Banking Local: Media Slant, Erosion of Trust, and Financial Decisions*

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Abstract

We study how media slant affects household banking decisions. Exploiting the staggered expansion of a local TV news operator that shifts coverage toward national events with a more negative tone, we find that households reallocate deposits and mortgage applications from national to local banks. The effects are stronger for households more likely to need flexibility from their bank, independent of income level, and are concentrated among local banks with organizational structures that support local decision-making. Survey evidence shows that the change in media slant reduces trust in banks and large businesses but not other locally-oriented institutions. Banks do not engage in credit rationing or offer more attractive prices. The results show how media-driven changes in trust alter household financial decisions, with potentially negative welfare consequences.

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"The public's trust in banks is an important aspect of a thriving and stable banking system. Without trust, banks cannot attract or retain customers, including depositors, or meet the credit needs of the communities they serve."

Office of the Comptroller of the Currency, Department of the Treasury (June 2023)[1]

1 Introduction

Does the media influence household banking decisions? If so, how and why? We study how media slant can generate uncertainty that erodes households' trust in financial institutions and, ultimately, where they choose to bank. Our paper documents that news media influences household banking decisions. We show that replacing one media outlet with another - a potentially minor change in a local media market - has an economically significant impact on where households hold deposits and seek credit. Research on media's role in financial decisions focuses primarily on more sophisticated agents engaging in sophisticated financial decisions and documents effects on outcomes such as corporate policies, equity prices, and household equity portfolios (Gurun and Butler, 2012; Kaviani, Li, Maleki, and Savor, 2023; Pan, Pikulina, Siegel, and Wang, 2024). By studying the banking system, our results highlight the breadth of media's influence: on the near-universe of U.S. households, on the principal institutions where they safely store savings and build wealth, and on financial relationships in which trust is essential (Calem, Henderson, and Wang, 2025; Brown, Cookson, and Heimer, 2019; Stein and Yannelis, 2020; Célerier and Matray, 2019).

Trust in financial institutions depends in part on the information households receive. The media play a central role in shaping this information: they disseminate and interpret news that influences how individuals form beliefs, build trust, and make decisions (Ahern and Peress, 2023; Stiglitz, 2008). By shifting the composition and presentation of information, media can increase uncertainty about the broader economy and its institutions and erode households' trust in financial institutions.[2]

[1] From a report by the OCC proposing and seeking feedback on an Annual Consumer Trust in Banking Survey, see Office of the Comptroller of the Currency (2023).

[2] See Mutz and Reeves (2005); McCarthy and Dolfsma (2014); Van Dalen, De Vreese, and Albæk (2016); Charron and Annoni (2021); Chahrour, Nimark, and Pitschner (2021); Ahern and Peress (2023)

We hypothesize that certain types of media coverage reduce this trust causing households to change the types of banks that they use.[3] Analyzing a natural experiment that shifted media slant towards negative national coverage in local geographies over time, we show that households responded by changing where they bank.

We exploit variation in media slant in local geographies brought on by the pan-American expansion of Sinclair Broadcast Group (SBG) across the U.S. between 2012 and 2017.[4] SBG has well-documented broadcasting behavior in which it shifts coverage towards national issues and presents these topics using a more negative tone. We develop a model of relational trust to conceptualize how this change in information affects household banking decisions. In our model, banking relationships contain both contractible terms and interactions in which banks have flexibility in how they respond to customers. Local relationships are the foundation for the discretionary component and households value a bank's willingness to accommodate needs that cannot be specified ex ante. However, households do not directly observe how closely a bank's interests align with their own. Instead, they infer this from both private information about institutions they observe locally and public information provided by the media. Because households can observe local banks more directly than national institutions, public media signals have a stronger effect on their beliefs about national banks. SBG's negative slant therefore reduces perceived trust in national banks relative to local banks.[5] At the same time, it may also change a household's beliefs about its need for such discretion. The model predicts that households near the margin of a viable national-bank relationship reallocate toward local banks.

