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

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ABSTRACT

We exploit new data on NGO campaigns that target banks financing fossil fuels (``brown'' banks) to build a measure of French banks' environmental reputation, which we merge with granular data on bank deposits and loans of households in France over 2010-2020. We find that banks receive relatively fewer household deposits when they are perceived as browner. Depositors mostly react to their bank's brown reputation after the implementation of a new regulation that cuts down the transaction costs of changing banks. Last, using a large database of new mortgage loans, we show that browner banks also face a relatively lower demand for housing loans, implying lower mortgage loan rates offered to their customers.

Keywords: Climate change, Households Finance, Brown Banks, Green Preferences.

JEL classification: G21, G51, Q54.

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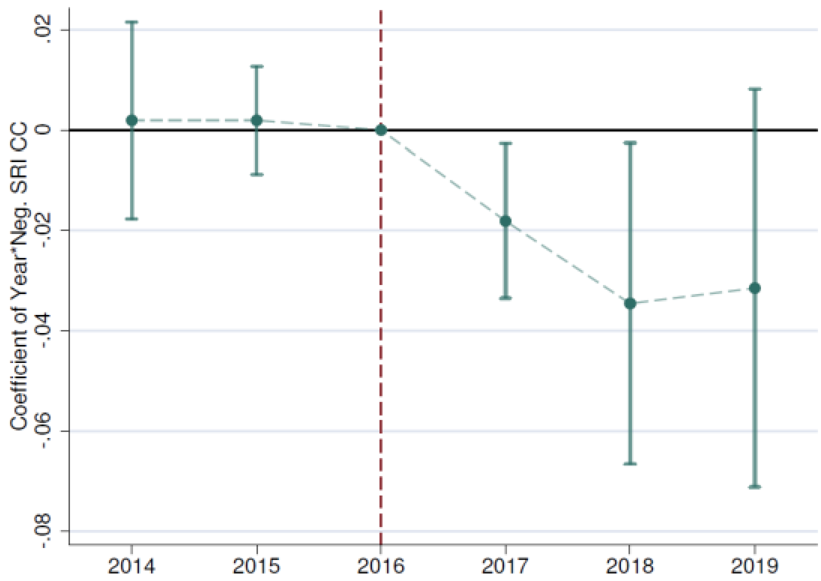
Non-Technical Summary

Since the 2015 Paris Agreement and the associated calls for more responsible private finance, environmental NGOs have increasingly tracked and made public the trillions of funds funnelled annually by large banks worldwide into fossil fuels companies and projects directly contributing to the global climate warming. Many large banking groups have joined voluntary alliances for the climate in recent years. However, activist groups have consistently depicted these pro-climate commitments as not being binding enough and accused banks of largely greenwashing their activities. Meanwhile, environmental NGOs have multiplied calls in the public for boycotting the banks depicted as brown because of their continued support to the fossil energy industry

In this study, we leverage new data on NGO campaigns blaming French brown banks. We get extensive information on NGO campaigns from Sigwatch, a European consultancy that monitors the activities of some 11,000 NGOs worldwide and advises targeted companies on how to engage with activism. We focus on campaigns that target the main brands of the seven largest banking groups operating in France for reasons related to climate change, as well as, separately, for other types of ES concerns. We assume that repeated NGO actions progressively increase the awareness of the public and construct a time-varying index of bank brands' brown reputation. We then take advantage of granular banking data from the Banque de France, which allows us to monitor households' deposits and loans for each individual bank affiliated to the targeted banking groups, in each of mainland France's 94 counties with monthly frequency. We match this information on individual banks' retail business with the brown reputation index of the bank's brand, using both information on banks' affiliation and the specifics of banks' names to reflect depositors' perception better.

Using this bank-county level data, we run panel regressions of bank deposits on banks' brown reputation indexes, controlling for local bank presence, as well as for local economic activity and unobserved bank and county characteristics. Causal identification relies on the reasonable assumption that NGO campaigns about banks' role in global climate warming is exogenous to French households' (local) saving and borrowing decisions. Our results show that banks with a reputation to be brown receive significantly less sight deposits from households.

Figure 1. Banks' brown reputation, household deposits, and the 2017 law on bank mobility: dynamic specification.



Note: Bank-county-level sample. Period: 2014-2019. Dep. variable: log sight deposits of households. The figure shows the estimated coefficients of the negative CC reputation index interacted with year dummies. Bars: 95% confidence intervals.

Further, we exploit a well-publicized provision of the 2015 "Macron law" which, from February 2017 on, made it much easier and (transaction) cost-free for individuals to move their main checking account from a bank to another bank. This ``Bank Mobility Regulation" supports our interpretation that NGO campaigns induce some depositors to exit brown banks. Indeed, we find that browner banks face a drop in sight deposits mostly after the implementation of the new regulation, when the costs of changing banks are minimal. While this holds on average, we also document some geographic heterogeneity. In counties with higher income, higher education, or more green voters, the impact of NGO campaigns on depositors' decision to change banks materializes also before the 2017 regulation, when transaction costs remain substantial.

Last, for a subsample of the same banks, we observe all individual housing loans granted to households by a representative sample of local bank branches throughout the country. We leverage this additional loan-level dataset to investigate whether NGO campaigns denouncing brown banks also have an impact on households' demand for housing loans. Controlling for loan, bank and municipality characteristics, we show that banks with a browner reputation charge lower rates than their green competitors. 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 last results also point to a (limited) willingness of bank depositors to pay for their environmental values.

« Certains ne l'aiment pas chaud » : déposants bancaires et campagnes des ONG contre les banques « brunes »

RÉSUMÉ

Nous exploitons des données sur les campagnes des ONG qui ciblent les banques finançant les combustibles fossiles (banques « brunes ») pour construire une nouvelle mesure de la réputation environnementale des banques, que nous fusionnons avec des données granulaires sur les dépôts bancaires des ménages en France sur la période 2010-2020. Nous trouvons que les banques reçoivent relativement moins de dépôts des ménages lorsqu'elles sont perçues comme plus brunes. Les déposants réagissent à la réputation brune de leur banque surtout après l'entrée en vigueur d'une nouvelle loi qui a réduit les coûts de transaction associés à un changement de banque. Enfin, nous exploitons des données individuelles de nouveaux prêts immobiliers pour montrer que les banques perçues comme plus brunes sont également confrontées à une demande relativement plus faible de prêts au logement, associée à des taux de prêts hypothécaires plus faibles offerts à leurs clients.

Mots-clés : changement climatique, finance des ménages, banques brunes, préférences vertes.

1 Introduction

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

Since the 2015 Paris Agreement and the associated calls for more responsible private finance, environmental NGOs have increasingly tracked and made public the trillions of funds funneled annually by large banks worldwide into fossil fuels companies and projects which directly contribute to the global climate warming.[1] In recent years, many large banking groups have joined voluntary alliances for the climate, such as the UNEP-FI Principles for Responsible Banking, the FSB's Task Force on Climate-related Financial Disclosure (TCFD) or the GFANZ Net Zero Banking Alliance. However, activist groups have consistently depicted these pro-climate commitments as not being binding enough and accused banks of largely greenwashing their activities.[2] Meanwhile, environmental NGOs have multiplied calls in the general public for boycotts of the banks depicted as *fossil* or *brown* because of their continued support to the fossil energy industry.[3]

In this study, we leverage new data on NGO campaigns blaming French brown banks.

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

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

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

We combine this data with detailed information on households' bank deposits in France over the years 2010 to 2020 in order to shed light on how individual customers respond to news revealing that their bank's business contributes to climate warming. We find that, other things equal, banks receive less deposits whenever they are perceived as browner by the public because of repeated accusations of financing unsustainable fossil companies or projects.

France is an ideal setting for our purpose. First, unique administrative data on households' deposits and loans with French banks is collected by the French central bank for all individual banks at the level of each of the 94 counties of Metropolitan France, which allows controlling for local characteristics of households and banking markets in our regressions.[4] Second, an important regulatory move suppressed in 2017 the administrative burden faced by depositors when changing banks: the new bank then takes in charge all the administrative costs associated with the transfer of checking accounts between institutions. This regulatory change provides us with a quasi-natural experiment which cuts the transaction costs that prevent individuals from aligning their choice of a deposit bank with their environmental values.

Identification relies on the assumption that NGO campaigns about banks' role in global climate warming is exogenous to French households' (local) saving and borrowing decisions. This assumption is plausible for two reasons. First, NGOs campaigns regarding large banks and climate change mostly relate to international activities of the corporate and investment banking (CIB) arm of banking groups (such as arranging a syndicated loan that funds a pipeline in an African country) and arguably not with variations in the retail banking business of the same groups' retail banking arm in French counties. Second, the French banking system is quite concentrated, with seven large banking groups accounting for the bulk of retail deposit taking and household lending in France. The ES responsibility of these large banking groups has been scrutinized by French NGOs for decades. Recent changes in the market shares of these bank brands in French retail

[4] The French name for these administrative units is *départements*. We denote them counties for simplicity throughout.

banking, if any, are therefore unlikely to drive the decision of NGOs to start investigating their ES-related wrongdoings, and launch campaigns.

We get extensive information on NGO campaigns from Sigwatch, a European consultancy which monitors the activities of some 11,000 NGOs worldwide and advises targeted companies on how to engage with ES activism. We focus on campaigns that target the main brands of the seven largest banking groups operating in France for reasons related to climate change, as well as, separately, for other types of ES concerns. We assume that repeated NGO actions progressively increase the awareness of the general public and construct a time-varying index of each bank brand's (bad) reputation for sustainability based on accumulated negative alerts from NGOs on each type of ES issues. We first document the increasing pressure exerted by NGOs on the main French banking groups since the early 2010s and the strong increase in the number of actions that point at banks' funding of fossil fuel industries. Interestingly, banks' reputation index for funding fossil companies (which we denote below *brown* reputation index) exhibits a lot of variance both over time and across bank brands. We additionally show that NGO campaigns are likely to reach depositors through traditional mass media and through social media (focusing here on X, formerly Twitter). For this purpose, we web-scraped and analyzed a large number of online newspaper articles and tweets about these campaigns. We find that around 70% of NGO campaigns are picked up and amplified by both mass media and social media. This amplification is crucial, as it indicates that NGO campaigns have a significant reach and can influence public opinion and awareness of sustainability issues.

