for bank deposits. Section 7 provides additional insights on the demand for housing loans and on offered housing loan rates. Section 8 concludes.

2 Institutional Background

Many NGO campaigns run in France since 2010 have explicitly urged the customers of "brown" banks to change banks. However, changing banks entails *a priori* substantial transaction costs for the depositor, who must take care of the continuity of all regular payments and transfers (such as rents, tax payments, subscriptions etc) associated with her bank account. These transaction costs have long been identified as a reason for the observed low rate of bank switching in France, as in other European countries. We exploit in this paper a major regulatory change, which, from February 2017 on, cut down to zero the transaction costs of switching bank accounts for individuals in France. Moving deposits out of a brown bank into a greener one then became much easier after this date for any bank customer.

This reform was brought about by a provision of the so-called "Macron Law" of 6 August 2015 (hereafter denoted Article 43 LCACE), which entered into force on 6 February 2017.[12] This article notably transposed a European Directive of 2014 that aimed at regulating the information on bank fees and facilitating the opening and switching of bank accounts in EU countries.[13] In practice, the new regulation requires that (i) closing any deposit account with a bank is cost-free for individuals and (ii) the new bank offers a free "bank switching service" to the customer who has just opened a new checking account, which means that the new bank will take in charge all the paperwork on behalf of the customer.

[12] Cf. Article 43 of Law 2015-990 of August 6, 2015: *Loi pour la croissance, l'activité et l'égalité des chances économiques*, in short LCACE. At the time, the law was dubbed "Macron law" after the name of the then Finance minister, Emmanuel Macron, who promoted it.

[13] Directive 2014/92/EU of the European Parliament and of the Council of 23 July 2014 on the comparability of fees related to payment accounts, payment account switching and access to payment accounts with basic features (OJ L 257, 28.8.2014, pp. 214-246).

By simply signing the bank switching mandate proposed by the new bank, and providing the details of the bank account held at the old bank, the customer authorizes the former to obtain from the latter all relevant information relating to valid direct debits, recurring transfers and undrawn cheques, and to inform the issuers of the new bank details of the customer. Once the customer has opened a deposit account with the new bank, the service enables the secure transmission between banks of the information needed for issuers to change the direct debit and recurring transfer bank details. Customers can also ask their new bank to close their account at their old bank and transfer their credit balance. The system is automated and swift: within 2 working days of signing the mobility mandate, the new bank sends a request to the old bank to collect the relevant information on ongoing, unwound operations and on recurring transfers over the last 13 months. However, the law does not cover the paperwork for switching term and savings deposits beyond the main checking account, which remains in charge of the customer.

This reform was soon perceived as a success. As soon as one month after its implementation, newspapers accounted for a visible impact of this regulation on customers' behavior.[14] With the benefit of more hindsight, a report by the *Conseil Consultatif du Secteur Financier*, an official evaluation committee backed by the French central bank, confirmed this early assessment in June 2018.[15] The report presents the findings of a survey conducted in April 2018 with some 2,100 French bank customers. According to this survey, 67% of French people were aware of the new bank switching service one year after the reform was implemented. Further, 70% of the customers who had opened a new bank account since the reform had been offered the service and 85% of the users declared themselves fully satisfied. Over the first year of implementation alone, banks had to deal with some 1.2 millions of bank account switches.

Overall, this reform provides us with a quasi-natural experiment that exogenously cuts the transaction costs of bank switching for individual customers. Interestingly, the reform affects the costs of their switching checking accounts (hence moving sight deposits), but not the costs of their switching also term or savings accounts and the associated balances. As a matter of fact, the CCSF's report tells us that 60% of the surveyed bank switchers had kept at least one other account open in their old bank.

[14]For instance, France's reference daily newspaper, *Le Monde*, reports on March 7, 2017, about the "promising start of the Macron law" (see here).

[15]Cf. CCSF (2018). *Réforme de la mobilité bancaire: le bilan.* June. Available at: https://www.banque-france.fr/fr/publications-et-statistiques/publications/reforme-de-la-mobilite-bancaire-le-bilan.

3 Research Hypotheses

In this section, we spell out our research hypotheses. As detailed below, we exploit data on NGO campaigns that denounce the funding of fossil energy (or *brown*) projects and companies by French banking groups. We use these campaigns to construct a measure of French banks' "brown" reputation with the general public. 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 banks are perceived in that respect by individual bank customers. We provide evidence below that the campaigns in our dataset are on average largely echoed both in traditional mass media and social media, which confirms our hypothesis.

We then make the following hypotheses. First, we assume that climate-conscious bank customers react to the information conveyed by negative NGO campaigns and, to some extent, follow NGOs' advice to boycott "brown" banks. Under the assumption that the proportion of such motivated depositors is high enough, banks with a reputation of funding fossil projects detrimental to the climate should then face a lower *demand* for their deposits.[16] We test this hypothesis by regressing the (log of) households' outstanding sight deposits on the brown reputation index of banks.

Second, climate-conscious bank customers may in theory react along both the intensive margin, i.e., reduce the amount of deposits they hold with the brown bank and reallocate some money with their other banks if they own checking accounts with several banks, or along the extensive margin: exiting the brown bank altogether. We assume that the extensive margin is the most relevant one in this context, since (i) NGOs blaming brown banks unambiguously call customers for exiting them and (ii) only a minority of French individuals hold more than one bank account.[17]. The extensive margin is however limited by the transaction costs of switching banks. Accordingly, any exogenous shock that cuts these costs should increase households' incentives to switch banks. We test for the importance of switching costs by using the Article 43 LCACE reform as a quasi-natural experiment, which transferred the administrative burden of changing banks from the customer to the new bank. Interestingly, as explained above, the reform should have an impact on the demand for sight deposits across banks, but not, or a smaller impact, on

[16]We use throughout the following language convention: the bank supplies (or issues) deposits, i.e., it faces a demand for deposits by households (who themselves supply funds, i.e., savings). This demand supposedly increases with the interest rate paid by banks on deposits.

[17]According to the 2022 issue of the survey conducted by the French Banking Federation and Ifop, only 37% of French depositors are clients of two or more banks.

the demand for savings deposits, which we can test below.

Funding the purchase of their home is one of the main reasons 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 (e.g., 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. However, the impact of NGO campaigns on mortgage lending by brown banks is an equilibrium outcome that may combine (i) a lower demand from climate-motivated households and (ii) a lower supply of loans by banks when they face a lower supply of deposits (i.e., a traditional bank lending channel). To disentangle supply and demand effects, we need both volume and price data. We obtain the latter from our additional loan-level dataset on newly granted mortgage loans in a large sample of French municipalities. We therefore test for the hypothesis of a dominant decrease in the demand for mortgage loans from brown banks by separately regressing (i) the (log of) outstanding housing loans (at the bank-county level), and (ii) the interest rate of new housing loans, on the brown reputation index of banks.

4 Data

4.1 Data on NGO Campaigns

Presentation and cleaning. Our data on environmental NGO campaigns comes from Sigwatch.[18] 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. Sigwatch covered 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. 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

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

activist organizations.[19] 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 (name, parent company, country, country of parent etc.) and details of the campaign action(registration date in Sigwatch's database, internet links, keywords, excerpts of manifestos naming the companies, country of the targeted audience, etc.).

Sigwatch also adds qualitative information by coding several proprietary variables: a measure of the NGOs' outreach or "power" (ranging from 0.5 to 2.5), a sentiment indicator (ranging from -2 to +2), and a prominence indicator which measures how exposed the named company is in the campaign (ranging from 1 to 4). 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 (see figure 1).[20] This campaign was registred by Sigwatch on 28 March 2018. Sigwatch rated the campaign against SG as very negative (sentiment equal to -2) and very prominent (prominence equal to +4), and indeed this call for a "citizen boycott" of the bank was echoed in several newspapers at the time.

For our purpose, we focused on campaigns (i) targeting French banks, (ii) because of some environmental and social (ES) issue and in particular on issues related to climate change, (iii) run by at least one French NGO, (iv) and/or addressing a French audience.[21] 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 through the identification of the first set of keywords, keywords such as "battery poultry", "pollution", "rainforest", "palm oil", "water use" were used to pick other environment-related

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

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

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

campaigns (OE). Last, remaining ES campaigns (i.e. after exclusion of a few campaigns related to non-ESG topics, such as consumer protection) were defined as social (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, illegitimate debt and poverty, social impact of mining activities, among others.[22]

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). These brands correspond to only seen large banking groups that account for the bulk of retail banking in mainland France.[23] 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 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.[24]

Descriptive Statistics. Our cleaned dataset of relevant NGO campaigns naming French bank brands includes 361 distinct ES alerts with a negative sentiment ("negative alerts") over the period 2010-2020. Among these negative alerts, 244 relate to climate change issues (68%), 46 to other environmental issues (13%) and 71 to so-called social issues (19%).[25]

Figures 2 provides an overview of this data. Figure 2 shows the yearly number of negative 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

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

[23]CCoop and LCL are affiliates of CM-CIC and CA, respectively. These two banks account for only three campaigns observations including all ES-related issues and are dropped during the matching process with bank-level data.

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

[25]We also identify 79 "positive" ES alerts. Positive alerts are not only less frequent but also generally less prominent and we do not consider them in our baseline analysis. Including them separately as a control in the regressions (in the form of "Green Reputation index" that we construct in the same way as the BRI) does not change our results as the corresponding variable is never significant.

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.

Table 1 sheds light on who are the most active NGOs. Some campaigns are run by a coallition of NGOs. In such cases, we consider here only the NGO ordered first by Sigwatch.[26] 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.

Last, regarding targeted bank brands over the 2010 decade, which is our period of interest, BNP Paribas, SG and CA come out as the most often blamed banking groups. This ranking holds whenever we consider all ES issues, where these three brands account together for 80% of negative campaigns, as well as when we focus on climate change-related ones only (84% of the campaigns targeting these three brands). This does not come as a surprise: these three banking groups are, among those headquartered in France, the most internationally active ones, with large CIB arms funding projects (including brown ones) abroad. In contrast, other groups, such as CM-CIC and BPCE, are more retail-oriented and have a stronger domestic focus.[27]

4.2 Bank Data

Our main variables of interest are volumes of outstanding households deposits issued held by French banks in each county (in French: *département*) of mainland France.

We obtain bank-county-level information on deposits 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 households by individual credit institutions (hereafter, banks) in each of the 94 counties of mainland France. 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 (also called checking accounts)

[26] 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.

[27] Note however that we systematically include (bank or bank-county) fixed effects in our regressions to control for these invariant differences in banks' business models.

vs term and savings deposits.[28]

Outstanding amounts of household deposits are observed with monthly frequency. We restrict the sample of banks to credit institutions which belong to one of the seven largest banking groups operating in France.[29] 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. After some basic cleaning[30], we are left with an unbalanced sample of 100 individual banks (accounting for 23 different brands) affiliated with the seven major banking groups of the country, and close to 127,000 bank-county-month-level observations over January 2011 to November 2020.[31] In the baseline regression, we restrict the sample to banks for which we observe both key financial ratios and the interest rate paid on sight deposits (see below for details). However we also show that our main results hold in the larger sample of some 100 banks. The baseline regression sample therefore includes 57 individual banks, which are all affiliated to the same 7 banking groups but correspond to 19 different bank brands. Over the 2011-2020 period, this amounts to close to 97,000 bank-county-month observations, or equivalently close to 6,000 bank-month observations when we collapse the data at the bank level.

Last, for analyzing the effect of banks' brown reputation on housing loan rates in the extensions section, we exploit geo-localized, loan-level data on newly issued housing loans in France over the years 2014-2020 that we obtain from another proprietary dataset of the Banque de France (MCONTRAN). This dataset collects 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.[32] We exclude bridge loans and

[28] In an extension below we also consider housing loans granted to resident households, which we sort into regular housing loans vs regulated housing loans (e.g. lending schemes with capped interest rates or public subsidies targeting poorer households, such as "zero-interest-loans"). Our focus below is on regular loans.

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

[30] We notably compute monthly rates of growth of deposits and drop observations of the variables in levels corresponding to outlier growth rates (at the first and 99th percentiles), in order to mitigate the impact of possible reporting breaks (associated, e.g., with mergers of local banks).

[31] Note that since the Brown Reputation Index of banks builds on NGO alerts lagged by up to 12 months (see section 5 below for details), we loose the first year of observations. The final regression sample therefore starts in 2011 instead of 2010.