In our analysis, we use hand-collected data on SBG's acquisitions of TV stations over the past 30 years from SBG company filings, acquired companies' websites, and independent media

[3] See Brown et al. (2019); Demirgüç-Kunt and Klapper (2012); Koomson, Koomson, and Abdul-Mumuni (2023); Barajas, Beck, Belhaj, Naceur, Cerra, and Qureshi (2020); Galiani, Gertler, and Navajas-Ahumada (2022)

[4] The manner in which news media report economic news affects consumer confidence and trust in government (Alsem, Brakman, Hoogduin, and Kuper, 2008; Charron and Annoni, 2021; Cappella and Jamieson, 1997; Mutz and Reeves, 2005). The television news media is a particularly powerful intermediary as it is the primary news source for many U.S. households. It covers issues that shape public trust in areas such as perception of risk, consumer sentiment and spending, and business sentiment and behavior (McCarthy and Dolfsma, 2014). Trust is essential because the services that financial institutions provide are difficult to observe and involve information asymmetry (Harrison, 2003; Barajas et al., 2020; Demirgüç-Kunt and Klapper, 2012).

[5] Survey evidence shows that people have more trust in local banks than national banks (Sapienza and Zingales, 2012).

reports. The data include information on the acquired stations and their designated media areas (DMAs). The treatment variable is the acquisition of a TV station in a given county and year. Our outcome variables are measured at the county-year level and include deposits; mortgage loan applications, approvals, and borrower demographics; and branch-level deposit and mortgage rates from the FDIC Summary of Deposits, HMDA, and RateWatch, respectively. We use Call Report data to estimate the component of a bank's deposits attributable to households for a subsample of banks. Our measure of trust is based on respondent-level microdata from the Gallup opinion polls. We define local banks using their geographic footprint, which is most closely aligned with the relational component of trust in our setting (Mayer, Davis, and Schoorman, 1995; Federal Deposit Insurance Corporation, 2012).

Over our sample period, SBG acquired news stations operating in 44 states across the U.S. In addition, SBG attempted to acquire Tribune Media Corporation, but was blocked due to antitrust concerns. We use the failed acquisition to identify markets in which SBG wanted to enter but was prevented from doing so. Our identification strategy compares banking outcomes in places where SBG successfully entered to those where SBG wanted to enter but was blocked due to the failed acquisition. We use the Dube, Girardi, Jorda, and Taylor (2023) staggered difference-in-differences LP-DiD method to estimate the treatment effects, which addresses concerns regarding potential heterogeneous treatment effects over time and across units and also captures heterogeneity in cohort-specific average treatment effects across adoption cohorts.[6]

We find that households reallocate their banking activity from national to local institutions following SBG entry. The county-level share of deposits held at local banks increases by approximately one percentage point per year in years one and two following entry, while the national-bank share declines proportionally. Subsample results using approximations of household deposits from the Call Reports confirm these findings. In addition, we observe a shift in mortgage applications from national to local banks in years three through five following SBG entry. The reallocation

[6]This method subsumes many recent estimators such as those developed by Callaway and Sant'Anna (2021) and Cengiz, Dube, Lindner, and Zipperer (2019). Its advantages are that it allows for more flexible weighting strategies and, in the context of financial variables that tend to have complex autocorrelation structures, it allows us to control for these properties in estimation.

reflects household demand rather than credit supply: loan approval rates remain unchanged at both local and national banks and approval shares match application shares as applications shift toward local banks. The shift in lending occurs for both high- and low-income households. The reallocation across income groups suggests a broader change in households' banking preferences rather than a response specific to a particular income group. In addition, regardless of income level, greater income uncertainty can change a household's perception of the likelihood of requiring discretion in the future. Consistent with this prediction, we find that the shifts in the deposit share and loan applications are stronger in counties with higher pre-treatment wage volatility.

We run further analysis to precisely identify the aspects of relational trust that drive our results. First, we refine our measure of local banks to exclude local banks within multi-bank BHCs. Although local banks within multi-bank BHCs are geographically local, their ownership structure likely allocates decision authority and incentives outside of the local geography. Consistent with the model, the increase in deposits and loan applications is concentrated among local banks outside multi-bank BHCs, where decision authority and incentives are more likely to remain local. Second, we provide direct evidence of the trust mechanism: following SBG entry, Gallup respondents report lower confidence in banks and big businesses, but not in small businesses, churches, or police. Together, these results suggest that households respond to the media shock by shifting toward institutions aligned with local relationships.