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

Using this bank-county level data, we run panel regressions of bank deposits on banks' brown reputation indexes, controlling for local bank presence, as well as for local economic activity and unobserved bank and county characteristics using fixed effects. Our results show that banks with a brown reputation receive significantly less sight deposits from households. Further, we exploit a well-publicized provision of the 2015 Macron law which, from February 2017 on, made it much easier and (transaction) cost-free for individuals to move their main checking account from a bank to another bank. This "Bank Mobility Regulation" vindicates our interpretation that NGO campaigns induce some depositors to exit brown banks. Indeed, we find that browner banks face a drop in sight deposits mostly *after* the implementation of the new regulation, when the costs of changing banks are minimal. While this holds on average, we also document some geographic heterogeneity. In counties with higher income, higher education, or more green voters, the impact of NGO campaigns on depositors' decision to change banks materializes also before the 2017 regulation, when transaction costs remain substantial.

Last, for a subsample of the same banks, we observe all individual housing loans granted to households by a representative sample of local bank branches throughout the country. 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. Controlling for loan, bank and municipality characteristics, we show that banks with a browner reputation charge lower rates than their greener competitors. 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 our results also point to a (limited) willingness of households to pay for their environmental values.

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

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

Since the source of ESG information we consider is campaigns by activist groups, our paper also relates to the literature on boycotts. Koenig and Poncet (2019), who also exploit the Sigwatch database, show that imports of clothes from Bangladesh after the Rana Plaza scandal drop in countries whose firms were directly involved in the collapse of the Rana Plaza building, which suggests that consumers in these countries reacted negatively to NGO campaigns naming their domestic companies and apparel brands. Closer to our study, Homanen (2022) documents a decrease in deposit growth with banks involved in the controversial Dakota Access Pipeline in the US. In a similar vein, Jeung (2022) finds that banks shamed by activist groups because they fund the gun industry experienced a relative decrease in deposit growth after a deadly school shooting in Florida in 2018. While these papers exploit a unique event in a difference-in-differences setting, we consider the accumulated impact of NGO campaigns on banks' reputation for sustainable business over a decade and evaluate the differential response of bank customers depending on the type of ES issue at stake.[5]

[5] Most recently, Dursun De Neef and Ongena (2023) find a lower growth of US households' deposits with branches of large US and international banks that are listed in the "Banking for climate chaos" annual report, in counties that are affected by abnormally high temperatures. They interpret this as evidence that US depositors react to the local material consequences of climate change by exiting allegedly brown banks.

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

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

2 Research hypotheses

In this section, we spell out our research hypotheses. As detailed below, we exploit data on NGO campaigns to construct a measure of French banks' reputation with the general public on various ES issues. In the main part of the study, we focus more specifically on campaigns that denounce the funding of fossil energy (or *brown*) projects and companies by French banking groups. NGO campaigns generally target a general audience, so that a measure of banks' reputation for climate responsibility built on NGO alerts naming and shaming banks is a reasonable proxy of how brown banks are perceived 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-motivated bank customers react to the information conveyed by negative NGO campaigns and, to some extent, follow NGOs' advice to boycott fossil banks. Under the assumption that the proportion of such attentive, green depositors is high enough, banks with a reputation of funding fossil projects detrimental to the climate should then face a lower *supply* of deposits.[6] We test this hypothesis by regressing the (log of) outstanding household deposits on the negative reputation index of banks.

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 other banks, or along the extensive margin (exiting the brown bank altogether). While the intensive margin is limited by the number of depositors owning several bank accounts, the extensive margin is limited by the transaction costs of switching banks. Accordingly, any regulatory change that cuts these costs should increase households' incentives to switch banks. We assume that the extensive margin is the most relevant one in this context, since NGOs blaming brown banks unambiguously call customers for exiting them. We test for the importance of switching costs by using a 2017 regulatory change in France in support of increased bank mobility, which transferred the administrative burden

[6] We use throughout the following language convention: the bank supplies loans and demands (or collects) deposits, i.e., it faces a demand for loans and a supply of deposits (i.e., savings) by households. Clearly, bank deposits are contracts which are designed by banks, and therefore "supplied" (or issued) to the public. However, for clarity in what follows, we prefer to stick to the convention above, following the practice in, e.g., Freixas and Rochet (2023), chap. 3.

of changing banks from the customer to the new bank.

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 (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.

3 Data

3.1 NGO campaigns

3.1.1 Presentation and cleaning

Our data on environmental NGO campaigns comes from Sigwatch.[7] Sigwatch is a European consultancy which tracks and collects detailed information on NGO campaigns targeting companies worldwide. This consultancy was founded at the beginning of the 2010s to help companies engage with activist groups and manage their reputation risk. According to their website, Sigwatch covers in 2023 the campaigns of some 11,000 activist

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

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

For each country covered, Sigwatch monitors a list of active NGOs, which they regularly update. They then collect data on campaign actions by browsing the websites of the identified activist organizations.[8] In the dataset provided by Sigwatch, individual observations are better described as company-specific *alerts*. An alert is created for each company named within the frame of a new campaign action. For instance, when a new NGO campaign targets three banks simultaneously for jointly funding a new fossil fuel extraction project, three new alerts are recorded in the dataset, one for of each of the banks. For each alert, detailed information is collected on the participating NGOs (name, home country), the company blamed or, sometimes, praised (name, parent company, country, country of parent etc.), the campaign's details (registration date in Sigwatch's database, internet links, keywords, excerpts of manifestos naming the companies, country of the targeted audience).

Sigwatch also adds qualitative information by coding several proprietary variables: a measure of the NGOs' outreach (NGO power), a sentiment indicator (from very negative to very positive sentiment) and a prominence indicator which measures how exposed the named company is in the campaign. For instance, on 23 March 2018, the French environmental NGO *Les Amis de la Terre* (the French arm of Friends of the Earth International), in association with another French NGO called *i-boycott.org*, launched a new campaign to denounce the funding by Société Générale (SG) of two contended fossil energy projects: the Rio Grande LNG terminal and the Rio Bravo gas pipeline in Texas.[9] This campaign

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

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

was registred by Sigwatch on 28 March 2018. Sigwatch rated the campaign against SG as very negative and very prominent, as the call for a "citizen boycott" of the bank was echoed in several newspapers at the time. Interestingly, the webpage of the campaign also mentions BNP Paribas on a more positive note, emphasizing recent commitments by this bank to exit unconventional fossil fuels in response to alleged public pressure. This information translates in Sigwatch's dataset into a second alert within the frame of the same campaign (same campaign action identifier), this time naming BNP Paribas. This second alert is associated by Sigwatch with a positive sentiment and an intermediate level of prominence.

For our purpose, we focused on campaigns (i) targeting French banks, (ii) because of some environmental and social (ES) issue, (iii) run by at least one French NGO, (iv) and/or addressing a French audience.[10] We parsed the campaigns' keywords provided by Sigwatch to construct our own dictionary of terms identifying climate change (CC)-related campaigns, vs campaigns related to other environmental (OE) issues and campaigns related to social (S) issues. For instance, keywords such as "coal", "oil", "gas", "shale", "pipeline", "fracking", "drilling", "fossil fuel", "climate change" or "carbon" were used to pick climate change-related campaigns. Among campaigns not related to climate change, keywords such as "battery poultry", "pollution", "rainforest", "palm oil", "water use", "greenwahsing" were used to pick other environment (OE)-related campaigns. Last, remaining ES campaigns (i.e. after exclusion of a few campaigns related to non ESG topics, such as consumer protection) were defined as S. Campaigns we labelled as "social" point at a variety of social or ethical issues, such as human rights abuses, labor rights abuses, tax avoidance and tax havens, complicity in money laundering, illegitimate debt and poverty, social impact of mining activities, among others.[11]

NGO campaigns targeting banks generally mention the common name of large banking

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

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

groups, such as *BNP Paribas* or *Crédit Agricole*, i.e. banking brands which are well known to retail customers, some of which may however not be the ultimate parent company. We identified nine banking brands in the cleaned campaigns dataset: Banque Populaire-Caisses d'Epargne (BPCE), BNP Paribas (BNP), Crédit Agricole (CA), Crédit Coopératif (CCoop), Crédit Lyonnais (LCL), Crédit Mutuel-CIC (CM-CIC), HSBC, La Banque Postale (LBP), and Société Générale (SG). We then matched individual campaign alerts with these bank brands. For instance, an alert naming BNP Paribas Wealth Management was identified as an alert pointing at the BNP brand. We are interested here 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.[12]

3.1.2 Descriptive statistics

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

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

Figure 2 focuses then on CC-related alerts and plots the number of negative vs positive

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

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

Table 1 focuses on negative alerts and sheds light on who are the most active NGOs.[13] Some campaigns are run by a coallition of NGOs. In such cases, we consider here only the NGO ordered first by Sigwatch.[14] As shown in Table 1, *Amis de la Terre* comes out as the most active NGO in denouncing ES misbehavior by French banks, with 59% of negative alerts on all ES issues and almost 70% of alerts on climate change-related issues. Together, only four NGOs (*Amis de la Terre*, Oxfam, ATTAC and Reclaim Finance) account for some 87% of all negative CC alerts targeting French banks. Meanwhile, *Amis de la Terre* and Reclaim Finance, a recent spin-off of the former, account for more than 77% of positive alerts of the issue.

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

[13] Table A4 provides the corresponding statistics for positive alerts from NGO campaigns.

[14] 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.

3.2 Bank data

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

We obtain bank-county-level information on deposits and loans in France over the years 2010-2020 from CEFIT, a proprietary dataset of the Banque de France. Specifically, CEFIT provides us with details of the outstanding volumes of deposits issued and loans granted to non-financial customers by individual credit institutions in each of the 94 counties of mainland France. Credit institutions (hereafter, banks) are identified by a unique number (*Code d'identification bancaire*, CIB). We focus (i) on deposits issued to resident households, which we sort into sight deposits (or checking accounts) vs term and savings deposits, and (ii) housing loans granted to the resident households, which we sort into standard 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"). Deposits and loans amounts 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.[15] These groups account for more than 95% of outstanding household deposits throughout the period. Some smaller credit institutions only report to CEFIT with quarterly frequency. We drop these smaller banks and focus on the subsample within major groups which report with monthly frequency. We compute monthly rates of growth of deposits and loans and 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 local bank mergers). We are left with an unbalanced regression sample of 100 individual banks affiliated to one of the seven major banking groups of the country, and 122,368 bank-county-month-level observations over

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

January 2011 to November 2020.[16]

We obtain geo-localized, loan-level data on newly issued housing loans in France over the years 2013-2020 from MCONTRAN, another proprietary dataset of the Banque de France. More precisely, MCONTRAN collects the details of all new loans to non-financial customers granted by a representative sample of branches of resident banks in the first month of each quarter. Banks report a unique loan identifier and all relevant characteristics of the loan: amount granted, interest rate, maturity at issuance, type of loan, type of collateral if any, identifier and municipality (ZIP-code) of the issuing bank branch, etc. We focus on regular (i.e., non-regulated), fixed-rate housing loans with resident households in mainland France.[17] We exclude bridge loans and renegotiated loans, as well as loans with missing total amount, interest rate or initial maturity. For consistency across our evaluation exercises, we restrict the sample to banks for which we also observe county-level information on outstanding deposits and loans volumes from CEFIT. *La Banque Postale*, the French post bank, reports all its housing loans to MCONTRAN as if they were issued by one unique branch, a hub located in Paris, although customers actually deal with the loan officer in their local post office. Since we use in our regressions local controls that relate to the ZIP code of the municipality where the issuing bank branch is actually located, we further exclude loan observations reported by the French post bank. Last, we drop municipalities with less than 10 different loan observations over the period. We also drop municipalities which do not host at least three bank branches throughout. Our final sample is a quarterly dataset of 246,657 individual loans for housing purchase, issued by the local branches of 77 individual banks and located in 1,070 municipalities across 93 counties between the second quarter of 2013 and the last quarter of 2020. Figure A1 in the Appendix shows the map of municipalities included in our final sample, their

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

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

average number of bank branches and the total number of loans issued by these branches over the period that we observe in our cleaned dataset. The figure confirms that our final selection of municipalities is spread out across the whole country and representative of all regions.