[32] The French mortgage loan market is dominated by fixed-rate loans. According to the French supervisory

renegotiated loans, as well as loans with missing total amount, interest rate or initial maturity. We also drop loans for which Global Effective Rate (GEF), the reference all-in-rate for mortgage loans, is missing or which exhibit outlier levels of this interest rate (above the 99th percentile). 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.[33] 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 close to 212,000 individual loans for housing purchase (166,000 once matched with available bank-level data), issued by the local branches of 76 individual banks (which correspond to 14 different brands) and located in 1,059 municipalities across 93 counties between the first quarter of 2014 and the last quarter of 2020.[34]

We then construct bank-related controls using various additional sources. Firstly, we use Banque de France's *Fichier des implantations bancaires* (FIB), which monitors the population of active bank branches of all banks in France, to construct local measures of bank size in retail banking markets with monthly frequency. For each bank, we compute the (log) number of branches in each county as a proxy for the size of the bank's local size. We use this variable as our main bank-county-level control in regressions explaining the level of deposits or loans.[35] We also compute the (log) number of bank branches within each municipality (ZIP-code), which we use 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. SURFI is structured in a variety of sub-datasets, or "reporting forms". First, M-SITMENS provides

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).

[33] *La Banque 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.

[34] Figure A4 in the online 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.

[35] Loan officers of the French Post Bank, *La Banque Postale* (LBP), are located in local post offices. These post offices are not recorded in the FIB dataset, which only includes regional hubs of LBP. As a consequence, observations related to LBP are dropped from the regression sample when the number of branches at the bank-county level is used as a control variable.

simplified balance sheet items with a monthly frequency for a large subsample of banks. We use this data to construct monthly measures of bank size (log of total assets), leverage (capital and reserves to assets), reliance on retail deposits (debt to non-financial customers to assets),which we include in our regressions explaining changes in the volumes of sight deposits or housing loans. Second, we also use the sub-datasets called SITUATION and CPTE-RESU to construct quarterly financial ratios of banks, which we include as controls in the loan-level regressions explaining the interest rate on new housing loans.[36]

Last, we recover bank-level measures of deposit and housing loan rates from two additional sub-datasets. INTDEPO provides outstanding amounts of deposits and associated interest payments flow. We use this data to construct monthly measures of bank-level *apparent* interest rates on *existing* sight deposits (or checking accounts). We express these apparent rates on sight deposits in percentage points. For some extensions, we also obtain the bank-specific, average interest rates on new, longer-term (above 2 years), savings deposit contracts issued in a given month as well as the bank-specific, average interest rate on new mortgage loans issued at a fixed interest rate (i.e., the majority of mortgage loans in France) from the M-INTNOUA sub-dataset (also expressed in percentage points).

5 Measuring Banks' Brown Reputation

5.1 NGO campaigns and mass media

We aim to construct a monthly measure of French banks' "brown" reputation 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, 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, and, second, we study social media reactions through the analysis of tweets related to NGO campaigns posted on X (ex-Twitter).

Newspapers' websites. We first gauge the impact of NGO campaigns on retail bank customers

[36]These controls are bank size (log of total assets), leverage (capital and reserves to assets), asset liquidity (cash and interbank assets to assets), the ratio of credit to non-financial customers to assets, as well as a non-performing loans ratio (loan losses and provisions to credit to non-financial customers). Income statements (from 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.

by web-scraping a broad selection of French information websites for corresponding mass media releases.[37] 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 30 days after the recorded alert date.[38]

Social media. Social media platforms like X (ex-Twitter) serve as agoras where individuals engage in discussions, express opinions and share information on a large scale. Analyzing the tweets that relate to NGO campaigns can therefore help us to assess how the public is affected by these initiatives. We therefore fine-tuned our web-scraping algorithm to also identify the tweets which pertain to the NGO campaigns in our dataset. We focused our search on a time window spanning from 5 days before to 30 days after the beginning of the campaign. We collected over a thousand tweets, and on average 8.3 negative tweets per campaign.

We identify some newspaper (and other mass media) coverage for about a half of all negative, climate change-related, NGO campaign alerts targeting French banks over 2010-2020. When news releases are identified, the median NGO alert benefits from two releases, while the top 10% of media-covered campaign alerts are echoed by four media websites or more. We also identify related tweets for about 60% of all these NGO campaign alerts over the same period. For these alerts, the number of tweets spans from only one to more than 50. Overall, around 70% of the NGO campaign alerts in our cleaned dataset are covered either by newspaper articles, tweets, or both. Figure 3 shows the share of negative, climate change-related, alerts with (i) mass media coverage only, (ii) social media coverage only and (iii) both mass and social media coverage through time. 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 more than two thirds of alerts being echoed in newspaper articles or social media. In spite of possible shortcomings of our search algorithms, which may miss relevant newspaper articles or tweets, this evidence suggests that the NGO alerts in our sample are very likely to reach a broad audience among retail French bank customers.

[37] 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.

[38] We manually dropped irrelevant hits (false positive) that are not related to climate change.

5.2 Brown Reputation Indexes

5.2.1 Methodology

In this section, we detail how we use NGO campaigns related to the negative impact of banks lending policies on global warming to construct our index of banks' "brown" reputation. We construct this Brown Reputation Index (BRI) in three steps.

For each negative climate change-related alert naming a bank brand, we first 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 coalition 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 unit-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 headlines of the campaign's material) and at least one of the participating NGOs is viewed by Sigwatch as very powerful.[39]

This definition of an impact score of individual alerts follows closely on Sigwatch's own definition of the so-called Reputational Impact Score of NGOs' actions.[40] To further vindicate the relevance of this approach in our context, i.e., gauging whether NGO actions reach a general audience through the medias, we document the correlation of these S_{nbd}, P_{nbd}, and N_{nbd} variables with media coverage and social media attention. In practice, we regress the number of tweets or online articles of major newpapers and TV or radio broadcasts on Sigwatch's (unit-scaled) NGO power, (negative) sentiment, and prominence variables. Table 2 presents the results. We find confirmation that more negative NGO campaigns find more echoes on Twitter and in mass media. The prominence of bank's brand in a NGO campaign also significantly contributes to the success of this campaign on Twitter.[41]

[39]The maximum value of the NGO power variable is 2.75 for a global coalition.

[40]As Sigwatch puts it in their lastest Methodology booklet: "Because Reputational Impact scores measure the view of NGOs rather than from any ensuing media coverage (or in many cases, absence of coverage), they are a valuable indicator of what NGOs are really worried about and provide a unique early warning system for emerging reputational problems."

[41]Note that Sigwatch's measure of the NGOs' outreach does not come out as a significant driver of media

Second, 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.[42]

Motivated by research in cognitive science (Mullainathan, 2002; Kahana, 2012) which documents that recall probabilities decay over time, we assume that depositors retain awareness of NGO campaigns for a limited period.[43] Accordingly, a bank's brown reputation builds with successive (negative) climate-related NGO campaigns but decays over time as earlier events fade from public memory. We model this dynamic by constructing a monthly Brown Reputation Index (BRI), in which past campaigns are down-weighted using an exponential decay function:

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

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). We verify that our main results are robust to alternative calibrations of the time-decay parameter and to simpler definitions of the shocks, as detailed in the robustness section below.[44]

Figure 4 shows the resulting brown reputation index BRI_{bt} of the seven main bank brands

coverage. In a robustness exercise detailed below, we therefore checked that omitting this factor in the definition of the alert impact scores does not affect qualitatively our main results.

[42]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". We however checked that our main results are robust to an alternative definition of the MRS_{bt} variable, where we do not apply any concave transformation to the sum of alert-level scores.

[43]See also recent finance evidence of fading memory, e.g., (Nagel and Xu, 2022; Malmendier and Nagel, 2016, 2011).

[44]Figure A6 in the online appendix displays alternative measures of the brown reputation index of one major bank when we vary this calibrated parameter.

(BPCE, BNP, CA, CM-CIC, HSBC, LBP, SG) in France over the 2010 decade. Importantly for the empirical relevance of our exercise, the figure witnesses a lot of variation, both within banks and across banks.[45]

5.2.2 From Bank Brands to Individual Banks

We build brown reputation indexes for all the major bank *brands* in France. However, we observe deposits and loans, as well as individual housing loans for *individual banks*, and not for the brands they may share. We explain in this section how we match bank brands with individual credit institutions.

As said above, the nine brands identified in the Sigwatch dataset belong to the seven largest banking groups operating in France and we restrict our sample to the 100 individual credit institutions that are affiliated with these banking groups and report to CEFIT. We 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 individual customers. For clarity, Table 3 provides a few examples highlighting how individual banks are mapped into bank brands, which may or may not correspond to the name of their parent institution in the group they are affiliated with.

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 feel involved. In contrast, *Crédit du Nord* is a smaller 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 bank, are unlikely to see themselves as customers of its parent company,

[45] Figure A5 in the online appendix shows the same indexes when the computation of alert impact scores does not factor in Sigwatch's assessment of NGOs' outreach. The levels and volatility of the brown reputation indexes of the seven large bank brands are then somewhat higher, notably in the most recent years, as many recent campaigns are run by French NGOs whose "power" is assessed by Sigwatch as intermediate only (i.e., below one after re-scaling). Note, however, that the relative positions of the reputation indexes of the respective bank brands remain broadly unaffected by this change.

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 sample. Only the nine largest bank brands show up in NGO alerts covered by Sigwatch. The 16 banks associated with the 16 remaining brands are therefore never affected by NGO campaigns.[46]

6 Empirical design and main results

6.1 Panel Regressions

We aim to evaluate whether NGO campaigns affect households' demand for deposits from "brown" banks, blamed for "banking on climate change". Although the treatment is at the bank (brand) level, we conduct the main analysis using monthly data at the bank-county level, which is better suited to the structure of the French banking system and also allows for finer, local, controls potentially affecting deposit demand. We however show in the robustness section that the results hold whenever we exploit less granular, bank-level information. Last, we also investigate potential heterogeneous effects across counties depending on the characteristics of local bank depositors.

Using monthly data on households deposits at the bank level, we estimate the following empirical model (within regression):

$$\begin{aligned} ln(D_{bct}) = \beta.BRI_{bt} + \gamma.r_{bt} + \theta.Z_{b,t-1} \\ + \kappa.nbb_{bct} + \delta_{bc} + \delta_{ct} + u_{bct} \end{aligned} \tag{1}$$

where D_{cbt} is the outstanding amount at the end of month t of sight deposits issued to households of county c by bank b. The main independent variable of interest is our index of banks' brown reputation (BRI_{bt}). We expect coefficient β to be negative. Note here that BRI_{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 the baseline regression, we control for the rate of interest paid by each bank on its sight deposits in month t, r_{bt}, as well as for a set of (lagged) monthly bank-level balance sheet

[46] See the online appendix for a list of these banks.

variables stacked in $Z_{b,t-1}$.[47] We include in Z the (log) total assets of the bank, its leverage and its reliance on deposits. In a variant, we also control for the (log) number of bank b's branches in county c, nbb_{bt}. Last, we control for bank-county fixed effects δ_{bc} 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), including at the local level. The latter account for unobserved time-varying macroeconomic and local factors (such as local economic activity, or the monetary policy stance) that may impinge on the local demand for bank deposits by households. In all regressions, we cluster standard errors at the level of individual banks, which is the dimension of treatment. Table 4 presents descriptive statistics for the dependent and independent variables used in the baseline regression.

To highlight the role of transaction costs in constraining the reaction of bank customers, we then estimate the following augmented specification, where we interact the bank's brown reputation index with a dummy variable for the period posterior to the implementation of the bank switching reform in February 2017 ($Post$):

$$\begin{aligned} ln(D_{bct}) = &\beta.BRI_{bt} + \beta_{Post}.BRI_{bt} \times \text{Post}_t \\ &+ \gamma.r_{bt} + \theta.Z_{b,t-1} \\ &+ \kappa.nbb_{bct} + \delta_{bc} + \delta_{ct} + u_{bct} \end{aligned} \tag{2}$$

6.2 Results

6.2.1 Baseline specification

Table 5 reports the estimation results of equations (1) in columns (1-3) and (2) in columns (4-7). The dependent variable is the volume of households' sight deposits with a bank and the main independent variable of interest is the bank's brown reputation index. Columns (1) and (3) control for the local number of branches of the bank as well as fixed effects, while other columns also control for time-varying bank balance sheet ratios and the interest rate on checking accounts.[48]

Considering first the average effect over the whole 2011-2020 period (columns 1-6), we find

[47] The deposit rate is an apparent rate, computed as the ration of interest payment over the current month to the outstanding volume of deposits at the end of the previous month. There is therefore no need to lag this control variable in the regression.