We document that our results are not driven by changes in the local banking supply or local economic conditions. Aggregate county deposits and GDP do not change following SBG entry. Banks do not systematically enter or exit affected markets, alter their branching networks, or change approval standards. Local banks do not offer more attractive rates to attract households. In fact, local banks reduce deposit rates and increase mortgage rates following SBG entry, while national-bank rates are largely unchanged.

We also examine the effect of concurrent developments in the national banking market on our results. First, we exclude Wells Fargo banks from our sample to rule out the possibility that the misconduct of Wells Fargo during our sample period drives our estimated shift away from national banks. Second, we account for the potential effects of post-financial-crisis stress testing on bank lending. We calculate a county-level exposure to stress-tested banks and find that our deposit-share results are present in both high and low exposure counties and our loan application share results are present only in low exposure counties. Together with the BHC evidence, these tests make it unlikely that regulatory pressure, bank-specific scandals, or contemporaneous changes at large banks explain the reallocation.

Our results are robust to alternative samples and estimators. They persist in a propensity-score-matched sample, become stronger when we restrict treatment and control counties to states containing both SBG and Tribune media markets, and are similar across alternative estimators for staggered treatment. Following Rambachan and Roth (2023), we also show that the deposit results remain robust to moderate linear and nonlinear deviations from parallel trends.

The reallocation has potential welfare implications. Households move toward local banks even though these banks do not offer more favorable contractible terms: following SBG entry, local deposit rates decline and mortgage rates increase. The model rationalizes this behavior because households value both posted financial terms and the credibility of discretionary accommodation. A household may therefore willingly accept worse prices in exchange for a banking relationship it perceives as more trustworthy. If SBG's slant causes households to underestimate the trustworthiness of national institutions without changing their underlying behavior, however, households re-sort across banks in response to a distorted signal. In this case, media slant changes not only beliefs but the allocation of household financial relationships, potentially reducing welfare.

Our paper's primary contribution is to provide causal evidence that media coverage shapes how households interact with the banking system. Existing work shows that salient failures and scandals can trigger withdrawals from particular banks (Homanen, 2018; D'Acunto, Ghosh, and Rossi, 2021; Sandri, Grigoli, Gorodnichenko, and Coibion, 2023; Coibion, Georgarakos, Gorodnichenko, Kenny, and Weber, 2024). However, in our setting, the uncertainty does not arise directly through negative information or events about financial institutions. Instead, SBG delivers information in a way that changes households' beliefs about institutions whose behavior they cannot directly observe. Households respond by reallocating deposits and borrowing activity toward local banks that can be evaluated based on local information and relationships. The results therefore show how generalized changes in uncertainty and trust can reshape the allocation of household finance.

More broadly, our results highlight an economic role for relational trust in household finance. Banking contracts cannot specify every future interaction between a household and its financial institution. Relationships therefore matter not only because banks acquire soft information about borrowers, but also because households value banks' willingness and ability to use discretion on their behalf. Our evidence shows that this component of trust affects where households bank. Because household deposits are an essential source of bank funding and banks are a primary channel through which households save, borrow, make payments, and manage risk, changes in relational trust can affect the allocation of both households and funding across financial institutions (Demirgüç-Kunt and Klapper, 2012; Foà, Gambacorta, Guiso, and Mistrulli, 2019; Ampudia and Palligkinis, 2018; Aguirregabiria, Clark, and Wang, 2025).

Our findings also contribute to the literature on media and economic decision-making. Prior research shows that media slant affects electoral outcomes, local government policy, and behavior by public institutions (DellaVigna and Kaplan, 2007; Ash and Galletta, 2023; Mastrorocco and Ornaghi, 2020), while political affiliation and partisan information affect corporate policies, portfolio choices, and investment recommendations (Kempf and Tsoutsoura, 2021; Cookson, Engelberg, and Mullins, 2020). We show that media slant also affects a more fundamental household financial decision: which institution households trust to hold their savings and provide credit. Importantly, the media shock is not aligned with information about banks themselves. Instead, changes in media slant alter households' beliefs about geographically distant financial institutions such that they switch their banking relationships to local institutions.