We then construct bank-related controls using various additional sources. Firstly, we use Banque de France's *Fichier des implantations bancaires* (FIB) to construct local measures of bank size and competition in retail banking markets. The FIB dataset monitors the population of active bank branches of all banks in France, including their postal address, with monthly frequency. For each bank, we first compute the (log) number of branches in each county as a proxy for the size of the bank's local business. We use this variable as our main bank-county-level control in regressions explaining the level of deposits or loans.[18] We then also compute the (log) number of bank branches within each municipality (ZIP-code) and the share of branches of each local bank in a ZIP-code at quarter's end. We use these two variables as proxies for the degree of retail banking competition in each ZIP-code and for the market power of each bank within a ZIP-code. We include them as controls in our regressions explaining the level of housing loan interest rates across banks and ZIP-codes.

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

[18]Loan officers of the French Post Bank, *La Banque Postale* are located in local post offices. These post offices are not recorded in our extraction of 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.

(debt to non-financial customers to assets), which we include in our regressions explaining deposits and loan volumes.

We also use two other sub-datasets with quarterly frequency but with a broader coverage, SITUATION and CPTE-RESU.[19] We use this data to construct quarterly measures of bank size (log of total assets), leverage (capital and reserves to assets), asset liquidity (cash and interbank assets to assets), business model (credit to non-financial customers to assets) as well as non-performing loans (loan losses and provisions to credit to non-financial customers), which we include in our regressions explaining the interest rate of new housing loans.

3.3 Other data

Socio-demographic data. We use Census data from 2008 to measure age and education at the city-level (ZIP code).[20] The dataset comprises information on educational attainment, categorized into 7 levels, of individuals aged 16 and over, who were not enrolled in school. It is segmented by gender and age group. We use this data to compute the share of adults with college education or higher education attainment, at both the city and county (*départements*) levels as of 2008. We also leverage fiscal data from *Impot sur le Revenu des Communes de France* (IRCOM) to measure income per capita.[21] The data provides a snapshot of taxation from the previous year as of December 31 of the current year, as well as information on the number of tax households and the total amounts of salaries, wages, or pensions for each region, department, or commune. We use this data to compute the average income per household at both the city and county levels as of 2010. Last, we sort counties and cities into quartiles of the respective distributions of these measures of educational attainment and average income. Figure A3 in the appendix show the geographical distributions of these variables.

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

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

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

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

4 Measuring banks' reputation for sustainability

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

We aim to construct a monthly measure of French banks' reputation for sustainability 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

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

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 by web-scrapping a broad selection of French information websites for corresponding mass media releases.[23] 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. We manually drop irrelevant hits (false positive) that are not related to climate change.

Social media. Social media platforms like X (ex-Twitter) serve as agoras where individuals engage in discussions, express opinions and share information on a global scale. Analyzing the tweets that relate to NGO campaigns can therefore help to assess how the public assesses these initiatives. We developed a web scraping algorithm to identify the tweets which pertain to the selected NGO campaigns in our dataset. The algorithm runs targeted search queries containing the names of both the NGO initiating the campaign and the targeted bank, along with variations of their names, keywords and hashtags. We focus 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.[24]

Overall, we identify some newspaper (and other mass media) coverage for about a half of all negative, climate change-related, NGO campaign alerts over 2010-2020. When news releases are identified, the median alert benefits from two releases, while the top 10% of media-covered campaign alerts are echoed by four media websites or more. Regarding

[23] 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.

[24] Interestingly, we found no tweets associated with "positive" campaign events (according to Sigwatch's sentiment variable).

social media, we gather at least some tweets related to about 60% of all negative, climate change-related, campaigns over the same period. For these campaigns, 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, CC-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 French bank customers.

4.2 Sustainability Reputation Indexes

4.2.1 Methodology

In this section, we detail how we use NGO campaigns to construct our index of banks' reputation for irresponsible business. In the following presentation, we focus on climate change-related NGO alerts, but we proceed similarly for each type of ES alerts (CC, OE, S and all ES). Since we have no basis for assuming that bank depositors pay an equal attention to negative and positive news, and therefore do not know how they may combine them, we deal with negative and positive alerts separately, using the same methodology. We therefore construct a Sustainability Reputation Index (SRI) reflecting negative CC-related alerts (in short "negative CC SRI") and another one that reflects positive CC-related alerts ("positive CC SRI"). For simplicity, we focus below on how we construct the negative CC SRI. For each negative CC-related alert, we use the qualitative information provided by Sigwatch to compute an alert-specific impact score AIS_{nbd}:

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

where n denotes the NGO (or 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 headline of the campaign) and at least one of the participating NGOs is viewed by Sigwatch as very powerful.[25]

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.[26] 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.[27]

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):

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

[26] 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."

[27] Note that Sigwatch's measure of the NGOs' outreach does not come out as a significant driver of media coverage. In a robustness exercise, we therefore checked that omitting this factor in the definition of the alert impact scores does not affect qualitatively our main results, cf. robustness section below and Table A6 in the online appendix.

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

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.[28]

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

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

where the decay parameter $\theta = ln(2)/6$, so that the memory of past NGO campaign alerts halves after six months. This shortcut amounts to assuming that 50% of the targeted audience forgets about these news after 6 months (75% after 12 months, 100% after more than one year).[29] This approach is motivated by influential research findings on human memory (Mullainathan, 2002; Kahana, 2012), notably the finding that recall probabilities decay exponentially over time.

Figure 4 shows the resulting reputation index for negative climate impact $SRI(CC)^{-}_{bt}$ (or

[28] 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, see below.

[29] We checked that our main results are robust to alternative calibrations of this time-decay parameter, see below. As an example, Figure A6 in the appendix displays alternative measures of the brown reputation index of one major bank when we vary this calibrated parameter.

brown reputation index for brevity) of the seven main bank brands (BPCE, BNP, CA, CM-CIC, HSBC, LBP, SG). Importantly for the empirical relevance of our exercise, the figure witnesses a lot of variation, both within banks and across banks.[30]

4.2.2 From bank brands to individual banks

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

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

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

In contrast, *Crédit du Nord* is a small banking group, mostly present in Northern France, which belongs to the larger *Société Générale* (SG) group. Until 2022, the visual identity of

[30]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.

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, BPCE group, mostly known for its large network of regional cooperative banks and local savings banks. We therefore associate *Banque de Savoie* with its own, specific brand and not with BPCE. We end up having 23 different brands for the 100 banks in our regression sample. Only the nine largest bank brands show up in NGO alerts covered by Sigwatch. The 16 banks associated with the 16 remaining brands are therefore never affected by NGO campaigns.[31]

5 Brown banks and their depositors: empirical analysis

5.1 Methodology

We aim to evaluate whether NGO campaigns affect households' supply of deposits with "brown" banks, blamed for "banking on climate change". As explained above, NGO campaigns are arguably exogenous to local developments in the domestic bank deposits of French households.

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

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

where Y_{bct} is the outstanding amount at time t of deposits issued by bank b to customers in

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

county (*département) c*. The main independent variable of interest is our index of banks' brown reputation (SRI^{-}_{bt}). According to our hypotheses, we expect coefficient β^{-} to be negative. Note here that SRI^{-}_{bt} is defined at the level of a bank brand, which reflects in general the name of the consolidating parent bank. Within a banking group, some banks are affected by the reputation index of the group's brand and some are not because their affiliation to the group is not obvious to retail customers.

In this baseline regression, we control for the banks' *positive* reputation index regarding climate change issues (SRI^{+}_{bt}), the (log) number of bank b's branches in county c ($ln(BB_{bct})$, and for a set of (lagged) monthly bank-level balance sheet variables stacked in $Z_{b,t-1}$. We include in Z the (log) total assets of the bank, its leverage and its reliance on retail deposits for funding. Last, we control for bank fixed effects δ_b and for county-time fixed effects δ_{ct}. The former absorb all invariant unobserved bank characteristics (including for instance the bank type, i.e. cooperative vs commercial bank). The latter account for unobserved time-varying local and macroeconomic factors (such as the level of local economic activity, house prices, or the monetary policy stance) that may impinge on the local supply of retail deposits and the local demand for housing loans.[32] In all regressions, we cluster standard errors at the level of individual banks, which is the dimension of treatment.

Table 3 presents descriptive statistics for the dependent and independent variables used in these regressions.

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

5.2 NGO campaigns targeting brown banks and the supply of sight deposits

5.2.1 Baseline result

Table 4 reports our findings when the dependent variable in equation 1 is the volume of households' sight deposits and the main independent variable is the bank's brown reputation index. Columns (1) an (2) control for bank and county-time fixed effects, while columns (3) to (5) include time-varying bank controls. The supply of households' sight deposits decreases significantly when negative NGO campaigns weigh down on the reputation of the bank: the coefficient of SRI^- is negative and significant at the 1 percent level. Interestingly, the impact of NGO campaigns on bank depositors seems to be asymmetric: the coefficient on the positive, CC-related, reputation index is much smaller than the coefficient of the negative one, and never significant.