[48] Including the size of bank branching networks helps to control for changes in the supply of retail deposits by banks, but it comes as a cost as this information is not available for the network of the French Post bank (*La Banque Postale*), which consists of local post offices (not covered by the FIB dataset). This bank is then dropped from the regression sample in columns (3) and (6-7).

that the demand of sight deposits by households decreases significantly when negative NGO campaigns heighten the brown reputation of the bank: the coefficient of the brown reputation index is negative and significant at the 1 percent level whatever the controls and even when the inclusion of bank-level controls reduces the size of the sample from 98 to 57 banks. Interestingly, the results in columns (4-6) also show that the negative effect of NGO alerts denouncing brown banks is actually only significant *after* Article 43 LCACE is implemented. This confirms our hypothesis that bank customers punish banks perceived as brown by exiting them and switching to greener competitors, but only when the transaction costs of doing so are small enough.[49]

Regarding control variables, we find that a larger bank size (measured in terms of total assets), a stronger local physical presence (size of the local branching network) and a larger share of deposits to total liabilities are associated with a larger amount of households sight deposits. Also, albeit this correlation is less significant, deposits tend to be larger for banks with a lower capitalization ratio (which is consistent with the fact that such deposits are insured by the public deposit insurance scheme but also with the fact that larger banks are less capitalized and less dependent on deposits for funding on average). However, we do not find evidence of any significant effect of the interest rate paid on the volume of these deposits.

This last result may seem surprising at first sight. Indeed, banks are commonly expected to compete on the interest rate they pay on deposits.[50] This low interest rate sensitivity of sight deposit volumes can nevertheless be easily rationalized in the French institutional context.[51] Paying interests on checking account balances has long been prohibited by the law in France and this regulation was only removed in 2005. However, even after this date, most banks, and in particular the banks affiliated with the main banking groups, have kept offering checking accounts that *do not* bear interest to the holder.[52] Indeed, since January 2009, all credit institutions in France are allowed to offer to their customers regulated savings deposits, the most popular of which is called *Livret A*.[53] On such a savings account, an individual can save

[49]Note that, in additional tests, we also find evidence of a significant, though smaller, decrease in the amount of *savings* deposits held with browner bank after February 2017, although managing the transfer of savings deposits is *a priori* not covered by the mandate of the new bank (which implies that moving them to a new bank entails paperwork for the bank customer), see table A9 in the online appendix.

[50]Note however that many papers have shown that the interest rate sensitivity of sight deposit rates and volumes to market rates is low because the deposit franchise gives banks market power in deposit markets. See, e.g., Drechsler et al. (2021) and references therein.

[51]See, for instance, Duquerroy et al. (2024) for more details.

[52]For instance, according to the Banque de France, the average interest rate paid on sight deposits in France was 0.06% as of November 2024, to be compared to a policy rate (ECB's repo rate) at 3.40% and a 3-month Euribor rate at 3.01%. In our sample of banks, the average apparent interest rate on checking accounts is only 0.02% (annualized).

[53]Other regulated savings accounts, such as *LDD*, *Livret Jeunes* etc, with smaller outstanding volumes than the *Livret A* work along very similar lines.

up to 22,950 euros.[54] The interest rate paid on these regulated savings accounts is set by the law and thus the same for all banks.[55] Interests earned are tax-free and the *Livret A* is highly liquid, as amounts held can be instantly transferred from and to the holder's checking account at will and without cost. These very attractive features explain why most French individuals hold bank checking accounts that do not pay any interest and simultaneously hold one such regulated savings account at the same bank, which they use to earn interest on their idle checking account balances.[56] As a consequence, the interest rate paid on sight deposits is very unlikely to be a significant driver of households' bank choice in France.

The estimated effect of negative campaigns against brown banks is economically significant, but small. Other things equal, a one-standard-deviation (0.90) larger brown reputation index induces a drop in households' sight deposits by some 2% to 2.7% thereafter (using the coefficients in columns 5-6 of the table). In euros, the baseline, conservative estimate (-2%) translates into a drop in households' sight deposits for the average bank-county pair by some 4.6 million euros once transaction costs have been cut. Although this may seem large, this number is small compared with the standard deviation of sight deposits at the bank-county level, at 412 million euros.

6.2.2 Robustness

We checked the robustness of our baseline results along a number of dimensions. First, these results are robust to variants in how we construct the brown reputation index. As shown in Table 6, the baseline results above remain qualitatively unchanged when (i) we drop the "NGO power" factor in the definition of the alert-specific impact score AIS_{nbd}, (ii) we additionally drop all alerts for which we cannot pick at least one related online newspaper article or at least one tweet on X/Twitter, and (iii) we replace the brown reputation index with a dummy variable that takes the value of one when the bank brand is hit by at least one negative campaign alert within the month. Second, Table 7 shows how estimation results in column (5) of Table 5 change when the time-decay parameter θ is set to reflect alternative assumptions regarding the

[54] This does not include capitalized interests. This ceiling was increased from 15,300 euros in two steps, in October 2012 and January 2013.

[55] The interest rate paid on the *Livret A* is calculated by the French Central Bank twice a year, on January 15 and July 15, and becomes effective on February 1 and August 1, respectively. The formula used is set by law and depends on year-on-year CPI inflation and current short-term market rates on the interbank market.

[56] For instance, as of November 2024, French individuals held some 1,862 billion euros of bank deposits, of which 29% of sight deposits and 37% of regulated savings accounts (21% for the *Livret A* alone). Note that some banks, notably online "neo-banks", nevertheless pay an interest on the sight deposits they issue, but this interest income is taxed and the after-tax benefit is generally very close to the benefit earned by the holder of a *Livret A*.

persistence in peoples' mind of past monthly bad reputation scores (MRS_{bt}). For the sake of comparability across columns, the main variables of interest (alternative versions of BRI_{bt}) are here standardized. The first column shows the results under the assumption of no memory of past 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 negative impact of a bank's brown reputation seems to increase markedly, then level off, when θ grows from 1 to 6 months, which supports our calibration. Last but not least, we also checked that our results still hold when we cluster standard errors at the finer bank-county level (see table A6 in the online appendix).

Beyond, one may be concerned that the bank mobility regulation comes into force roughly when NGO campaigns blaming brown banks become more salient, i.e., after the 2015 Paris Agreement, while we observe a surge in the number of media articles and tweets echoing these campaigns (see figure 3). To prove that the impact of Article 43 LCACE is not confounded with this salience effect (and a potentially associated rise in the climate-consciousness of bank customers), we show in column 7 of table 5 that the results still holds when we restrict the period of estimation to the years 2015-2017, when the number of campaign alerts against brown banks as well as their coverage by mainstream media is comparatively high. Importantly, there is no significant effect in the period between COP21 and the 2017 reform, when climate awareness was already high but switching frictions remained substantial.

Finally, we replicate the baseline analysis above but using more aggregated data at the bank level instead of the bank-county level. Table 8 shows estimation results for within-regressions similar to equations (1) and (2) when we observe sight deposits volumes at the bank level. The results are virtually unchanged. In economic terms, we also find that, after Article 43 LCACE, sight deposit demand by households drops by an average 2% following a one-standard-deviation increase in the brown reputation of a bank (using the coefficient of -0.038 in column 5 of table 8).[57]

A potential concern with this bank-level analysis is however that cooperative banking groups, which are represented by a network of regional/local cooperative banks in the sample, receive an excessive weight in the regression: once collapsed at the bank level, a brand represented by 15 regional banks corresponding each to one of the 15 main administrative regions of mainland France would weigh 15 times more than a major capitalist banking group with national outreach

[57]Descriptive statistics of our data at the bank level are presented in Table A3 (large sample) and A3 (sample restricted to banks with available balance-sheet controls) in the online appendix. The standard deviation of the brown reputation index in this less granular regression sample is 0.50.

and branches of its main brand in all French counties. To alleviate this concern, we also present in the online appendix the results of alternative weighted least square (WLS) regressions, where bank-level observations are weighted by the inverse of the number of banks in each brand at each date in time (see table A7). Our conclusions remain qualitatively robust to this correction.

Bank-level regressions prove nevertheless useful to get a sense of the total impact of a worsening broad reputation on total bank funding. In table A8 in the online appendix, we show the results of simple OLS and WLS regressions of (log) total assets and total non-financial deposits of banks on their brown reputation index, where we control for bank and time fixed effects. The coefficients of interest are sometimes negative but small and always statistically insignificant. This suggests in turn that brown banks can manage to compensate the decreased demand for their household deposits by issuing other types of liabilities. However, since households' sight deposits bear almost no interest, this substitution is likely to come at a cost.

6.3 Difference-in-Differences Approach

As a last test vindicating our general approach, we focus on a narrower time window around the implementation of Article 43 LCACE (from February 2016 -12 months before- to February 2018 -12 months after-) and run a proper difference-in-differences regression. For this purpose, we first sort individual banks into two groups, depending on the brown reputation index of their respective brands as of December 2016. According to our measure, three large brands, accounting for 37 banks in our full sample of some 100 banks, then stand out as "brown" before the implementation of the reform (see also Figure 4). We expect that banks belonging to these brands (i.e., "treated" banks) will face a lower demand for deposits by households after February 2017, when the transaction cost of aligning an individual's bank choice with her concerns about climate warming becomes very small. The other banks are considered a control group in this respect. We then estimate the following regression:

$$\begin{aligned} ln(D_{bct}) = {} & \beta.\text{Brown}_b \times \text{Post}_t \\ & + \gamma.r_{bt} + \theta.Z_{b,t-1} + \kappa.nbb_{bct} + \delta_{bc} + \delta_{ct} + u_{bct} \end{aligned} \tag{3}$$

where, again, the dummy variable Post_t takes a value of one for all dates after February 2017. The coefficient of interest is the coefficient of the interacted term $\text{Brown}_b \times \text{Post}_t$. The two components of this interacted term are absorbed by the fixed effects. As shown in columns 3 and 4 of Table 9, which refer to the sample of 56 banks for which we observe all control variables, banks identified as brown face a decrease in sight deposits by some 2.1% to 2.6% on average in the 12 months following the reform. The results are again similar when we consider all 98 banks, including those for which we lack monthly balance sheet information.

Last, Figure 5 shows the estimated coefficients of interest for a dynamic version of the same test, where the treatment dummy for brown banks is interacted with year-month dummies. The figure confirms that the usual parallel assumption holds, which validates this last result.[58]

6.4 Heterogeneous effects across counties

Last, we investigate whether the impact of negative NGO campaigns denouncing brown banks has heterogeneous effects depending on the local characteristics of customers and markets. Meier et al. (2023) show for instance that the local sales of consumer goods responds more to good or bad ES news about the producer firms in US counties with more Democrat voters and higher income. Using county-level information on income from the French Census (as of 2010) and on votes for green parties (at the 2014 elections for EU Members of Parliament), as well as a county-level measure of bank competition for sight deposits by households (based on a HH index of local deposit shares), we run regressions on sub-samples corresponding to the counties in either the lowest or highest quartile in each of these three dimensions of heterogeneity: income, political preferences for pro-environmental policies and local competition in the market for bank deposits.[59]

As shown in table 10, the results suggest a marginally stronger reaction to a worsened brown reputation of banks in counties with higher income and a higher share of green voters. As far as income is concerned, the stronger reaction holds throughout the period, while as far a political preferences are concerned, it holds mostly in the post Article 43 period. In contrast, the intensity of local bank competition, at least when measured at the county level, does not seem to influence significantly the size of this response. However, measures of bank competition at the county-level may not be precise enough measures of the true options faced by households, who are more likely to look for a competitor deposit bank in their own city than in the whole county.

[58] Figure A7 in the online appendix shows that we observe a similar pattern when we run the same dynamic regression on the bank-level sample instead.

[59] See the online appendix for details on the data sources and construction of these these socio-demographic variables.

7 Brown banks and the demand for housing loans

7.1 Methodology

In this section, we exploit both data on outstanding volumes of housing loans at the bank-county level and loan-level information (from the M-Contran database) on new housing loans granted by banks, in order to identify a lower demand of mortgage loans associated with the browner reputation of lenders. Indeed, while shifts in both supply and demand may lead to a lower volume of mortgage loans from brown banks, the sign of the associated change in loan interest rates is key to ascertain whether demand effects indeed dominate.

We proceed in two steps. First, we run bank-county-level regressions similar to (1) where the dependent variable is the (log) amount of regular (i.e., non-regulated) housing loans, instead of households' sight deposits. We again control for the same bank financial ratios as before and for the size of local bank branches networks. We however now substitute a bank-specific measure of the interest rate on new mortgage loans for the interest rate on checking accounts.

Second, we investigate whether NGO campaigns against brown banks affect the interest rates of such housing loans. We look at potentially differentiated effects of the brown reputation of banks after 2017. We observe new fixed-rate loans granted in the first month of each quarter for a sub-sample of the previous population of banks over 2014 to 2020. Using this data, we estimate the following empirical model:

$$
\begin{aligned}
r_{ibmt} = &\beta BRI_{bt} + \beta_{Post}.BRI_{bt} \times \text{Post}_t \\
&+ \gamma \times X_i + \zeta \times Q_{mt} + \theta \times Z_{bt} \\
&+ \delta_b + \delta_{ct} + u_{ibmt}
\end{aligned} \tag{4}
$$

where r_{ibmt} is the 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 brown reputation index (SRI_{bt}). We again expect the coefficient β and/or β_{Post} to be negative in equations (4).