Finally, our study provides insight into the economic role of local banking relationships. A growing literature asks whether fewer, larger banks, FinTech innovations, and branchless banking can fulfill economic roles traditionally performed by smaller banks (Thakor, 2020), and prior work shows that diversity in bank organizational forms can be important for financial inclusion

(Berger, 2022; Berger and Seegert, 2024). Our results identify a distinct role for local financial institutions: they provide relational trust that households value when confidence in more distant institutions declines. Importantly, geography alone does not generate this advantage. The reallocation is concentrated among local banks outside multi-bank holding companies, where local decision authority and the bank's exposure to its customers are likely to be strongest. Thus, local banks serve as a form of "flight to safety" not simply because they are small or geographically proximate, but because their organizational structure can support relationships that are difficult for more distant institutions to replicate.

The paper is organized as follows. Section 2 discusses the U.S. banking system and the media industry, presents the setting that we use for our identification strategy, and builds our hypothesis. Section 3 describes our empirical model and alternative methods that we use to test the robustness of our main analysis. Sections 4 and 5 present our main results. Section 6 develops our theoretical framework. Section 7 presents the results of robustness analyses. Section 8 concludes.

2 Setting and Hypotheses

In this section we describe local TV news media, its potential effects on consumer trust, and the relationship between consumer trust and the banking sector. In addition, we describe the data sources used in our analysis.

2.1 Background: Trust, Banking, and Broadcast TV

2.1.1 Trust

Information media play a central role in financial markets: they disseminate and interpret information that is essential to how individuals form beliefs, build trust, and make decisions (Ahern and Peress, 2023; Stiglitz, 2008). In addition to the information itself, the manner in which news media report economic news affects public confidence and trust (Alsem et al., 2008; Charron and Annoni, 2021; Cappella and Jamieson, 1997; Mutz and Reeves, 2005). The news media covers issues that shape the public's perception of reality, reflected in areas such as consumer sentiment and spending, perception of risk, and business sentiment and behavior, which are the cornerstones of public trust (McCarthy and Dolfsma, 2014). As households update beliefs, this uncertainty can erode trust in the economy and in financial institutions.[7]

2.1.2 Banking

Trust is a central component of a well-functioning banking market. Beliefs about the stability of banks and the banking system affect household banking decisions.[8] Survey evidence suggests that trust is an essential component of a respondent's choice of where to save, borrow, make payments, and manage risk (Demirgüç-Kunt and Klapper, 2012).

The U.S. banking system is comprised of thousands of banks, and as a result, there are a diverse range of banks within the banking system. Given the diversity of banks, the concept of trust has several dimensions. Regulators, regulations, and guarantees create confidence in the overall banking system. Beyond those guarantees, trust in specific types of banks is also relevant. Although any bank has the potential to build trust with customers, some are better positioned to do so. For example, survey respondents report higher trust in local banks compared to national banks (Sapienza and Zingales, 2012).

Local banks have an advantage in engendering trust for several reasons. First, a physical presence in a local area with in-person physical interactions is an essential component of trust.[9] Second, closely integrating local community leaders into the leadership and economics of the bank builds trust.[10] Finally, having not only the knowledge but also the decision authority to act on local information is essential for building trust.[11]

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[7] See McCarthy and Dolfsma (2014); Ahern and Peress (2023); Van Dalen et al. (2016)

[8] Of course, although not relevant to our paper, banks need information to make new loans and to monitor existing loans, the subject of a rich and well-established literature.

[9] The 2025 Annual Survey of Community Banks reports that the physical presence of regional or national banks makes them potential competitors. Those without a physical presence do not pose a threat.

[10] The 2025 Journal of Community Bank Case Studies volume 10 reports that the leadership and people of community banks are woven tightly into the local community. Bank CEOs and bank board members are local leaders. They advise and also refer business to the bank. Asset liabilities and compliance committees have local representation, which allows the community to build confidence in the solvency of the bank.