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

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

The estimated effect of negative campaigns against brown banks is economically significant. Other things equal, a one-standard-deviation larger brown reputation index induces a drop in households' deposits by 3.5In euros, this translates into an average drop in sight deposits at the bank-county level by some 9 million euros.[33]

5.2.2 Robustness

In the baseline, we control for unobserved bank characteristics using bank-level fixed effects. For robustness, we tried an alternative specification and included bank-county-level fixed effects among controls instead. This amounts to a more standard "within" panel regression, where identification is achieved within a bank-county pair using only the variations through time of deposits and bank reputation indexes and controlling for unobserved, time-varying county-level factors. Table A5 in the online appendix presents the results. The estimates of the main coefficient of interest, β^-, are almost unchanged and still highly significant.[34]

These baseline results are also robust to a number of changes in how we construct the brown reputation index. For brevity, we only mention the results of our various robustness checks here, while the corresponding tables are left for the online appendix. 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, (iii) we do not apply a concave transformation to the sum of alert scores targeting a bank brand within a month when defining the monthly reputation score MRS_{bt}, (iv) we replace the negative (resp. positive) reputation index SRI^-_{bt} (resp. SRI^+_{bt}) with a dummy variable that takes the value of one when the bank brand is hit by at least one negative (positive) campaign within the month.[35]

[33]Although this may seem large, this number is small compared with the standard deviation of sight deposits at the bank-county level, at 403 million euros.

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

[35]For details, please look at Tables A6, A7, A8 and A9, respectively, in the online appendix.

Last but not least, Table A10 in the online appendix shows how estimation results in column (3) of Table 4 change when the time-decay parameter θ is set to reflect alternative assumptions regarding the persistence in peoples' mind of past monthly bad reputation scores (MRS_{bt}). For the sake of comparability across columns, the main variables of interest ($SRI(CC)^{-}_{bt}$ and $SRI(CC)^{+}_{bt}$) are here standardized. The first column shows the results under 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.

5.2.3 Depositors are mostly concerned about climate change

We focus in the baseline above on the impact on deposit supply of NGO campaigns that denounce fossil energy funding by brown banks. However, NGO also blame banks for funding projects which raise other types of ES concerns (e.g., human right abuses). Which ES issue do bank depositors value most? To answer this question, we run the same regression as in column (3) of table 4 above, but this time replacing the climate change-related negative SRI with the bad reputation indexes related to the other ES issues.

Table A11 in the online appendix reports the results of these alternative specifications. As shown in columns (2) and (3), we find no evidence that depositors react much to NGO campaigns blaming their bank for reasons related to other environmental (OE) or social (S) issues. Although estimated coefficients are negative, they remain far from significance, even when we consider all types of alerts together (column 5). We conclude that the overall negative reaction of bank depositors to banks' bad ES reputation (column 4) is actually mostly driven by the reaction to news related to climate change. In other words, depositors really "don't like it hot".[36]

[36] For robustness, table A12, also in the appendix, shows that estimation results are almost unchanged

5.3 Exiting brown banks: the role of transaction costs

More than a third of French depositors hold more than one bank account.[37] Discontent depositors aware of the environmental wrongdoings of one of their banks may choose to reduce their supply of deposits to the brown bank and rebalance their savings towards other banks (intensive margins), or to exit the brown bank and switch all their money to another bank (extensive margin). Since prominent NGO campaigns explicitly urge customers of brown banks to change banks, it is reasonable to assume that the extensive margin prevails and drives the estimated effect.

To shed more light on this, we exploit a policy move in 2017 which dropped the transaction costs of changing banks for individuals in France to zero. Changing banks indeed 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, various subscriptions etc) associated with her bank account. A provision of the so-called "Macron law" of 6 August 2015 (article 43), which entered into force on 6 February 2017 only, requires the new bank to take in charge all this paperwork on behalf of the individual customer who is changing banks.[38] Moving sight deposits out of brown banks into greener ones then became much easier after this date. Indeed, newspapers accounted for a visible impact of this regulation on customers' behavior as soon as one month after its implementation.[39] However, the law does not mandate the new bank to do the paperwork when customers choose to close and move their term and savings deposits instead. We therefore expect a weaker effect of the law on the supply of savings deposits to brown banks.

To vindicate our interpretation of the baseline result above, we therefore run an additional regression, where we interact banks' brown reputation index with a dummy variable for

in the alternative within-county-bank specification .

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

[38] Cf. law 2015-990 of August 6, 2015: *Loi pour la croissance, l'activité et l'égalité des chances économiques*.

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

the period posterior to the implementation of the policy ($Post$):

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

Table 5 presents the results. In columns (1-4) of the table, the dependent variable is the volume of sight deposits. The negative effect of NGO alerts denouncing brown banks is much larger after the new law than before and strongly significant. In columns (5-6), we show the results when the dependent variable is the volume of term and savings deposits instead. As expected, the reaction of savings deposits to negative NGO campaigns is less or not significantly affected by the law. Overall, this evidence suggests that the extensive margin plays an important role in shaping the total response of customers' deposits to NGO campaigns.[40]

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

Last, figure 5 shows estimates of the main coefficient of interest (β^{-}_{Post}) in a dynamic specification of equation (2), where the brown reputation index of the bank is interacted with year dummies instead of the $Post$ step variable. The equation is estimated over a window of three years before and after the change in regulation. As the figure shows, the impact of banks' brown reputation on the supply of sight deposits is significantly negative

[40]Again, results are almost unchanged in the alternative within-county-bank specification, as shown by Table A13 in the online appendix.

(at the 95% level) in the first two years of the new policy regime. Importantly, the usual parallel assumption holds, since no effect is visible before 2017.[41]

5.4 Heterogeneous effects of households characteristics and bank competition

In this section, we test whether the impact of negative NGO campaigns denouncing brown banks is larger among more climate-conscious, or green-motivated, investors. We do not observe individual bank customers and even less their political preferences. However, electoral studies suggest that electors who vote for green parties, arguably climate-motivated customers, are on average more educated, and to some extent, more urban and well off. To confirm this in our data, table A3 in the appendix shows the pairwise correlations between (quartiles of) average levels of education, income, bank competition (here a proxy for city size) and green vote across French counties at the end of the 2000 decade. The correlation coefficients of income, bank competition and college education with green vote are 0.44, 0.55 and 0.77 respectively.

We therefore take advantage of observing bank deposit volumes at the level of counties and exploit heterogeneity in county-level demographics and electoral outcomes. For this purpose, we augment our empirical model in equation 2 and include in the regression additional interaction terms with variables that account for geographical heterogeneity in key dimensions of households' characteristics:

[41]Figure A7 in the online appendix shows instead the same coefficients when we drop the "NGO power" factor in the definition of the alert-specific impact score AIS_{nbd}. The parallel pre-trend assumption still holds and the effect is significant at least in the first year *ex post*.

$$
\begin{aligned}
ln(Y_{bct}) = {} & \beta^{-} \times SRI^{-}_{bt} \\
& + \beta^{-}_{Post} \times SRI^{-}_{bt} \times \text{Post}_t + \beta^{-}_{X} \times SRI^{-}_{bt} \times \text{TopX}_c \\
& + \beta^{-}_{X,Post} \times SRI^{-}_{bt} \times \text{Post}_t \times \text{TopX}_c \\
& + \beta^{+} \times SRI^{+}_{bt} + \gamma \times ln(BB_{bct}) \\
& + \delta_b + \delta_{ct} + u_{bct}
\end{aligned}
\tag{3}
$$

where $TopX_c$ denotes a dummy variable for counties above the median in terms of, respectively, the share of households with college education, households income, and the share of green votes in the elections of MEP. All these variables are measured before the beginning of our sample as explained in the data section above.

Table 6 shows our findings. Each column investigates in turn one dimension of heterogeneity. We cluster here standard errors at the bank level as before.[42] Although our proxies for the green motivation of depositors are arguably imprecise, our estimation results point to a stronger impact of NGO campaigns on deposits held in the wealthiest, most educated and politically greenest counties, *throughout the period*. While average depositors react to NGO campaigns mostly after the enforcement of the "Bank mobility" regulation, "motivated" (and wealthier, more educated) households seem to be willing to exit brown banks even in the presence of transaction costs and they do react a bit more when these costs are cut.

Last, we also test for the role of bank competition. Intuitively, switching banks should prove easier in a more competitive banking environment, even in the presence of transaction costs. We sort counties into bank competition quartiles based on the Herfindahl index of households' bank deposits in each county as of 2010.[43] Results are presented in the last column of table 6. The coefficient of the interaction between the brown reputation index and a dummy for counties above the median level of bank competition is negative

[42]Results still hold if we cluster standard errors at the bank-county level instead.
[43]Figure A2 in the appendix shows the geography of bank competition across counties.

and of similar size as the coefficients of other interacted terms in the previous columns, albeit not significant.

6 Brown banks and the demand for housing loans

6.1 Methodology

In this section, we exploit both CEFIT 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 induced by the browner reputation of lenders. Indeed, as said above, 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 regressions similar to (1) where the dependent variable is the (log) amount of regular (i.e., non-regulated) housing loans, instead of sight deposits. Second, we investigate whether NGO campaigns against brown banks affect the interest rates of such housing loans. We observe new loans granted in the first month of each quarter for a sub-sample of the previous population of banks over 2013 to 2020. Using this data,we estimate the following empirical model:

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

where r_{ibmt} is the (fixed) interest rate of loan i issued at time t by bank b in municipality (ZIP code) m. The main independent variable of interest is bank b's brown reputation index (SRI^{-}_{bt}). We again expect coefficient β^{-} to be negative.

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

Table 8 presents descriptive statistics for the dependent and independent variables used in these regressions.

6.2 Results

We first look at the response of the volume of housing loans to a browner reputation of banks. Table 7 presents the results in the same format as table 4 did for sight deposits. The reduction in amounts lent is again 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 close to 6%.

Last, we turn to regressions on loan interest rates using the loan data. Table 9 presents estimation results for alternative specifications. In all regressions, we include loan-level controls and fixed effects. In column (2), we add city-level controls. In columns (3-5), we also include bank-specific controls. In the last column, we restrict the sample to loans issued in larger cities with more than 20 local bank branches throughout, i.e. more competitive local bank markets. The coefficient of the brown reputation index is negative and strongly significant: banks' brown reputation is associated with lower interest rates on new housing loans. This negative effect holds whenever we control for all loan, city and bank characteristics. Last, this price effect is significantly larger in (larger) cities where there are more bank branches and competition between bank brands on the local mortgage loan market is therefore more intense. Combined with our previous result of a lower volume of outstanding housing loans for browner banks, this therefore confirms that bank customers tend to reduce their demand of new housing loans from brown banks.

The size of the estimated effect of NGO campaigns on the interest rate of new housing loans is arguably small: when the brown reputation index of the lender is higher by one standard deviation (0.89 in this sample), the offered interest rate is lower by close to 2 basis points (bp), to be compared with an average interest rate of 2.58%. Note however that this small spread (a few basis points) has the same magnitude as the difference between the yields of comparable green and conventional bonds (the so-called *greenium*) in the 2010s, cf. for instance Zerbib (2019) and Flammer (2021) for recent estimates.