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 municipality's population (dummies for municipalities in the third and fourth quartiles of i) income, ii) college education, both before the sample period, and iii) the share of green votes at the 2014 MEUP elections, see the online appendix for details on data sources and construction). Third, Z_{bt} includes 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, we control for bank fixed effects and county-time fixed effects. Standard errors are clustered at the bank level. Table 12 presents descriptive statistics for the dependent and independent variables used in these regressions.

7.2 Results

We first look at the response of the volume of housing loans to a browner reputation of banks. Table 11 presents the results in the same format as table 5 did for sight deposits. The reduction in amounts lent is large and both statistically and economically significant. Other things kept equal, when the brown reputation index of a bank is higher by one standard deviation, the volume of housing loans borrowed from this bank decreases by some 3% (after February 2017). Interestingly, all the action takes place after Article 43 LCACE. This is not surprising, as households must open a checking account with the bank from which they take a mortgage loan. Although a borrower does not have by law to choose the lending bank as her main bank (and channel her wages to the checking account opened with this bank), doing so is often part of the deal with the loan officer who finally approves the loan. Households who would not like to borrow from a brown bank can then more easily change banks and move their main checking account to their preferred institution.

Last, we turn to regressions on loan interest rates using the loan data. Table 13 presents estimation results for alternative specifications. In all regressions, we include loan-level, bank-level and municipality-level controls, as well as fixed effects. In the first column, we show that a banks' brown reputation is associated with slightly lower interest rates on new housing loans on average over the period: a larger BRI by one standard deviation translates into a lower mortgage interest rate by some 2 basis points.[60] However, this effect is larger, not smaller, before 2017, as shown in columns 2 and 3. This may suggest that demand effects from motivated borrowers (although not visible on borrowed volumes at the more aggregated bank-county level)

[60] Note however that this arguably small spread has the same magnitude as estimates of 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).

would drive the impact of NGO alerts before Article 43 LCACE while this lower demand is partly compounded by supply effects, possibly associated with the documented decrease in deposits with browner banks, thereafter. On other explanation could be that the post-2017 period corresponds to the last phase of very low policy interest rates in the euro area, when housing loan rates reached an historical low. Overall, the distribution of housing loan rates became then tighter, leaving less room for potential discounts by browner banks compared to greener ones.

We then investigate further the role of local bank competition by adding interacted the former independent variables with a dummy for municipalities hosting more than 20 bank branches.[61] Column 3 of the table shows the results. We find evidence of a significantly more negative reaction to the brown reputation of banks after 2017 in more competitive local retail banking markets. This again suggests that browner banks adjust their price downward to meet the relatively lower demand for loans in these municipalities where households can more easily switch to competitors.

8 Conclusion

We provide evidence in support of a growing influence of sustainability considerations in shaping financial decisions of households. We find that French bank customers significantly react to NGO campaigns spotlighting banks' adverse contributions to climate warming. A non-negligible proportion of depositors actively withdraw their deposits from banks perceived as environmentally irresponsible and seek greener alternatives. Additionally, using a reform that facilitated bank switching from February 2017 on, we highlight the limiting role of transaction costs. The average customer does not react to the news blaming her brown bank before the administrative costs to do so have become negligible. However, customers in counties were pro-environmental concerns are more widely shared -as proxied by votes for green parties- tend to act based on their ES preferences even in the presence of such costs. These findings contribute to the literature in sustainable finance by shedding light on retail customers' responsiveness to banks' environmental reputation. Our paper 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.

[61] This threshold corresponds roughly to the median of the number of local bank branches i the loan-level sample.

These findings have implications for banks, NGOs, and policymakers. For financial institutions, they suggest that reputational exposure to climate-related NGO campaigns may influence deposit stability, particularly when frictions to switching are low. This highlights the potential value of credible and transparent commitments to sustainable practices in mitigating reputational risk. For NGOs, the results indicate that targeted campaigns can shape depositor behavior, thereby serving as a channel for broader environmental influence through the financial system. Finally, for regulators, the evidence suggests that reducing transaction costs associated with switching banks can enhance market discipline and may facilitate a shift toward more environmentally responsible banking.

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

NGO Name	**Climate Change-related 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
Greenpeace	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: NGO campaigns against brown banks and their coverage on Twitter and in major newspapers: exploring the determinants.

	Tweet Count				Newspaper count			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NGO Power	-0.211			-0.309	-0.308			-0.465
	[0.579]			[0.581]	[0.570]			[0.575]
Neg. sentiment		0.998**		0.804**		0.337		0.659**
		[0.396]		[0.405]		[0.219]		[0.280]
Prominence			1.277***	1.122**			-0.225	-0.394
			[0.445]	[0.458]			[0.398]	[0.404]
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	249	249	249	249	234	234	234	234
Pseudo R2	0.215	0.231	0.240	0.250	0.065	0.024	0.065	0.075

Note. Period: 2012-2020. Dependent variable in columns (1-5): count of Tweets for each NGO campaign alert. Dependent variable in columns (5-8): number of media releases (online articles) for each NGO campaign alert. Negative and neutral alerts are included. Regression method: PPML. *NGO power*, *Negative sentiment*, *Prominence*: qualitative variables from Sigwatch, with positive sign, rescaled to unity. Robust standard errors.

Table 3: Mapping individual banks into bank "brands": examples.

Bank name	Banking group	Bank brand
CA Ile de France	CA	CA
LCL	CA	LCL
Société Générale (SG)	SG	SG
Société Marseillaise de Crédit	SG	Société Marseillaise de Crédit
Crédit du Nord	SG	Crédit du Nord
Banque Populaire Rives de Paris	BPCE	BPCE
Banque de Savoie	BPCE	Banque de Savoie

Note. The table shows examples of our mapping of individual banks, for which we observe deposits at the county level, with their parent banking group and with a specific bank brand. NGO campaigns target only a handful of popular bank brands, corresponding to the names of the major banking groups, but affiliations of individual institutions to these groups is not always transparent to the public.

Table 4: Bank-county-level, baseline regression sample: descriptive statistics

	Mean	Std.Dev.	p10	p25	Median	p75	p90	Nb.Obs.
Sight deposits (mns)	229.22	411.61	12.39	39.85	109.52	246.18	546.27	96704
Sight deposits (log)	11.43	1.49	9.42	10.59	11.60	12.41	13.21	96704
Savings deposits (log)	11.93	1.56	9.82	10.96	12.05	13.11	13.82	94860
Housing loans (mns)	525.53	848.90	29.42	75.61	225.54	597.87	1379.61	96619
Housing loans (log)	12.26	1.46	10.35	11.27	12.34	13.31	14.14	94687
Brown RI	0.51	0.90	0.00	0.00	0.00	0.60	2.04	96704
Dummy neg. CC news	0.12	0.32	0.00	0.00	0.00	0.00	1.00	96704
Nb branches (log)	2.35	1.32	0.00	1.39	2.40	3.30	4.01	78760
Interest rate	0.02	0.03	0.00	0.01	0.01	0.03	0.05	96704
Housing loan rate	1.62	0.41	1.19	1.34	1.51	1.90	2.26	58085
Term dep. rate (long)	1.18	0.97	0.10	0.47	0.94	1.63	2.77	44623
Assets(-1) (log)	25.18	1.85	23.01	23.60	25.48	26.40	27.76	96704
Capital/Ass.(-1)	0.04	0.02	0.02	0.02	0.02	0.05	0.07	96704
Non-bank dep./Ass.(-1)	0.50	0.25	0.13	0.17	0.62	0.68	0.74	96704
Share green vote	13.83	5.46	7.91	9.29	12.62	18.21	22.02	96704
Share college educ.	0.22	0.07	0.16	0.18	0.20	0.24	0.30	96704
Income per hhld. (log)	3.13	0.15	2.98	3.03	3.10	3.18	3.29	96704
HHI deposits (pp)	1.24	0.58	0.53	0.82	1.17	1.67	2.02	96704

Note. Bank-county-level sample. Period: 2011-2020. Deposits and loans are expressed in euro millions. Interest rates are in percentage points.

Table 5: Banks' brown reputation and the demand for sight deposits: baseline.

	2011-2020						2015-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Brown RI	-0.043***	-0.023***	-0.030***	-0.022***	-0.009	-0.010	0.002
	[0.010]	[0.006]	[0.009]	[0.006]	[0.005]	[0.006]	[0.007]
Brown RI × Post				-0.032***	-0.023**	-0.030***	-0.020***
				[0.010]	[0.009]	[0.009]	[0.006]
Nb branches (log)	0.211**		0.122*	0.219**		0.129**	0.092
	[0.102]		[0.064]	[0.101]		[0.062]	[0.063]
Assets(-1) (log)		0.124**	0.094*		0.123**	0.090*	0.033
		[0.053]	[0.048]		[0.051]	[0.046]	[0.032]
Capital/Ass.(-1)		-2.490*	-1.964		-2.705**	-2.214*	-0.261
		[1.288]	[1.257]		[1.243]	[1.223]	[1.012]
Non-bank dep./Ass.(-1)		0.843***	0.511**		0.858***	0.520**	0.355**
		[0.230]	[0.212]		[0.230]	[0.218]	[0.151]
Interest rate		0.016	-0.003		0.012	-0.013	0.079
		[0.133]	[0.161]		[0.132]	[0.160]	[0.068]
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	103995	96704	78760	103995	96704	78760	24633
Clusters	98	57	55	98	57	55	55
R2 Within	0.079	0.133	0.094	0.094	0.142	0.111	0.018

Note. Bank-county-level sample. Period: 2011-2020, except columns (7): 2015-2017. Dep. variable: log sight deposits of households. *Brown RI* is the brown reputation index of the bank. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches* is the number of branches of the bank *in the county.* SE clustered at the bank (CIB) level.

Table 6: Banks' brown reputation and the demand for sight deposits: alternative measures of brown reputation.

	Basel.		No NGO factor		Media		Neg. campaign dummy	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Brown RI	-0.023***	-0.009	-0.019***	-0.009*	-0.023***	-0.005	-0.022***	0.004
	[0.006]	[0.005]	[0.005]	[0.005]	[0.007]	[0.005]	[0.006]	[0.008]
Brown RI × Post		-0.023**		-0.012*		-0.021**		-0.047**
		[0.009]		[0.006]		[0.010]		[0.021]
Assets(-1) (log)	0.124**	0.123**	0.123**	0.124**	0.132**	0.131**	0.137**	0.136**
	[0.053]	[0.051]	[0.051]	[0.051]	[0.051]	[0.051]	[0.054]	[0.053]
Capital/Ass.(-1)	-2.490*	-2.705**	-2.592**	-2.706**	-2.674**	-2.742**	-2.411*	-2.495*
	[1.288]	[1.243]	[1.268]	[1.244]	[1.271]	[1.254]	[1.302]	[1.280]
Non-bank dep./Ass.(-1)	0.843***	0.858***	0.844***	0.857***	0.868***	0.876***	0.867***	0.871***
	[0.230]	[0.230]	[0.236]	[0.231]	[0.224]	[0.222]	[0.209]	[0.209]
Interest rate	0.016	0.012	0.024	0.013	-0.027	-0.022	-0.041	-0.043
	[0.133]	[0.132]	[0.134]	[0.132]	[0.132]	[0.135]	[0.138]	[0.136]
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	96704	96704	96704	96704	96704	96704	96704	96704
Clusters	57	57	57	57	57	57	57	57
R2 Within	0.133	0.142	0.138	0.142	0.135	0.137	0.123	0.127

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Brown RI* stands for alternative measures of the bank's brown reputation. Columns (1-2) show results when we use the baseline brwon reputation index (BRI). In columns (3-4), the index does not factor in Sigwatch's measure of the campaigning NGOs' "power". In columns (5-6), we furthermore consider only NGO alerts for which our web-scraping algorithm identifies at least one news release on the French mass media websites or at least one tweet on X (formerly Twitter). Last, in columns (7-8), we replace the baseline index with a dummy for at least one negative campaign in the month that blames the bank for their financing brown activities. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific interest rate on sight deposits. *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 demand for sight deposits: varying the persistence of the public's awareness.