[11] Local banks not only have knowledge of the local community but are also able, and willing, to act on it (Thomas,

2.1.3 Local TV news media

Local television channels are an important source of information in the U.S. Despite the explosion of news content offered by a multitude of alternative media sources, according to Pew Research, television continues to be the most popular source for gathering news for Americans. Nielsen's National Television Household Universe Estimates counts 125 million television households in the U.S., which amounts to 315.3 million people over the age of two.[12] In other words, the television industry reaches the vast majority of U.S. citizens and ostensibly has an important role in terms of media exposure. Although the number of Americans consuming TV news is declining, about 63% of U.S. adults still consume at least some news via local broadcast TV and local broadcast TV has a larger audience compared to Cable and Network TV.[13]

The U.S. television market is divided geographically into 210 Designated Media Areas (DMA) that cover several counties and often cut across state lines.[14] Television stations require a license from the Federal Communications Commission (FCC), which regulates broadcast, cable, and satellite transmissions. Traditionally, the FCC has looked at broadcast television as a decentralized market in each DMA, such that TV stations should compete for viewership and, in doing so, provide coverage of a broad range of news events from diverse viewpoints.[15] Federal law prohibits monopolies in local DMAs. However, news broadcast companies have found ways to circumvent regulations through shell companies and regional marketing agreements, which can lead to

2016). For example, they strategically locate bank branches based on hyper-local knowledge of customers. Local representatives of large banks may understand these nuances but have limited ability to act. Banks with high local market shares advertise on local TV and emphasize service and trust (Chen, Hu, and Ma, 2025).

[12] Nielsen's national definition of a TV household states that "homes must have at least one operable TV-monitor with the ability to deliver video via traditional means of antennae, cable set-top-box or satellite receiver and/or with a broadband connection." See: https://www.nielsen.com/insights/2024/beyond-big-data-the-audience-watching-over-the-air/.

[13] According to Pew Research, https://www.pewresearch.org/short-reads/2018/01/05/fewer-americans-rely-on-tv-news-what-type-they-watch-varies-by-who-they-are/. It may be noted that the number of Americans consuming TV news is declining, but about 63% of US adults still consume at least some news this way, as per Pew Research, https://www.pewresearch.org/journalism/fact-sheet/news-platform-fact-sheet/.

[14] This is a standard accepted by the FCC http://www.broadcastingcable.com/news/washington/fcc-nielsen-dmas-still-best-definition-tv-markets/157246 and created by Nielsen Research.

[15] For example, local broadcast stations typically limit their production to local news shows, and buy syndicated content for remaining time slots. In contrast, cable TV companies routinely buy local news content from TV stations and combine it with the set of channels offered to their customers.

concentrated media markets.

2.2 Empirical Setting

2.2.1 Sinclair Broadcast Group Acquisitions

Sinclair Broadcast Group (SBG) is the largest television station operator in the U.S. by number of stations. As of 2018, it owned 173 stations countrywide and operated roughly 20 additional stations through the use of Local Market Agreements. SBG started a rapid expansion campaign in 2012 that enabled it to gain access to 57 additional DMAs. These acquisitions are believed to have followed the Supreme Court's 2010 Citizens United decision, allowing fewer restrictions on corporate donations, thereby giving larger potential revenues in election years through political advertising.[16] Over the course of this expansion boom, SBG increased its presence from 134 to 236 electoral districts.

Figure 1 shows the expansion of SBG from 2012 to 2018 during which it more than doubled its presence across the entire U.S. Before 2012 it operated in five states (AL, ME, MN, MS, and NH) and by 2018 it had expanded operations to 41 states (all continental states except for AZ, CO, CT, DE, LA, ND, and NJ). It now has operations in most major urban centers and across different regions in the country. The number of counties it operates in increased by 126%, from 726 to 1606 counties. The number of potential viewers also increased by 103%, from 53 million to 109 million potential viewers.