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

7 Conclusion

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

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

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

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

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

Table 2: NGO campaigns 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 about on CC issue. Dependent variable in columns (5-8): number of media releases (online articles) for each NGO campaign about alert on a CC issue. Only negative and neutral alerts. Regression method: PPML. *NGO power*, *Negative sentiment*, *Prominence*: qualitative variables from Sigwatch, with positive sign, rescaled to unity. Robust standard errors.

Table 3: Bank-county-level regression sample: descriptive statistics

	Mean	Std.Dev.	p10	p25	Median	p75	p90	Nb.Obs.
Sight deposits (thds)	253521.88	402551.93	13339.00	42836.00	122849.00	302626.50	656251.00	122368
Sight deposits (log)	11.55	1.51	9.50	10.67	11.72	12.62	13.39	122368
Savings deposits (log)	12.05	1.61	9.85	11.04	12.21	13.31	14.01	122365
All deposits (log)	12.55	1.57	10.40	11.59	12.72	13.75	14.43	122484
Housing loans (thds)	668225.86	1.01e+06	31905.00	85971.00	277114.00	831315.00	1.78e+06	122362
Housing loans (log)	12.43	1.55	10.37	11.36	12.53	13.63	14.39	122362
Regul. hous. loans (log)	9.83	2.02	7.03	8.86	10.10	11.23	12.05	118919
All housing loans (log)	12.53	1.56	10.43	11.46	12.63	13.74	14.48	122376
Sight deposits (dlog)	0.01	0.03	-0.03	-0.01	0.01	0.02	0.04	123619
Neg. ES SRI	0.80	1.13	0.00	0.00	0.27	1.14	2.62	127154
Pos. ES SRI	0.15	0.40	0.00	0.00	0.00	0.00	0.58	127154
Neg. CC SRI	0.55	0.87	0.00	0.00	0.00	0.85	1.92	127154
Pos. CC SRI	0.13	0.39	0.00	0.00	0.00	0.00	0.48	127154
Neg. CC SRI (no NGO power)	0.73	1.23	0.00	0.00	0.00	0.98	2.54	127154
Dummy neg. CC news	0.13	0.33	0.00	0.00	0.00	0.00	1.00	127154
Nb branches (log)	2.39	1.37	0.00	1.39	2.48	3.43	4.08	110720
Assets(-1) (log)	25.15	1.87	22.93	23.56	25.47	26.41	27.77	95452
Capital/Ass.(-1)	0.04	0.02	0.02	0.02	0.02	0.05	0.07	95447
Non-bank dep./Ass.(-1)	0.49	0.24	0.13	0.16	0.61	0.68	0.74	95447
Share green vote	13.86	5.47	7.91	9.29	12.62	18.21	22.02	127154
Share college educ.	0.22	0.07	0.16	0.18	0.20	0.24	0.28	127154
Income per hhld. (log)	3.13	0.15	2.98	3.03	3.09	3.18	3.27	127154
HHI deposits (pp)	1.25	0.58	0.53	0.83	1.19	1.68	2.04	127154

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

Table 4: Banks' brown reputation and the supply of sight deposits: baseline.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.033***	-0.033***	-0.042***	-0.020***	-0.034**
	[0.010]	[0.010]	[0.013]	[0.007]	[0.013]
Positive CC		0.008	0.017	-0.007	0.047
		[0.019]	[0.018]	[0.026]	[0.046]
Nb branches (log)			0.964***		0.940***
			[0.053]		[0.052]
Assets(-1) (log)				0.146***	0.047
				[0.050]	[0.086]
Capital/Ass.(-1)				-2.209**	0.137
				[0.928]	[1.202]
Non-bank dep./Ass.(-1)				0.805***	0.379
				[0.239]	[0.296]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122368	122368	103995	91324	74545
Clusters	100	100	98	59	57
R2	0.772	0.772	0.936	0.816	0.947

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

Table 5: Mechanism: impact of the 2017 *Bank Mobility regulation.*

	Sight dep.				Savings dep.	
	(1)	(2)	(3)	(4)	(5)	(6)
				2015+2017		
Negative CC	-0.042***	-0.013	-0.009	-0.016	0.008	0.017*
	[0.013]	[0.009]	[0.010]	[0.012]	[0.009]	[0.010]
Neg. CC × Post		-0.043**	-0.041*	-0.023**	-0.043*	-0.047
		[0.017]	[0.022]	[0.010]	[0.026]	[0.036]
Positive CC	0.017	0.019	0.053	0.011	0.028	0.038
	[0.018]	[0.017]	[0.041]	[0.011]	[0.021]	[0.044]
Nb branches (log)	0.964***	0.964***	0.941***	0.967***	0.966***	0.945***
	[0.053]	[0.053]	[0.052]	[0.055]	[0.052]	[0.049]
Assets(-1) (log)			0.038			0.210**
			[0.087]			[0.081]
Capital/Ass.(-1)			-0.278			-0.227
			[0.986]			[1.376]
Non-bank dep./Ass.(-1)			0.394			0.404
			[0.284]			[0.302]
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	103995	103995	74545	21454	103905	74378
Clusters	98	98	57	97	98	57
R2	0.936	0.936	0.947	0.938	0.947	0.957

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

Table 6: Exiting brown banks: the role of local characteristics.

	Cutoff: p50 of X			
	(1)	(2)	(3)	(4)
	X=Educ.	Inc.	Green	Comp.
Neg. CC	0.002	0.006	0.003	0.002
	[0.008]	[0.008]	[0.010]	[0.011]
... × Post	-0.046***	-0.049***	-0.054***	-0.049***
	[0.015]	[0.016]	[0.020]	[0.017]
... × Top X	-0.031*	-0.041**	-0.034*	-0.031
	[0.018]	[0.020]	[0.018]	[0.026]
... × Post × Top X	0.008	0.014	0.023*	0.012
	[0.019]	[0.019]	[0.014]	[0.021]
Positive CC	0.021	0.021	0.020	0.020
	[0.017]	[0.017]	[0.017]	[0.017]
Nb branches (log)	0.965***	0.965***	0.965***	0.965***
	[0.053]	[0.053]	[0.053]	[0.053]
Bank FE	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes
Obs.	103995	103995	103995	103995
Clusters	98	98	98	98
R2	0.936	0.936	0.936	0.936

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*): negative (positive) SRI of the bank brand for issues related to climate change. *Nb branches*: number of branches of the bank in the county. *Top X*: dummy for counties above median of X (college education, income, green vote, bank competition). SE clustered at the bank (CIB) level.

Table 7: Banks' brown reputation and mortgage lending

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.060***	-0.059***	-0.065***	-0.050***	-0.064***
	[0.021]	[0.019]	[0.019]	[0.014]	[0.020]
Positive CC		-0.033	-0.022	-0.110***	-0.056
		[0.022]	[0.021]	[0.032]	[0.048]
Nb branches (log)			0.885***		0.855***
			[0.050]		[0.048]
Assets(-1) (log)				0.306**	0.245**
				[0.131]	[0.114]
Capital/Ass.(-1)				-1.915	0.853
				[2.238]	[2.634]
Non-bank dep./Ass.(-1)				0.638	0.020
				[0.468]	[0.537]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122362	122362	104054	91268	74548
Clusters	100	100	98	59	57
R2	0.805	0.805	0.944	0.835	0.953

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

Table 8: Loan-level sample: descriptive statistics

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

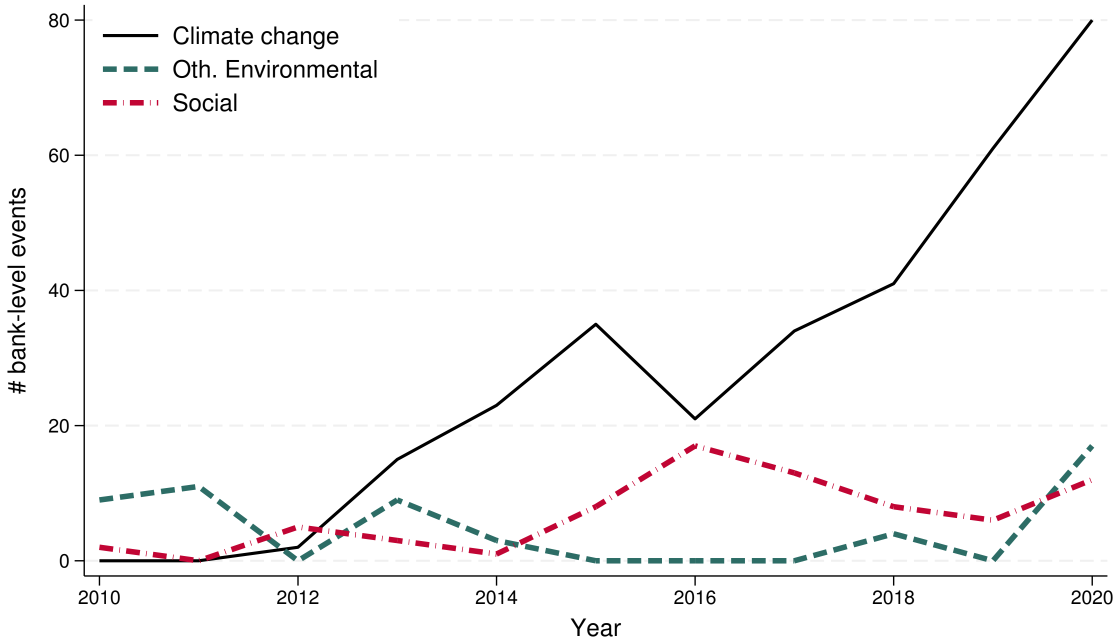
Note. Loan-level sample. Period: 2013-2020. Dep. variable: housing loan rate (TEG).

Table 9: Banks' brown reputation and interest rates on new housing loans.