	(1) No mem.	(2) HL: 1m	(3) HL: 3m	(4) HL: 6m	(5) HL: 9m
Brown RI (stdd)	0.003	0.001	-0.004	-0.007	-0.008
	[0.002]	[0.003]	[0.004]	[0.005]	[0.005]
Brown RI × Post (stdd)	-0.011***	-0.015***	-0.017***	-0.016**	-0.016**
	[0.004]	[0.005]	[0.006]	[0.006]	[0.006]
Assets(-1) (log)	0.138**	0.133**	0.126**	0.123**	0.122**
	[0.053]	[0.052]	[0.051]	[0.051]	[0.051]
Capital/Ass.(-1)	-2.494*	-2.600**	-2.682**	-2.705**	-2.713**
	[1.283]	[1.260]	[1.245]	[1.243]	[1.243]
Non-bank dep./Ass.(-1)	0.872***	0.870***	0.863***	0.858***	0.856***
	[0.209]	[0.215]	[0.225]	[0.230]	[0.231]
Interest rate	-0.049	-0.029	0.000	0.012	0.015
	[0.137]	[0.134]	[0.133]	[0.132]	[0.131]
Bank-County FE	Yes	Yes	Yes	Yes	Yes
Time-County FE	Yes	Yes	Yes	Yes	Yes
Obs.	96704	96704	96704	96704	96704
Clusters	57	57	57	57	57
R^2 Within	0.127	0.133	0.139	0.142	0.142

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Brown RI* is the brown reputation index of the bank, here standardized. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches* is the number of branches of the bank *in the county*. 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. SE clustered at the bank (CIB) level.

Table 8: Banks' brown reputation and the demand for sight deposits: bank-level tests.

	(1)	(2)	(3)	(4)	(5)	(6)
Brown RI	-0.061***	-0.029***	-0.025***	-0.019***	-0.010	-0.005
	[0.010]	[0.008]	[0.007]	[0.005]	[0.007]	[0.006]
Brown RI × Post				-0.056***	-0.038**	-0.037***
				[0.011]	[0.014]	[0.013]
Nb branches (log)	0.329		0.461***	0.330*		0.459***
	[0.199]		[0.094]	[0.191]		[0.093]
Interest rate, sight dep. (pp)		0.044	0.037		0.052	0.045
		[0.132]	[0.111]		[0.129]	[0.107]
Assets(-1) (log)		0.245***	0.116**		0.245***	0.117**
		[0.087]	[0.055]		[0.086]	[0.055]
Capital/Ass.(-1)		-3.294	-2.021***		-3.252	-1.981***
		[2.000]	[0.718]		[1.980]	[0.711]
Non-bank dep./Ass.(-1)		0.075	-0.101		0.087	-0.092
		[0.276]	[0.181]		[0.273]	[0.178]
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10945	5962	5803	10945	5962	5803
Clusters	98	57	55	98	57	55
R^2 Within	0.244	0.305	0.519	0.285	0.311	0.526

Note. Bank-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Brown RI* is the brown reputation index of the bank. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches* is the number of branches of the bank. SE clustered at the bank (CIB) level.

Table 9: Difference-in-differences test.

	(1)	(2)	(3)	(4)
Post × Brown	-0.019**	-0.026***	-0.021**	-0.026***
	[0.008]	[0.007]	[0.008]	[0.008]
Interest rate			0.119	0.111
			[0.137]	[0.130]
Nb branches (log)		0.152**		0.139*
		[0.076]		[0.074]
Assets(-1) (log)			0.092*	0.062
			[0.048]	[0.038]
Capital/Ass.(-1)			-0.256	-0.524
			[0.884]	[0.779]
Non-bank dep./Ass.(-1)			0.416**	0.297**
			[0.159]	[0.129]
Bank-County FE	Yes	Yes	Yes	Yes
Time-County FE	Yes	Yes	Yes	Yes
Obs.	26153	22313	20869	17079
Clusters	98	97	56	55
R^2 Within	0.006	0.030	0.019	0.031

Note. Bank-county-level sample. Period: February 2016-February 2017. Dep. variable: log sight deposits of households. *Brown* stands for banks belonging to the three "brownest" brands (highest brown reputation index) as of December 2016. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE in February 2017. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 10: Exploring heterogeneous responses due to local characteristics.

	Income		Green vote		Competition	
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	High	Low	High	Low	High
Brown RI	-0.004	-0.015**	-0.008	-0.011*	-0.011	-0.014*
	[0.008]	[0.007]	[0.006]	[0.006]	[0.008]	[0.008]
Brown RI × Post	-0.027**	-0.026***	-0.024**	-0.035***	-0.031**	-0.027***
	[0.012]	[0.008]	[0.009]	[0.009]	[0.013]	[0.008]
Nb branches (log)	0.013	0.175	-0.024	0.195***	0.049	0.248**
	[0.040]	[0.108]	[0.036]	[0.065]	[0.033]	[0.095]
Bank controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	17172	23588	18223	20922	14894	25940
Clusters	28	43	28	38	28	50
R2 Within	0.194	0.061	0.080	0.129	0.134	0.112

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Brown RI* is the brown reputation index of the bank. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches*: number of branches of the bank in the county. Results are shown for various sub-samples defined in terms of the average annual income of households (col. 1-2), the share of green votes at the 2014 EU-Parliament elections (col. 3-4), or local bank competition for deposits (col. 5-6). *Low*: counties in the bottom quartile of the respective characteristic. *High*: dummy for counties in the top quartile. SE clustered at the bank (CIB) level.

Table 11: Banks' brown reputation and mortgage lending

	(1)	(2)	(3)	(4)	(5)	(6)
Brown RI	-0.033***	-0.027***	-0.031***	-0.007	-0.004	0.001
	[0.007]	[0.007]	[0.008]	[0.016]	[0.014]	[0.013]
Brown RI × Post				-0.030*	-0.027**	-0.039***
				[0.015]	[0.013]	[0.010]
Nb branches (log)	0.198**		0.152	0.211**		0.164*
	[0.094]		[0.099]	[0.086]		[0.088]
Housing loan rate	-0.117*	-0.087	-0.127*	-0.120**	-0.089	-0.138**
	[0.062]	[0.071]	[0.071]	[0.058]	[0.070]	[0.064]
Assets(-1) (log)		0.293***	0.222***		0.294***	0.215***
		[0.099]	[0.077]		[0.095]	[0.066]
Capital/Ass.(-1)		-0.491	0.537		-0.977	-0.117
		[2.331]	[2.572]		[1.943]	[2.199]
Non-bank dep./Ass.(-1)		0.708*	0.123		0.781*	0.187
		[0.417]	[0.252]		[0.413]	[0.272]
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	61670	61314	50565	61670	61314	50565
Clusters	97	58	57	97	58	57
R2 Within	0.043	0.077	0.076	0.057	0.088	0.100

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: (log) regular mortgage loans to households. *Brown RI* is the brown reputation index of the bank. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific average interest rate on new, fixed-rate mortgage loans. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table 12: Loan-level sample: descriptive statistics

	Mean	Std.Dev.	p10	p25	Median	p75	p90	Nb.Obs.
Loan rate (GER)	2.43	0.63	1.72	1.96	2.31	2.79	3.39	165695
Maturity (months)	211.63	74.32	120.00	160.00	228.00	300.00	300.00	165695
Loan amount (EUR thd)	138.37	120.60	31.08	64.70	112.82	178.08	260.62	165695
Loan amount (log)	11.52	0.87	10.34	11.08	11.63	12.09	12.47	165695
Collateralized	0.39	0.49	0.00	0.00	0.00	1.00	1.00	165695
Local bank branches	48.48	80.55	5.00	8.00	17.00	60.00	124.00	165695
Local bank branches (log)	3.07	1.23	1.61	2.08	2.83	4.09	4.82	165695
Share local branches	0.15	0.10	0.05	0.09	0.12	0.20	0.29	165695
Brown RI	1.06	0.96	0.00	0.08	1.19	1.93	2.31	165695
Share college education (2008)	0.29	0.13	0.16	0.20	0.25	0.35	0.48	165695
Income per hhld (2010)	27.81	12.87	19.68	21.39	23.85	28.43	41.34	165695
Green vote (2009)	0.22	0.05	0.16	0.18	0.21	0.24	0.28	165695
Education Q4	0.57	0.49	0.00	0.00	1.00	1.00	1.00	165695
Income Q4.	0.29	0.45	0.00	0.00	0.00	1.00	1.00	165695
Green vote Q4	0.59	0.49	0.00	0.00	1.00	1.00	1.00	165695
Assets(-1) (log)	24.91	1.46	23.44	23.74	24.34	25.80	27.77	165695
Liquid assets/Ass. (-1)	0.16	0.08	0.06	0.10	0.15	0.21	0.28	165695
Capital/Ass.(-1)	0.07	0.04	0.02	0.02	0.08	0.10	0.12	165695
Cust. credit/Ass.(-1)	0.58	0.23	0.13	0.42	0.69	0.72	0.76	165695
Net NNP / Cust.cred. (-1)	-0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00	165695

Note. Loan-level regression sample. Period: 2014-2020.

Table 13: Banks' brown reputation and interest rates on new housing loans.

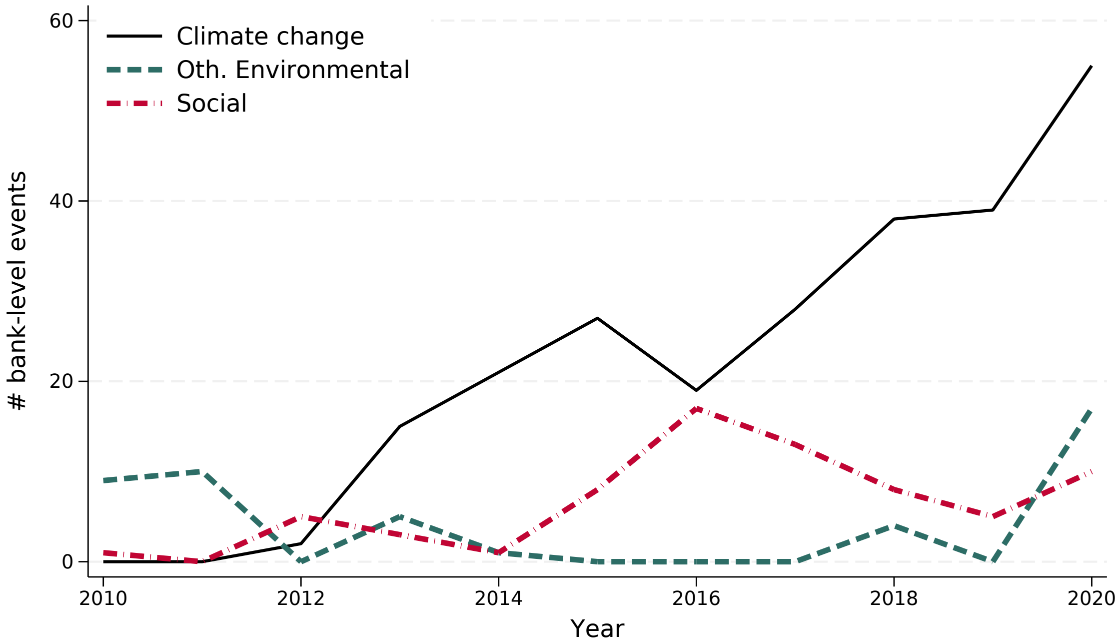
	(1)	(2)	(3)
Brown RI	-0.018**	-0.042**	-0.046**
	[0.007]	[0.017]	[0.018]
Brown RI × High Comp. × Post			-0.013**
			[0.006]
Brown RI × Post		0.029	0.035*
		[0.019]	[0.018]
Brown RI × High Comp.			0.006
			[0.007]
High Comp. × Post			0.015*
			[0.009]
Loan controls	Yes	Yes	Yes
Bank controls	Yes	Yes	Yes
Munic. controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes
Obs.	167751	167751	167751
Clusters	73	73	73
R2	0.732	0.732	0.732

Note. Loan-level sample. Period: 2014-2020. Dep. variable: interest rate of new housing loans, including fees (*GER: Global Effective Rate*). *High Comp.*: municipalities with more than 20 bank branches. SE clustered at the bank (CIB) level.