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

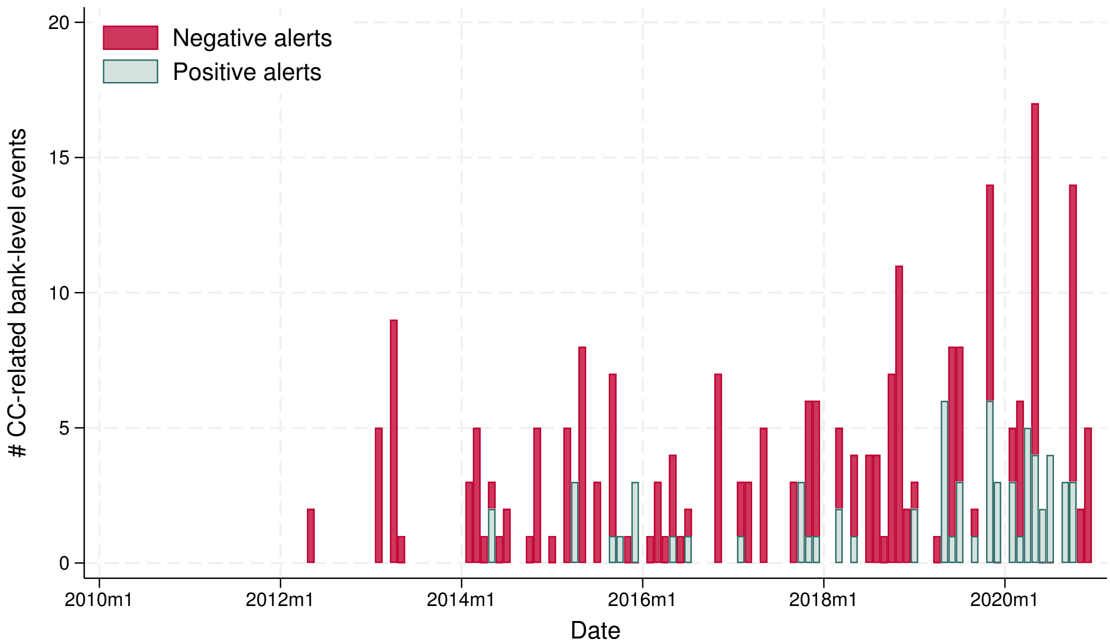
Note. Loan-level sample. Period: 2013-2020. Dep. variable: interest rate of new housing loans, including fees (*TEG*). *Local bank branches* is the total number of bank branches in the county, a measure of local bank competition. *Share bank branches* is the ratio of the bank's branches to the total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

Figure 1: NGO campaigns targeting French banks on ES issues, by type.



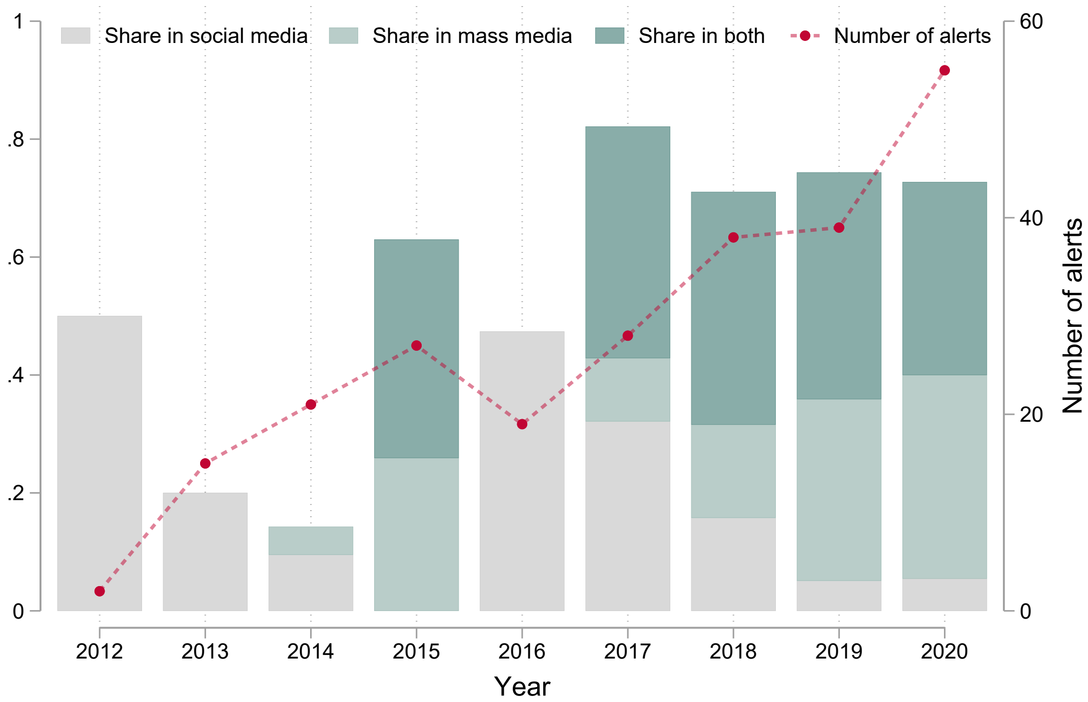
Note. Period: 2010-2020. All negative and positive NGO campaign alerts pointing at French banks (bank brands). An alert is defined by a campaign event and the name of the targeted bank. Source: Sigwatch, authors' computations.

Figure 2: NGO campaigns targeting French banks on climate change-related issues.



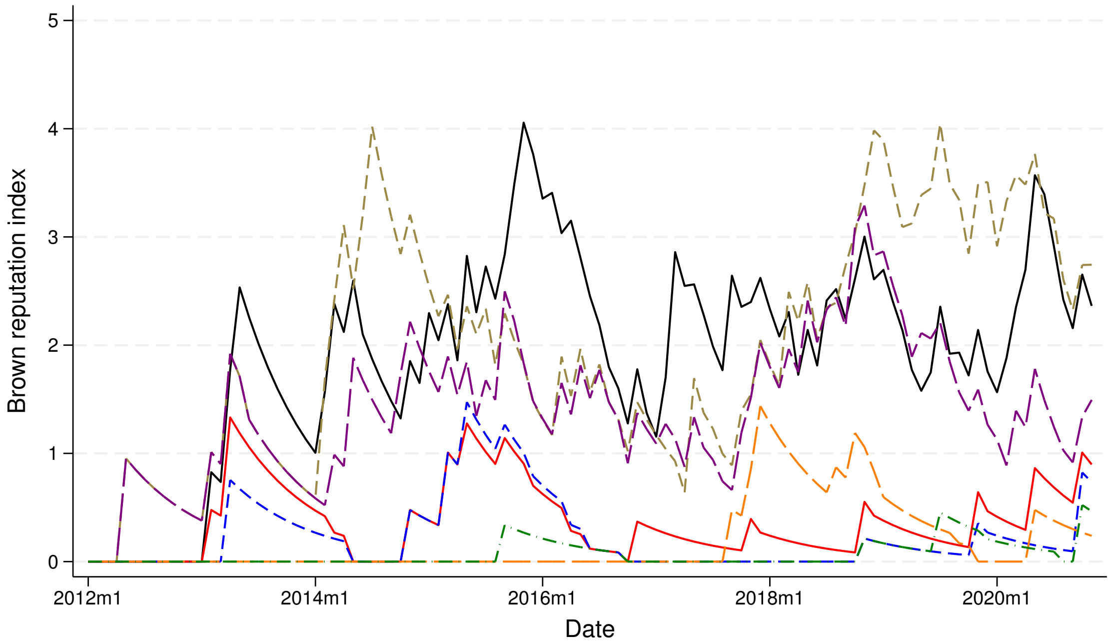
Note. Period: 2010-2020. All negative and positive NGO campaign alerts pointing at French banks (bank brands). An alert is defined by a campaign event and the name of the targeted bank. Source: Sigwatch, authors' computations.

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



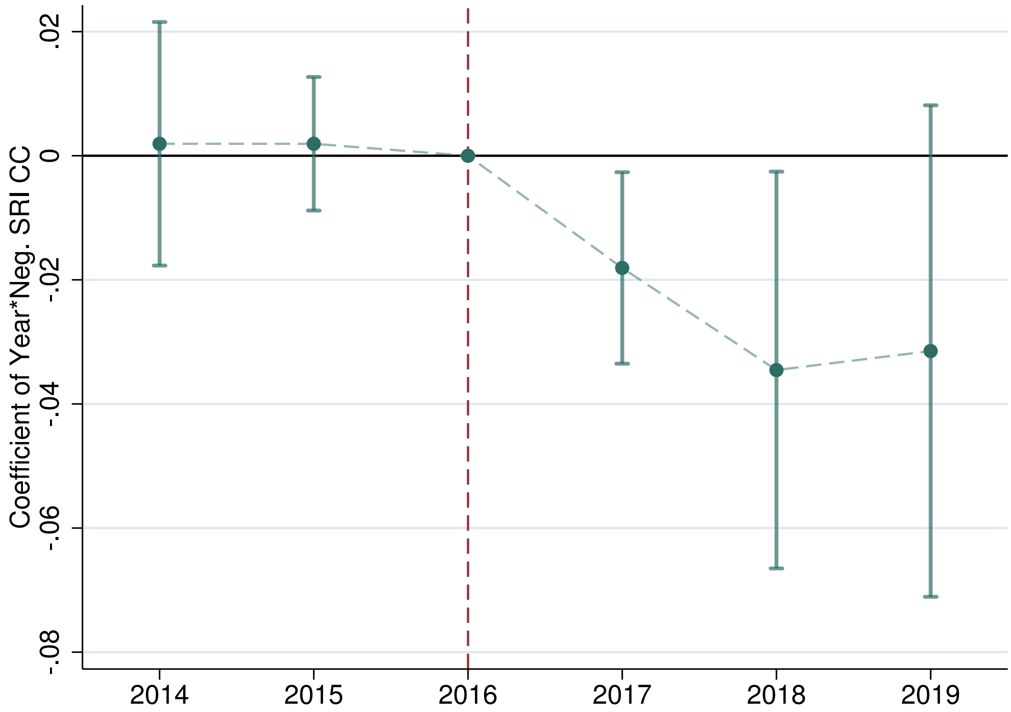
Note. Share of NGO alerts against brown banks for which we can identify news releases by major mass media (all national and major regional French daily and weekly newspapers, as well as French TV and radio broadcasts), and/or tweets mentioning both the NGO and the bank. Period: 2010-2020. Sample: negative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

Figure 4: Brown reputation indexes of the seven largest banking groups in France.



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

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



Note. Bank-county-level sample. Period: 2014-2019. Dep. variable: log sight deposits of households. The figure shows the estimated coefficients of the negative CC reputation index interacted with year dummies. Bars: 95% confidence intervals.

A Appendix

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

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

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

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

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

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

Table A4: Positive alerts targeting French banks: breakdown by NGO and ES topic.

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

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

Table A5: Banks' brown reputation and the supply of sight deposits: within bank-county specification.