Figure 1: A 2018 campaign by the French environmental NGO, *Les Amis de la Terre*

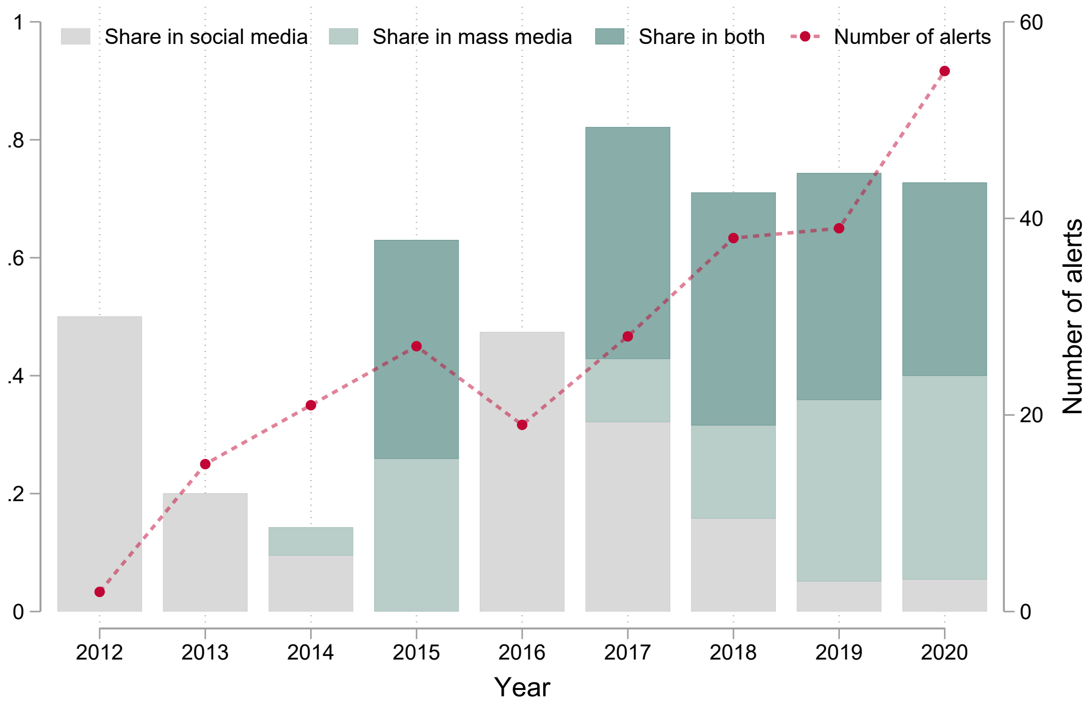
Note. Screenshot from a 2018 campaign by the French environmental NGO *Les Amis de la Terre* denouncing Société Générale's continued support for controversial fossil-fuel projects despite growing climate urgency. The campaign highlights the bank's key role in financing the Rio Grande LNG terminal and the Rio Bravo Pipeline in Texas, and claims that between 2014 and 2016 Société Générale provided over USD 6 billion in funding to some of the most environmentally and socially harmful energy projects worldwide.

Figure 2: NGO campaigns targeting French banks on ES issues, by issue type.



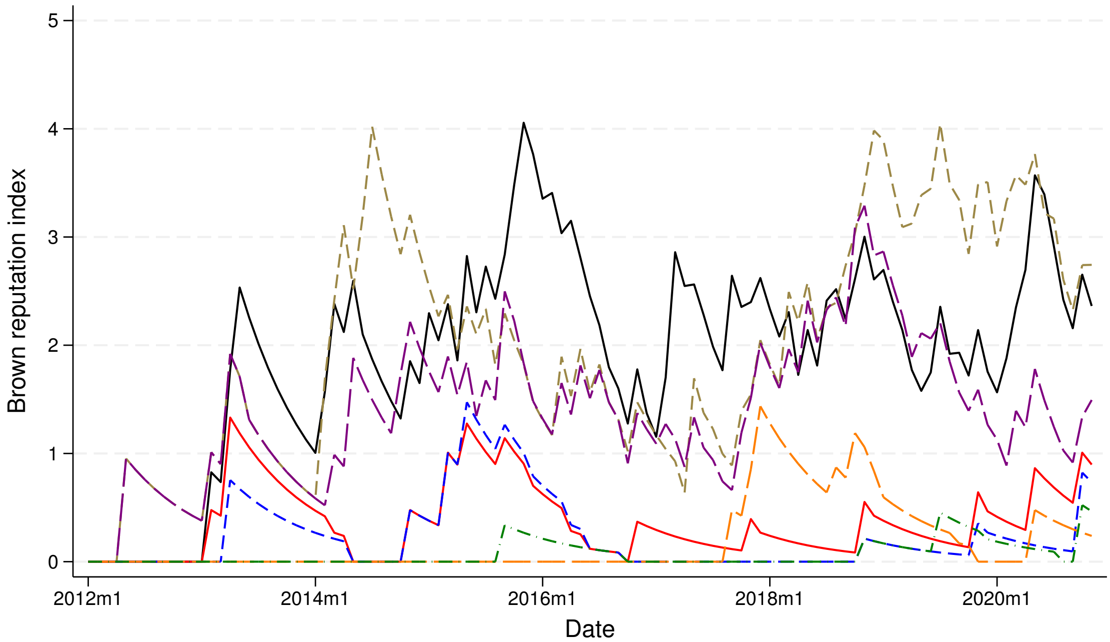
Note. Period: 2010-2020. Negative NGO campaign alerts pointing at French banks (bank brands). An alert is defined by a campaign event and the name of the targeted bank. Source: Sigwatch, authors' computations.

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



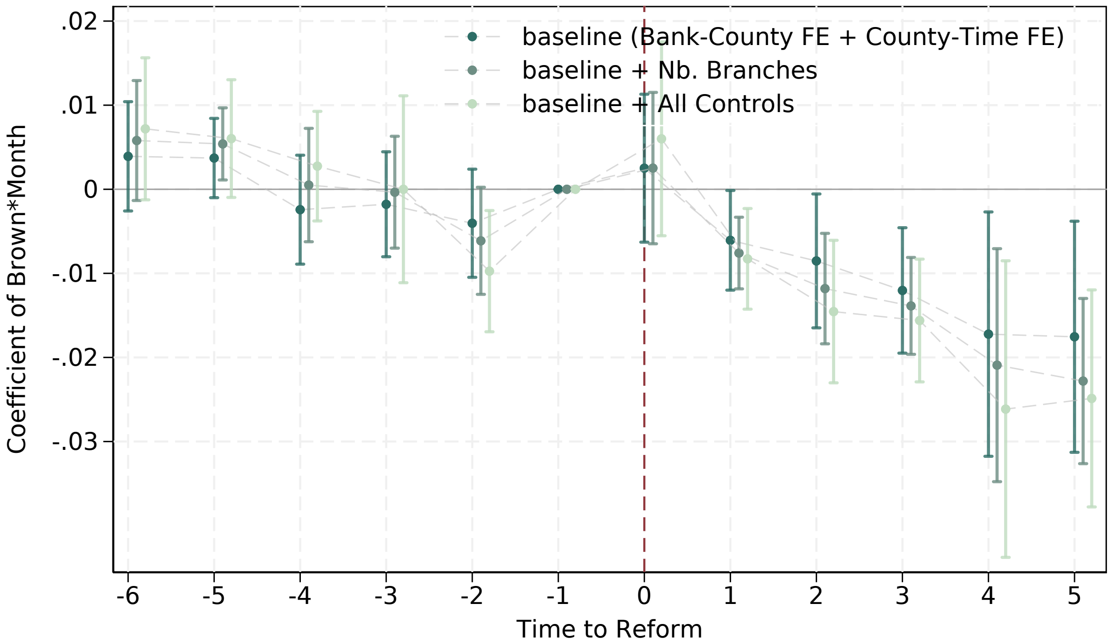
Note. Share of negative NGO campaign alerts against brown banks for which we can identify news releases by major mass media (all national and major regional French daily and weekly newspapers, as well as French TV and radio broadcasts), and/or tweets mentioning both the NGO and the bank. Period: 2010-2020. Source: Sigwatch, Twitter/X, media websites, authors' computations.

Figure 4: Brown reputation indexes of the seven largest bank brands in France.



Note. Negative NGO campaigns targeting the banking groups main brand. Source: Sigwatch, authors' computations.

Figure 5: Difference-in-differences test: brown banks vs controls before and after the 2017 bank mobility regulation.



Note. Bank-county-level sample. Period: July 2016-July 2017. Dep. variable: log sight deposits of households. The figure shows the estimated coefficients of the treatment dummy for brown banks (as of December 2016) interacted with year-month dummies. The vertical line marks the implementation date of Article 43 LCACE (February 2017). For readability, calendar years are adjusted to match the implementation month of Article 43 LCACE (February). For instance, "2017" is a dummy for the 12 months from February 2017 to January 2018. Bars: 95% confidence intervals. SE clustered at the bank (CIB) level.

Online Appendix

A Timeline of Article 43 LCACE

The regulatory reform at the heart of our identification strategy, the Article 43 of the Loi pour la croissance, l'activite et l'egalite des chances economiques (LCACE), emerged from broader political efforts to enhance consumer mobility and foster competition in retail financial services. Commonly referred to as the *Macron Law*, this legislative package was championed by Emmanuel Macron during his tenure as Minister of the Economy, Industry, and Digital Affairs in the second Valls government.

The idea of introducing a bank account switching service had circulated in French policy circles since at least 2013. It gained renewed traction in 2014 amid concerns over low switching rates and bank inertia. Macron, appointed in August 2014, made this initiative a symbolic component of a broader pro-consumer reform agenda. The draft bill was presented in December 2014 and introduced to Parliament in January 2015. After months of parliamentary debates and political tension, the government used Article 49.3 of the Constitution, allowing passage without a vote unless a no-confidence motion is adopted, to push the law through in July 2015. The final law was promulgated on August 6, 2015 and published in the official journal the following day.

Implementation Timeline. While the Macron Law covered a wide range of sectors, Article 43 specifically addressed retail banking. It transposed provisions from EU Directive 2014/92/EU on payment account switching, and required that, as of February 6, 2017, all French banks offering checking accounts implement a standardized, free account mobility service. Once authorized by the customer, the new bank must handle all formalities related to transferring automatic payments, direct debits, and incoming transfers from the old bank, including the option to close the old account. The reform significantly reduced switching frictions for retail customers. Notably, it applied only to checking accounts and regulated savings, but not to term deposits, thereby creating a natural contrast in depositor behavior across account types.

The effects were immediate: over 1.2 million bank account switches were recorded within the first year, and a 2018 survey by the French Financial Sector Advisory Committee (CCSF) found that 67% of consumers were aware of the service, 70% had been offered it when opening an account, and 85% of users were satisfied.

B List of media websites used for web-scraping

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.

C Other Data used: details

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.[62] Electoral results (number of electors, voters, and votes for each candidate) are notably available at the level of counties (*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*. Elections of MEUP are relevant for our purpose because they are held under the proportional representation system and French 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, we identify all candidates standing for green parties (*Europe Ecologie-Les Verts*, *Génération Ecologie*, *Cap 21* etc.) and add up the votes they obtain to compute their total share of expressed votes. We then sort counties as well as municipalities into quartiles of the respective distributions of green vote shares. Figure A3 in the appendix shows the geographical distribution of green votes across French counties.

Socio-demographic data. We use Census data from 2008 to measure the share of adults with college education or higher education attainment as of 2008, at either the county or the municipality level (ZIP code).[63] We also leverage fiscal data from *Impot sur le Revenu des Communes de France* (IRCOM) to compute the local average income per household as of 2010.[64] Last, we sort counties and municipalities into quartiles of the respective distributions of these measures of education and income. Figure A2 in the online appendix show the geographical distributions of these variables.

[62] Data available here: https://www.archives-resultats-elections.interieur.gouv.fr/resultats/europeennes 2009/index.php.

[63] Data from INSEE available here: https://www.insee.fr/fr/statistiques/1893149.

[64] Data available here: https://www.data.gouv.fr/fr/datasets/limpot-sur-le-revenu-par-collectivite-territoriale-ircom.

D Additional tables

Table A2: Credit institutions not associated with the main brand of their parent banking group (estimation sample).

Bank Name	Bank Group
Banque de Savoie	BPCE
Banque Chaix	BPCE
Banque BCP	BPCE
Crédit commercial du Sud-Ouest	BPCE
Banque Palatine	BPCE
Crédit lyonnais	CREDIT AGRICOLE
Lyonnaise de banque	CREDIT MUTUEL
Banque Transatlantique S.A.	CREDIT MUTUEL
BPE/Louvre Banque Privée*	LA POSTE
Banque Courtois	SOCIETE GENERALE
Crédit du Nord	SOCIETE GENERALE
Banque Laydernier	SOCIETE GENERALE
Boursorama	SOCIETE GENERALE
Banque Tarneaud	SOCIETE GENERALE
Banque Rhone-Alpes - Groupe Crédit du Nord	SOCIETE GENERALE
Société marseillaise de crédit	SOCIETE GENERALE

Note. (*) BPE was a subsidiary of Crédit Mutuel Arkea up to April 2013.

Table A3: Bank-county-level regression sample: descriptive statistics - All banks.

	Mean	Std.Dev.	p10	p25	Median	p75	p90	Nb.Obs.
Sight deposits (bns)	2.83	6.42	0.54	0.87	1.36	2.02	3.41	10100
Sight deposits (log)	14.17	0.97	13.20	13.67	14.12	14.52	15.04	10100
Brown RI	0.69	0.78	0.00	0.00	0.39	1.22	1.83	10100
Nb branches	238.22	622.25	3.00	32.50	122.00	203.00	322.00	10100
Nb branches (log)	4.19	1.89	1.10	3.81	4.81	5.32	5.77	9941
Interest rate, sight dep. (pp)	0.02	0.04	0.00	0.00	0.01	0.02	0.06	10100

Note. Bank-county-level sample. Interest rate on sight deposits in pp. Period: 2011-2020. Deposits and loans in euro billions.

Table A4: Bank-level regression sample: descriptive statistics - Banks with balance sheet controls.

	Mean	Std.Dev.	p10	p25	Median	p75	p90	Nb.Obs.
Sight deposits (bns)	3.71	8.21	0.44	0.76	1.33	2.13	4.55	5962
Sight deposits (log)	14.19	1.20	13.00	13.54	14.10	14.57	15.33	5962
Brown RI	0.30	0.49	0.00	0.00	0.09	0.42	0.90	5962
Nb branches	312.58	798.85	1.00	7.00	101.00	243.00	458.00	5962
Nb branches (log)	3.91	2.30	0.00	1.95	4.69	5.50	6.13	5803
Interest rate, sight dep. (pp)	0.03	0.04	0.00	0.00	0.01	0.03	0.10	5962
Assets(-1) (log)	23.75	1.27	22.34	23.07	23.53	24.14	25.48	5962
Capital/Ass.(-1)	0.05	0.02	0.02	0.03	0.06	0.07	0.08	5962
Non-bank dep./Ass.(-1)	0.60	0.16	0.35	0.56	0.64	0.69	0.73	5962

Note. Bank-level baseline regression sample: 57 banks with available monthly financial ratios and deposit interest rate. Interest rate on sight deposits in pp. Period: 2011-2020. Deposits and loans in euro billions.

Table A5: Socio-demographic variables, green vote and bank competition in French counties: correlation matrix

	Educ.	Inc.	Green 2009	Green 2014	Comp.
Education	1.00				
Income	0.74	1.00			
Green 2009	0.77	0.55	1.00		
Green 2014	0.63	0.24	0.77	1.00	
Bank comp.	0.65	0.60	0.44	0.22	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, resp. 2014, European Parliament elections, bank competition for deposits in 2010 (based on the HHI of deposits across banks within a county).

Table A6: Banks' brown reputation and the demand for sight deposits: bank-county-level clustering of standard errors.

	2011-2020						2015-2017
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Brown RI	-0.043***	-0.023***	-0.030***	-0.022***	-0.009***	-0.010***	0.002
	[0.002]	[0.002]	[0.003]	[0.002]	[0.002]	[0.002]	[0.002]
Brown RI × Post				-0.032***	-0.023***	-0.030***	-0.020***
				[0.003]	[0.003]	[0.003]	[0.002]
Nb branches (log)	0.211***		0.122***	0.219***		0.129***	0.092**
	[0.067]		[0.042]	[0.067]		[0.041]	[0.046]
Assets(-1) (log)		0.124***	0.094***		0.123***	0.090***	0.033*
		[0.027]	[0.024]		[0.026]	[0.023]	[0.017]
Capital/Ass.(-1)		-2.490***	-1.964***		-2.705***	-2.214***	-0.261
		[0.602]	[0.589]		[0.607]	[0.590]	[0.518]
Non-bank dep./Ass.(-1)		0.843***	0.511***		0.858***	0.520***	0.355***
		[0.069]	[0.086]		[0.069]	[0.085]	[0.068]
Interest rate		0.016	-0.003		0.012	-0.013	0.079
		[0.058]	[0.077]		[0.058]	[0.077]	[0.049]
Bank-County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	103995	96704	78760	103995	96704	78760	24633
Clusters	947	886	732	947	886	732	718
R2 Within	0.079	0.133	0.094	0.094	0.142	0.111	0.018

Note. Bank-county-level sample. Period: 2011-2020, except columns (5-6): 2015-2017. Dep. variable: log sight deposits of households. *Brown RI* is the brown reputation index of the bank. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches* is the number of branches of the bank *in the county.* SE clustered at the bank (CIB) level.

Table A7: Banks' brown reputation and the demand for sight deposits: bank-level WLS regressions.

	(1)	(2)	(3)	(4)	(5)	(6)
Brown RI	-0.032***	-0.020*	-0.019**	-0.009	-0.002	-0.004
	[0.011]	[0.010]	[0.008]	[0.007]	[0.010]	[0.008]
Brown RI × Post				-0.035***	-0.028**	-0.024**
				[0.012]	[0.011]	[0.011]
Nb branches (log)	0.764***		0.580***	0.757***		0.575***
	[0.112]		[0.067]	[0.110]		[0.067]
Interest rate, sight dep. (pp)		0.052	-0.026		0.071	-0.010
		[0.349]	[0.311]		[0.347]	[0.306]
Assets(-1) (log)		0.212*	0.074		0.213*	0.077
		[0.109]	[0.063]		[0.108]	[0.063]
Capital/Ass.(-1)		-8.493***	-3.792**		-8.421***	-3.754**
		[2.671]	[1.642]		[2.678]	[1.669]
Non-bank dep./Ass.(-1)		0.340	0.088		0.354	0.099
		[0.309]	[0.255]		[0.307]	[0.251]
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	10945	5962	5803	10945	5962	5803
Clusters	98	57	55	98	57	55
R^2 Within	0.566	0.543	0.700	0.576	0.549	0.705

Note. Bank-level sample. Period: 2011-2020. Weighted-Least Squares regressions, where weights are the inverse of the number of individual banks belonging to the same bank brand at a given date. Dep. variable: log sight deposits of households. *Brown RI* is the brown reputation index of the bank. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches* is the number of branches of the bank. SE clustered at the bank (CIB) level.

Table A8: Banks' brown reputation and bank balance sheets.

	Total Assets		Non-financial deposits	
	(1)	(2)	(3)	(4)
	OLS	WLS	OLS	WLS
Brown RI	-0.021	-0.024	-0.016	-0.006
	[0.025]	[0.015]	[0.021]	[0.009]
Brown RI × Post	-0.008	0.004	0.017	0.025
	[0.028]	[0.022]	[0.029]	[0.024]
Nb branches (log)	0.617***	0.800***	0.614***	0.680***
	[0.168]	[0.143]	[0.127]	[0.099]
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs.	5803	5803	5484	5484
Clusters	55	55	55	55
R^2 Within	0.202	0.334	0.208	0.312

Note. Bank-level sample. Period: 2011-2020. Dep. variable: log total assets (col. 1-2) and log total deposits of non-financial customers (col. 3-4). *Brown RI* is the brown reputation index of the bank. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. Within OLS regression in col. 1 and 3 vs WLS regessions in col. 2 and 4. SE clustered at the bank (CIB) level.

Table A9: Banks' brown reputation and the demand for sight deposits: sight deposits vs savings deposits.

	Sight dep.		Savings dep.	
	(1)	(2)	(3)	(4)
Brown RI	-0.009	-0.010	0.021**	0.021*
	[0.005]	[0.006]	[0.010]	[0.012]
Brown RI × Post	-0.023**	-0.030***	-0.038***	-0.043***
	[0.009]	[0.009]	[0.010]	[0.010]
Sight dep. rate	0.012	-0.013		
	[0.132]	[0.160]		
Term dep. rate			0.013***	0.011***
			[0.004]	[0.004]
Assets(-1) (log)	0.123**	0.090*	0.233***	0.181***
	[0.051]	[0.046]	[0.051]	[0.037]
Capital/Ass.(-1)	-2.705**	-2.214*	-3.068*	-1.639
	[1.243]	[1.223]	[1.789]	[1.368]
Non-bank dep./Ass.(-1)	0.858***	0.520**	0.921***	0.764***
	[0.230]	[0.218]	[0.155]	[0.120]
Nb branches (log)		0.129**		0.119
		[0.062]		[0.082]
Bank-County FE	Yes	Yes	Yes	Yes
Time-County FE	Yes	Yes	Yes	Yes
Obs.	96704	78760	47460	43203
Clusters	57	55	56	56
R^2 Within	0.142	0.111	0.166	0.168

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Brown RI* is the brown reputation index of the bank, here standardized. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE. *Nb branches* is the number of branches of the bank *in the county*. *Sight dep. rate* is the apparent rate on checking accounts (annualized) as before. *Term dep. rate* is the interest rate on new savings/term deposit contracts with an initial maturity of more than two years. SE clustered at the bank (CIB) level.

Table A10: Difference-in-differences test: 12-months window.

	(1)	(2)	(3)	(4)
Post × Brown	-0.010**	-0.013***	-0.011*	-0.016***
	[0.005]	[0.004]	[0.006]	[0.005]
Interest rate			0.060	0.071
			[0.101]	[0.095]
Nb branches (log)		0.015		0.011
		[0.016]		[0.016]
Assets(-1) (log)			-0.022	-0.023
			[0.014]	[0.020]
Capital/Ass.(-1)			-1.228	-1.024
			[1.126]	[1.043]
Non-bank dep./Ass.(-1)			0.190*	0.172
			[0.101]	[0.120]
Bank-County FE	Yes	Yes	Yes	Yes
Time-County FE	Yes	Yes	Yes	Yes
Obs.	13685	11690	10903	8934
Clusters	98	97	56	55
R^2 Within	0.002	0.004	0.003	0.005

Note. Bank-county-level sample. Period: July 2016-July 2017. Dep. variable: log sight deposits of households. *Brown* stands for banks belonging to the three "brownest" brands (highest brown reputation index) as of December 2016. *Post* is a dummy variable for the period after the implementation of Article 43 LCACE in February 2017. *Interest rate* is the bank-specific interest rate on sight deposits. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table A11: Difference-in-differences test: bank level, 24-months window.

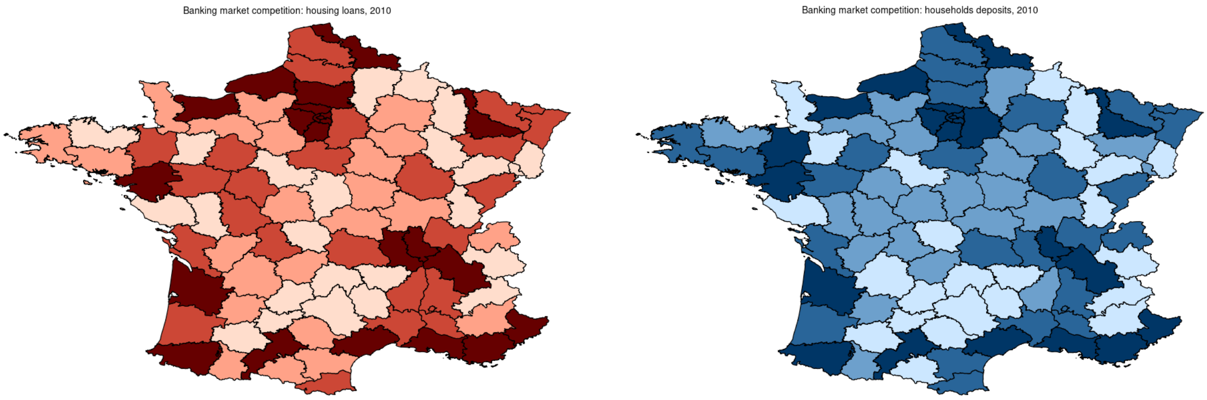
	(1)	(2)	(3)	(4)
Post × Brown	-0.032***	-0.034***	-0.024***	-0.019***
	[0.008]	[0.008]	[0.005]	[0.005]
Interest rate			0.137	0.065
			[0.149]	[0.112]
Nb branches (log)		0.118		0.304**
		[0.118]		[0.129]
Assets(-1) (log)			0.100	0.028
			[0.062]	[0.032]
Capital/Ass.(-1)			-1.684	-2.743***
			[1.574]	[0.790]
Non-bank dep./Ass.(-1)			0.093	0.049
			[0.090]	[0.065]
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Obs.	2338	2313	1285	1260
Clusters	98	97	56	55
R^2 Within	0.044	0.098	0.106	0.255

Note. Bank-county-level sample. Period: February 2016-February 2018. Dep. variable: log sight deposits (col. 1 to 4)of households. *Post* is a dummy variable for months after the implementation of *Loi Macron*'s article 43. *Treated* stands for banks belonging to the three "brownest" brands as of December 2016. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

E Additional figures

Figure A1: 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 A2: Income per household (2010), county-level heterogeneity.