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

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

Table A6: Banks' brown reputation and the supply of sight deposits: no NGO-power factor in alert impact scores.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.024***	-0.024***	-0.034***	-0.017***	-0.028**
	[0.008]	[0.009]	[0.012]	[0.005]	[0.012]
Positive CC		0.006	0.012	-0.004	0.035
		[0.013]	[0.013]	[0.018]	[0.033]
Nb branches (log)			0.964***		0.940***
			[0.053]		[0.052]
Assets(-1) (log)				0.145***	0.044
				[0.050]	[0.088]
Capital/Ass.(-1)				-2.303**	0.043
				[0.905]	[1.145]
Non-bank dep./Ass.(-1)				0.806***	0.350
				[0.242]	[0.283]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122368	122368	103995	91324	74545
Clusters	100	100	98	59	57
R2	0.772	0.772	0.936	0.816	0.947

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. In this table, individual alert impact scores do not factor in Sigwatch's measure of the campaigning NGO's power. *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 supply of sight deposits: no NGO-power factor in scores and using only alerts echoed by news releases or tweets.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.025*	-0.025*	-0.049***	-0.020***	-0.039***
	[0.013]	[0.013]	[0.015]	[0.007]	[0.014]
Nb branches (log)			0.964***		0.940***
			[0.053]		[0.052]
Assets(-1) (log)				0.151***	0.055
				[0.051]	[0.096]
Capital/Ass.(-1)				-2.373***	-0.146
				[0.886]	[1.057]
Non-bank dep./Ass.(-1)				0.832***	0.398
				[0.232]	[0.299]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122368	122368	103995	91324	74545
Clusters	100	100	98	59	57
R2	0.772	0.772	0.936	0.816	0.947

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. In this table, individual alert impact scores do not factor in Sigwatch's measure of the campaigning NGO's power. Furthermore, we aggregate here only NGO alerts for which our web-scraping algorithm identifies at least one associated news release on the main French mass media websites or at least on related tweet on X (formerly Twitter). *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table A8: Banks' brown reputation and the supply of sight deposits: no concave transformation of the monthly reputation score.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.030***	-0.031***	-0.032***	-0.016**	-0.024**
	[0.009]	[0.009]	[0.011]	[0.007]	[0.012]
Positive CC		0.010	0.026	-0.016	0.050
		[0.030]	[0.027]	[0.034]	[0.060]
Nb branches (log)			0.953***		0.925***
			[0.054]		[0.053]
Assets(-1) (log)				0.152***	0.067
				[0.051]	[0.084]
Capital/Ass.(-1)				-2.116**	-0.154
				[0.938]	[1.242]
Non-bank dep./Ass.(-1)				0.813***	0.582*
				[0.234]	[0.326]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122368	122368	106119	91324	76525
Clusters	100	100	99	59	58
R2	0.772	0.772	0.937	0.816	0.948

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index (SRI) of the bank brand for issues related to climate change. In this table, monthly reputation scores are the sum of alert-level impact scores within one month. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table A9: Banks' brown reputation and the supply of sight deposits: dummy for NGO campaigns instead of SR index.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.028***	-0.028***	-0.033***	-0.024***	-0.027***
	[0.008]	[0.008]	[0.008]	[0.007]	[0.008]
Positive CC		0.022	0.028	0.019	0.065
		[0.021]	[0.024]	[0.023]	[0.056]
Nb branches (log)			0.964***		0.940***
			[0.053]		[0.052]
Assets(-1) (log)				0.155***	0.071
				[0.051]	[0.088]
Capital/Ass.(-1)				-2.160**	0.102
				[0.928]	[1.183]
Non-bank dep./Ass.(-1)				0.835***	0.486
				[0.223]	[0.335]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	122368	122368	103995	91324	74545
Clusters	100	100	98	59	57
R2	0.772	0.772	0.936	0.816	0.947

Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *positive CC*) is a dummy that takes the value of one if the bank brand is named by at least one negative (positive) campaign related to climate change issues within a month. *Nb branches* is the number of branches of the bank in the county. SE clustered at the bank (CIB) level.

Table A10: Banks' brown reputation and the supply of sight deposits: varying the persistence of the public's awareness.

	(1)	(2)	(3)	(4)	(5)
	No mem.	HL: 1m	HL: 3m	HL: 6m	HL: 9m
Negative CC SRI (stdd)	-0.007***	-0.015***	-0.030***	-0.036***	-0.038***
	[0.002]	[0.004]	[0.009]	[0.012]	[0.012]
Positive CC SRI (stdd)	0.005	0.007	0.007	0.007	0.006
	[0.004]	[0.006]	[0.007]	[0.007]	[0.007]
Nb branches (log)	0.964***	0.964***	0.964***	0.964***	0.964***
	[0.053]	[0.053]	[0.053]	[0.053]	[0.053]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	103995	103995	103995	103995	103995
Clusters	98	98	98	98	98
R2	0.936	0.936	0.936	0.936	0.936

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

Table A11: Banks' negative reputation regarding climate change vs other ES issues: impact on sight deposits.

	(1)	(2)	(3)	(4)	(5)
Negative CC	-0.041***				-0.044***
	[0.013]				[0.014]
Negative OE		-0.022			-0.041
		[0.020]			[0.029]
Negative S			-0.027		-0.021
			[0.019]		[0.019]
Negative ES				-0.044***	
				[0.014]	
Positive ES				0.028*	0.026
				[0.015]	[0.016]
Nb branches (log)	0.964***	0.964***	0.964***	0.964***	0.964***
	[0.053]	[0.053]	[0.053]	[0.053]	[0.053]
Bank FE	Yes	Yes	Yes	Yes	Yes
County-Time FE	Yes	Yes	Yes	Yes	Yes
Obs.	103995	103995	103995	103995	103995
Clusters	98	98	98	98	98
R2	0.936	0.936	0.936	0.936	0.936

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

Table A12: Banks' negative reputation regarding climate change vs other ES issues: within bank-county specification.

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

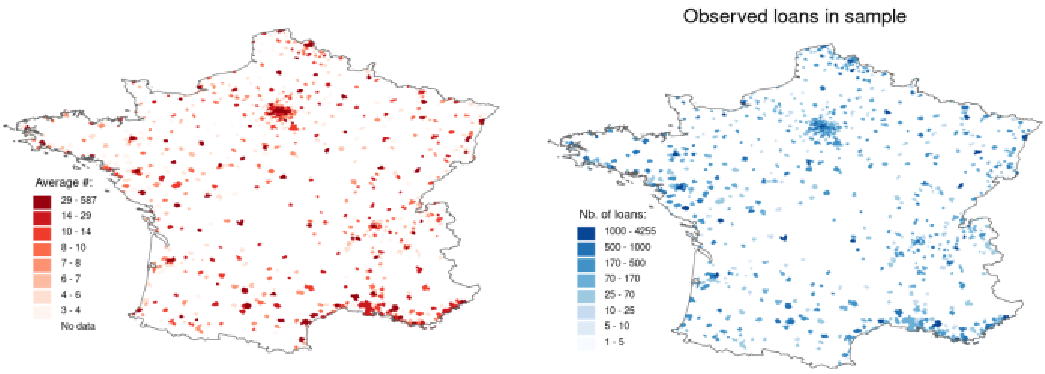
Note. Bank-county-level sample. Period: 2011-2020. Dep. variable: log sight deposits of households. *Negative CC* (resp. *Negative OE*, *Negative S* and *Negative ES*) is the negative reputation index (SRI) of the bank brand because of CC (resp. OE, S or ES) issues. *Nb branches* is the number of branches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

Table A13: Mechanism: impact of the 2017 *Bank Mobility regulation*: within bank-county specification.

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

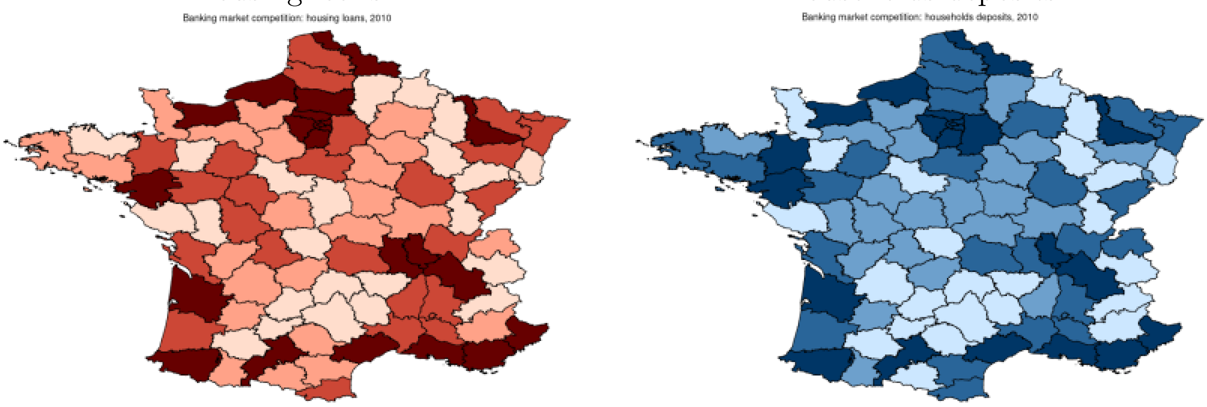
Note. Bank-county-level sample. Period: 2011-2020, except col. 4: 2015 and 2017 only. Dep. variable: log sight deposits (col. 1 to 4), or term and savings deposits (col. 5-6) of households as indicated in columns' titles. *Negative CC* (resp. *positive CC*) is the negative (positive) reputation index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

Figure A1: Geography of bank branches and granted housing loans, loan-level sample.
Nb. bank branches (average) Observed loans (total)



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

Figure A2: Bank competition, county-level heterogeneity.
Housing loans Households deposits



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

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

College education (2008) Income per household (2010)

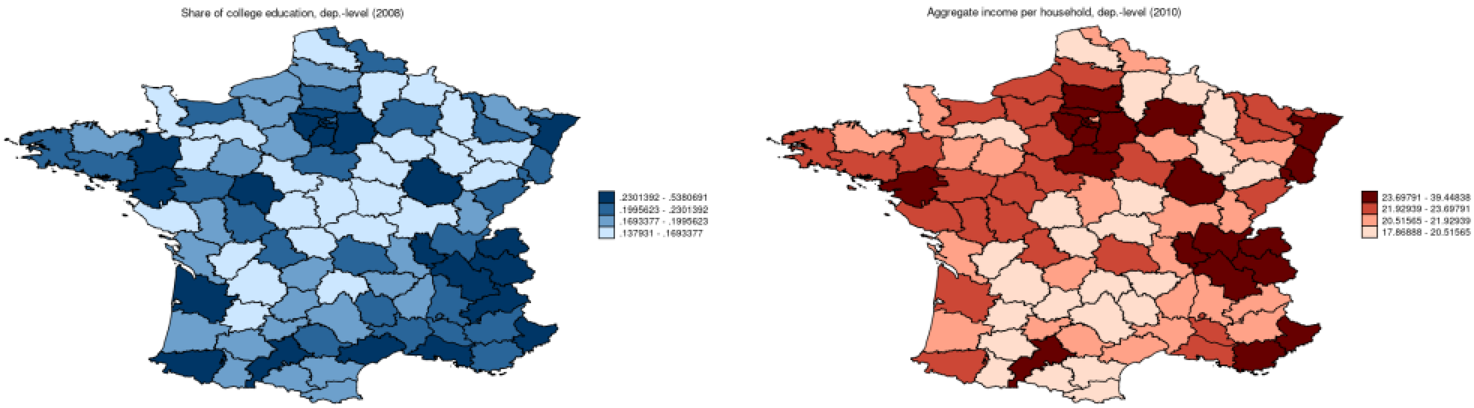


Figure A4: Vote for green parties at the EUP elections, county-level heterogeneity.