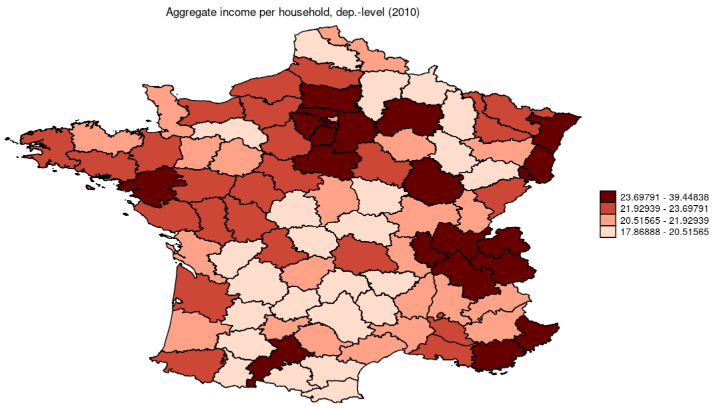
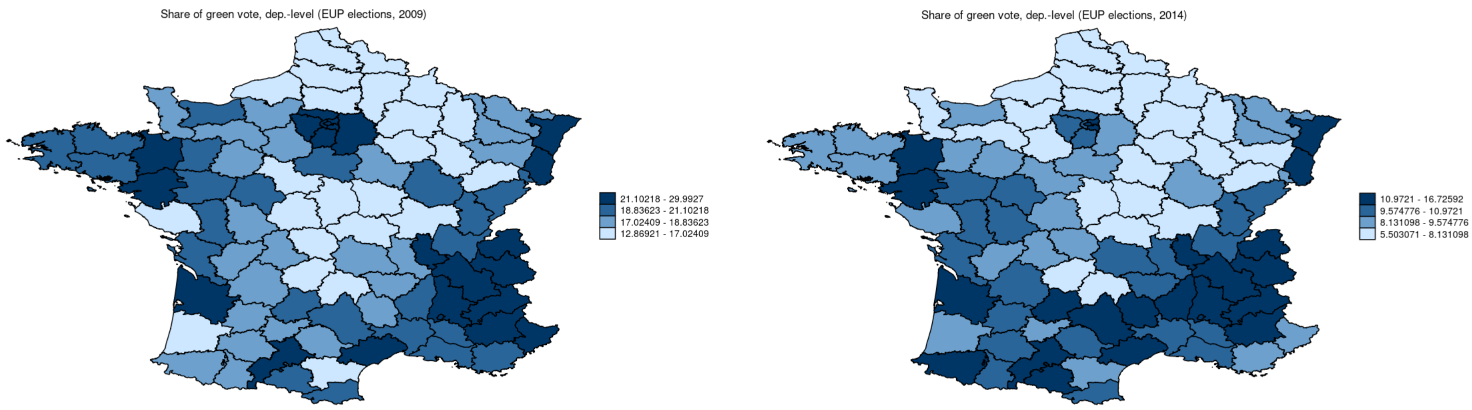


Figure A3: Vote for green parties at the EUP elections, county-level heterogeneity.

2009 *2014*



Note. Period 2013-2018. Left panel: average number of bank branches per municipality (ZIP code) over the period. Right panel: total number of new housing loans issued by banks in each municipality over the period.

Figure A4: Geography of bank branches and granted housing loans, loan-level sample.

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

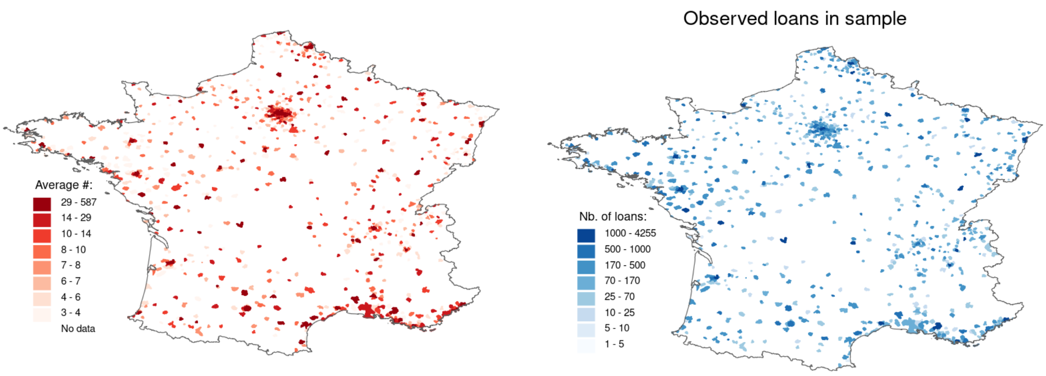
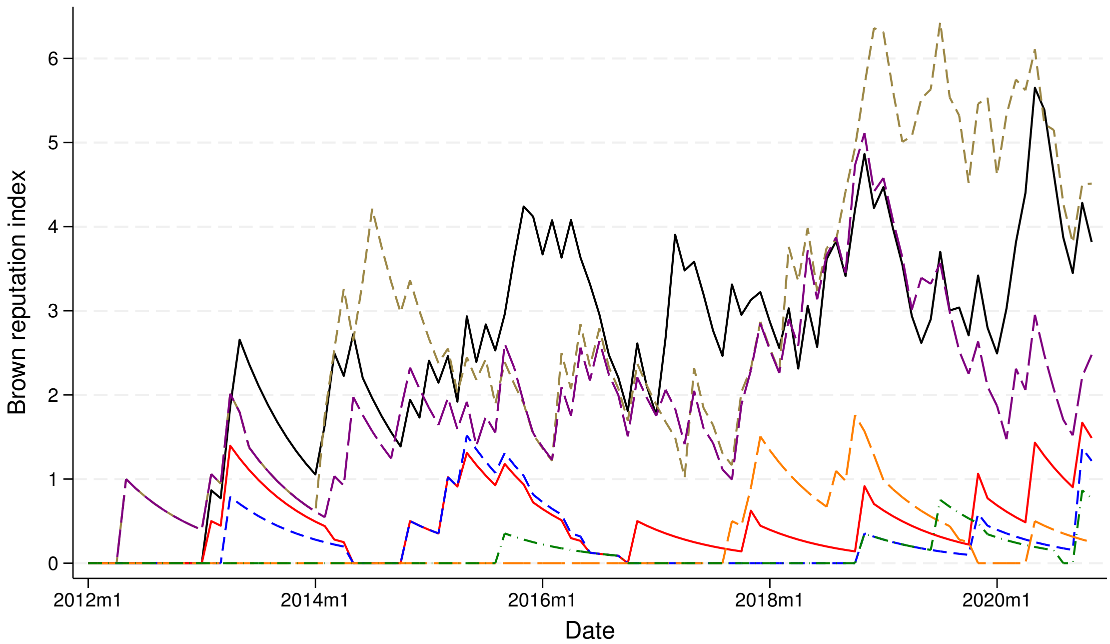
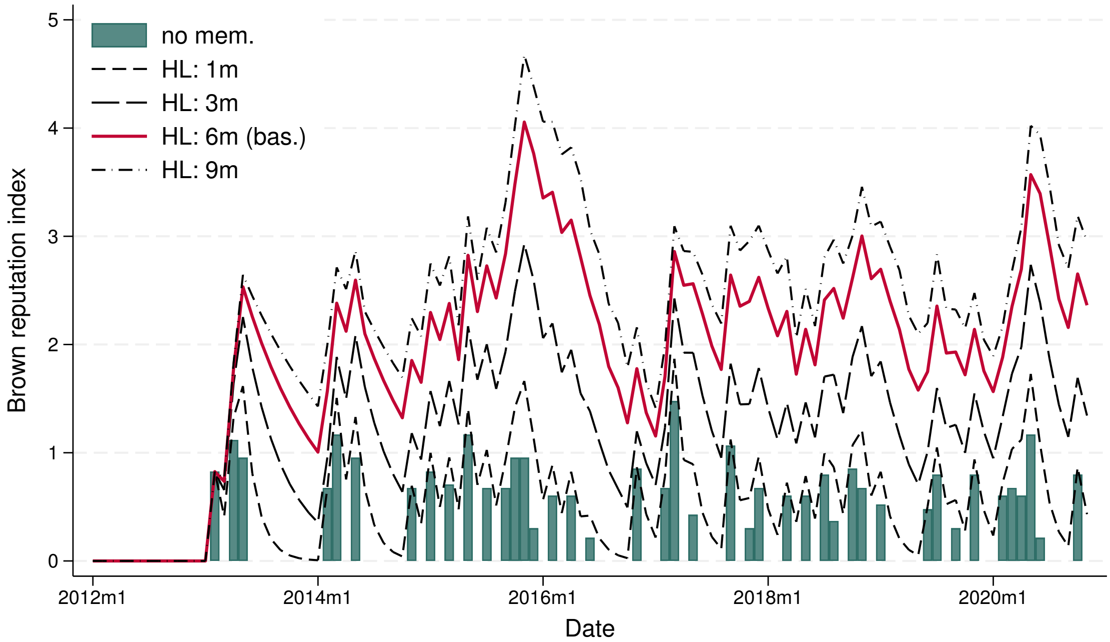


Figure A5: Banks' brown reputation: alternative definition (no account of Sigwatch's *NGO power*).



Note. In this figure, individual alert impact scores do not factor in Sigwatch's measure of the campaigning NGO's power. Source: Sigwatch, authors' computations.

Figure A6: Brown reputation index: alternative assumptions regarding news persistence in the public's awareness.



Note. The figure shows alternative measures of the 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 monthly brown reputation score, assuming that people stay aware for only one month. Lines show the computed brown reputation indexes series when the half-life (HL) of past news is 1, 3, 6 or 9 months. Source: Sigwatch and authors' computations.

Note. Bank-level sample. The figure shows the estimated coefficients of the treatment dummy for brown banks (as of December 2016) interacted with year-month dummies. The vertical line marks the implementation date of Article 43 LCACE (February 2017). For readability, calendar years are adjusted to match the implementation month of Article 43 LCACE (February). For instance, "2017" is a dummy for the 12 months from February 2017 to January 2018. Bars: 95% confidence intervals. SE clustered at the bank (CIB) level.

Note. Interest rate on new mortgage loans. Loan-level regression sample. Period: 2014-2020. Sample mean, inter-quartile range and extreme percentiles at each date.

Figure A7: Difference-in-differences test: bank-level sample.

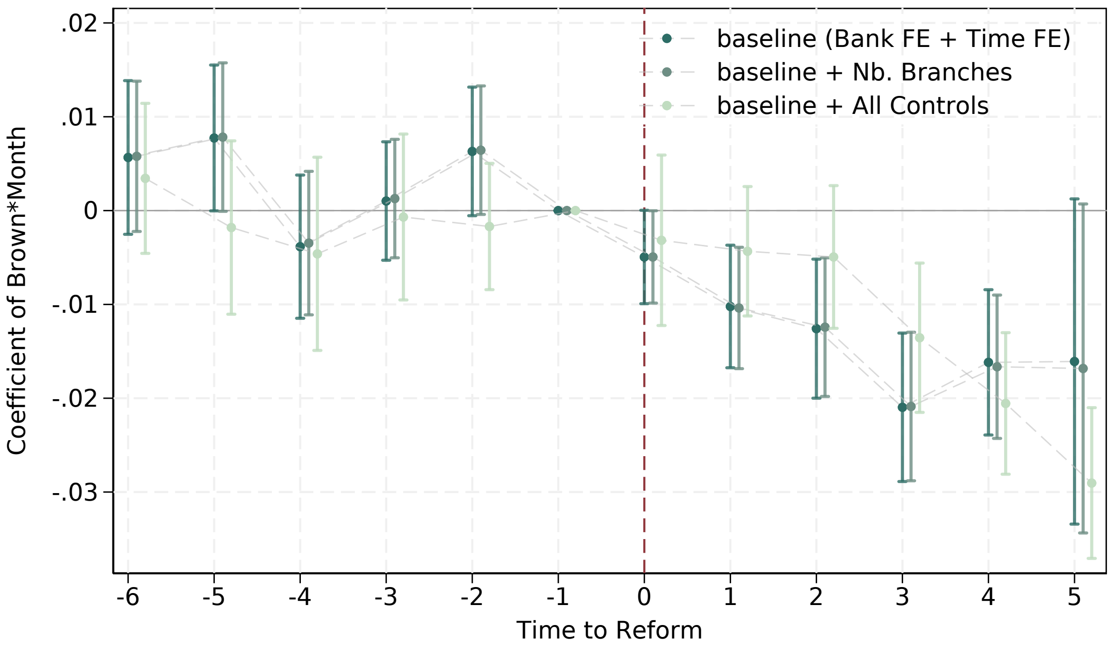


Figure A8: Distribution of interest rates on housing loans over 2014-2020.