2009 *2014*

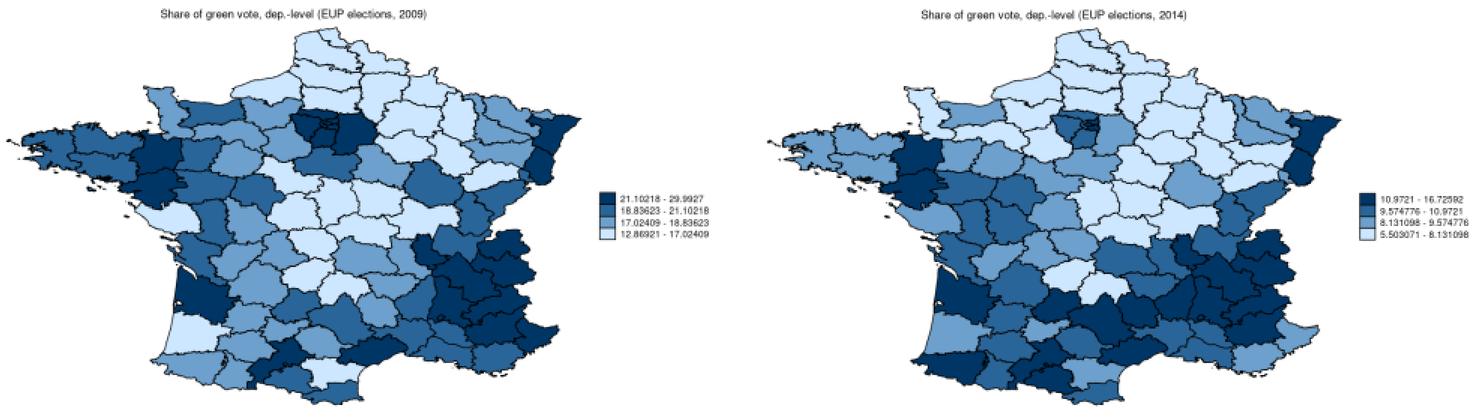
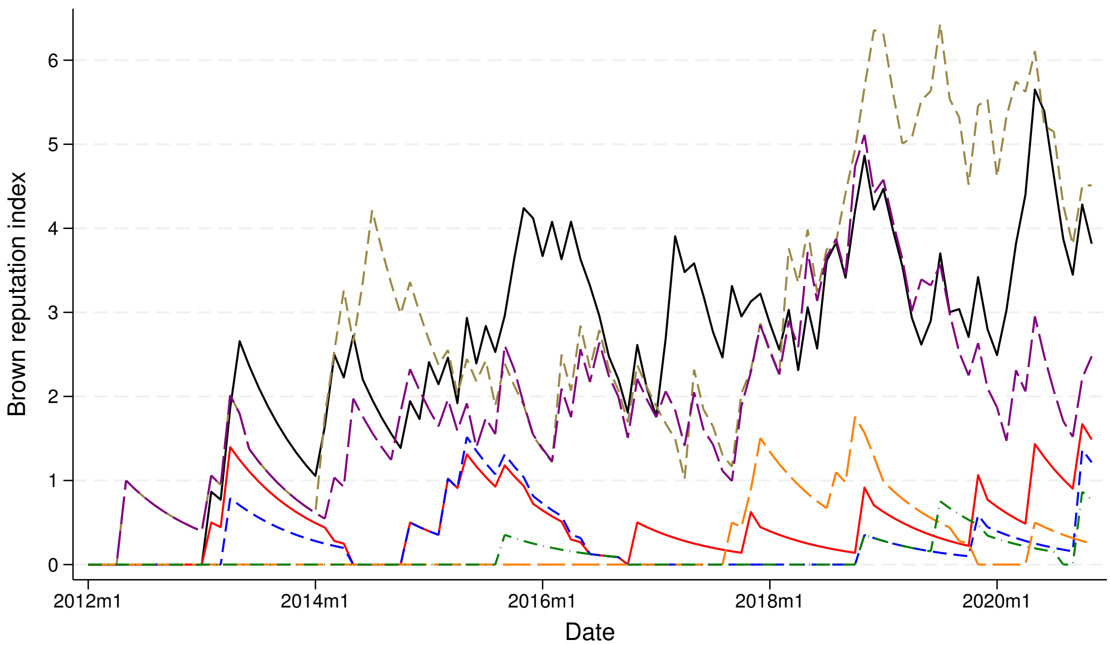
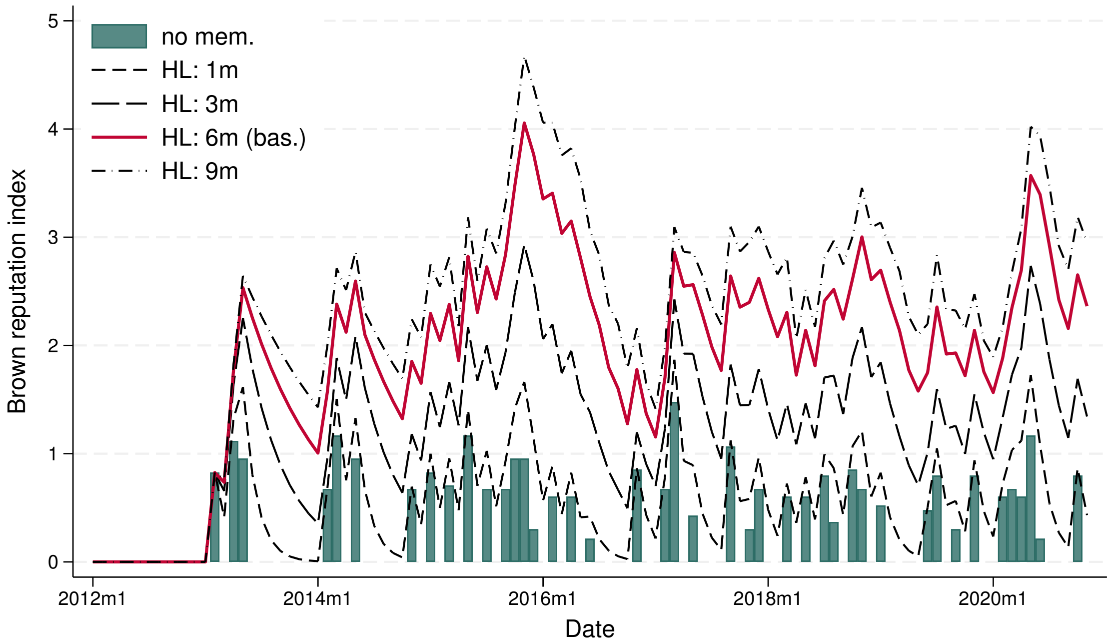


Figure A5: Banks' brown reputation: alternative definition (no account of Sigwatch's *NGO power*).



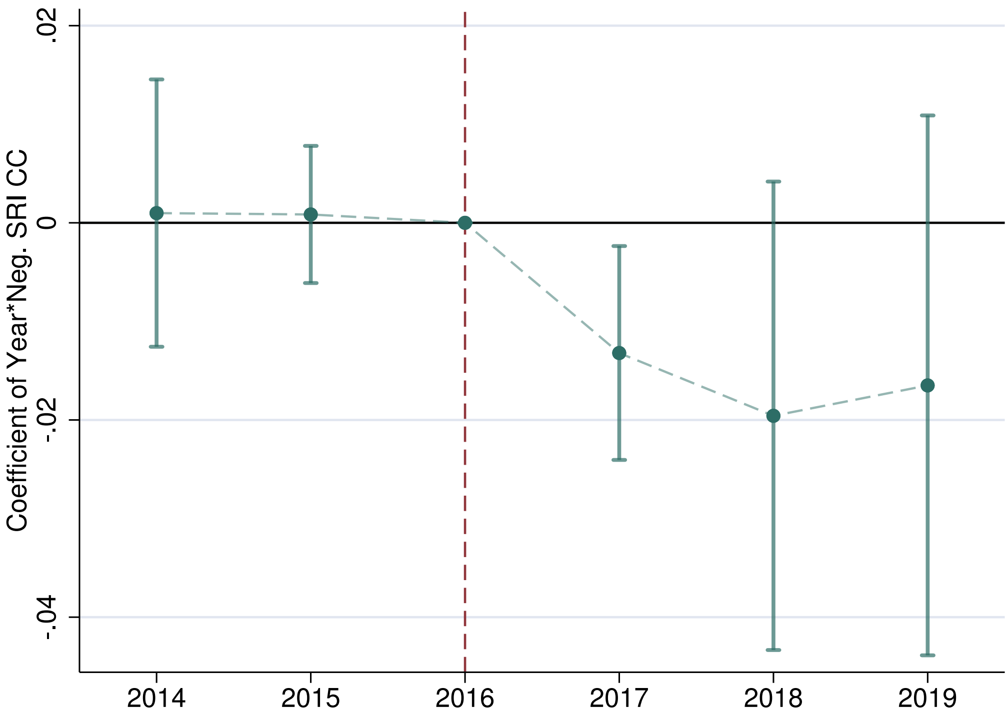
Note. Only negative NGO campaigns targeting the bank brand. In this figure, individual alert impact scores do not factor in Sigwatch's measure of the campaigning NGO's power. Source: Sigwatch, authors' computations.

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



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

Figure A7: Banks' brown reputation and the 2017 law on bank mobility: dynamic specification with alternative alert-level impact scores.



Note. Bank-county-level sample. Period: 2014-2019. Dep. variable: log sight deposits of households. The figure shows the estimated coefficients of the negative CC reputation index interacted with year dummies. In this figure, individual alert impact scores used to compute the reputation indexes do not factor in Sigwatch's measure of the campaigning NGO's outreach (*NGO power*). Bars: 95% confidence intervals.