[FIGURE 1 ABOUT HERE]

SBG has well-documented broadcasting behavior in which it shifts local news coverage to national events and imposes a more negative view of local and national news.[17] Despite having stations in counties across the U.S., SBG coordinates content at a national level. It maintains tight

[16]This is apart from the benefits of higher advertising revenues and retransmission fees https://www.pewresearch.org/short-reads/2017/05/11/buying-spree-brings-more-local-tv-stations-to-fewer-big-companies/.

[17]In particular Martin and McCrain (2019) find a supply-side slant story, in which SBG uses national politics to substitute for local politics, perhaps to achieve economies of scale.

editorial control by requiring all its stations to air "must-run" segments on various national issues. For example, between March-April 2018, news anchors were instructed to read from a common script warning viewers against "biased and false news."

The negative slant is a response to consumer demand. SBG polls viewers and uses the responses to guide future content. David Smith, the company's executive chairman, notes that a key question in SBG's annual survey of viewers is: "What are you most afraid of?" In addition, SBG recently acquired the local Baltimore newspaper, the Baltimore Sun, and critiqued it for overlooking "stories that readers crave about crime and government dysfunction".[18] The result is negative slant in programming that is geared towards engendering mistrust in institutions and mainstream narratives.[19] SBG's rapid expansion over the past decade has increased the number of counties in which this style of news coverage reaches residents and the subsequent consolidation of media markets strengthens its impact.

2.2.2 Natural Experiment: The Failed Acquisition of Tribune Media

In 2017, SBG announced its intention to acquire Chicago-based Tribune Media Corporation, which owned 43 media stations across the U.S. However, the acquisition was not completed due to antitrust concerns in the television broadcasting market. After more than one year of speculation and growing concerns about several aspects of the merger by interest groups, politicians, and the FCC, Tribune Media terminated the purchase. The purchase would have represented an increase of more than 95.86 million new potential viewers for SBG.

We use this failed merger as a natural experiment to identify areas where SBG was interested in operating but failed to do so. We argue that these areas serve as plausibly valid counterfactuals for areas that SBG successfully entered. Given SBG's interest, these markets are similar and therefore comparable with the places in which the acquisition was successful. In our analysis, we compare banking market outcomes in areas where SBG entered to those where SBG failed to enter.

[18] See SBGMedia_20240216

[19] For more information about the negative coverage provided by the TV stations owned by this group and its attempt to by-pass regulation, see: `https://tinyurl.com/SBGmedia20170814`.

2.2.3 Empirical Definition of Local Banks

There are several ways to define local banks. In our context, both the trust component of banking and our natural experiment are strongly linked to geography. Our empirical definition of a "local" bank captures these dimensions. We use a bank's geographic footprint as a proxy for the level of consumer trust that it garners. Local banks are depository institutions that operate branches within a single state; national banks are those that operate in multiple states.[20] Our definition of local banks and national banks is broad enough so that most counties have at least one local institution but narrow enough that the local banks do indeed cater to local clientele, have local skin-in-the-game, and have local ownership and control.[21]

We define an alternative measure of local banks that incorporates the geographic distance between bank branches for single-state banks. Specifically, we identify the geographic center of a bank's network of branches based on the deposit share of each branch. Local banks are those banks with all branches within 100 km (60 miles) around this geographic center.[22] This measure identifies banks with geographically concentrated operations relative to multi-state banking institutions. Not only are these single-state banks, but this approach increases the likelihood that these banks have decision authority, local accountability, and local ownership and control.

2.3 Data

We combine several data sources for our empirical analysis. First, we use hand-collected data on the SBG broadcast network and its acquisitions. Second, we compile data about financial institutions using the FDIC, HMDA, and RateWatch. Third, we compile data on local demographics and public trust patterns using data from the Bureau of Economic Analysis and the Gallup public opinion polls. Our final dataset covers the period from 2007 through 2019.

[20] All our results are robust to splitting the set of single-state banks into subsamples of single-county and multi-county banks separately.

[21] We define local and national banks as of 2011 (prior to SBG entry) and keep this fixed throughout the sample period.

[22] The method can be thought of in the following way: if banks are arranged in the corners of a square, the center of the network will be in the center of the square. By using the deposit-share weights, each corner side will "push" the center towards the side with biggest share of deposits.

We collect data covering SBG's history of acquisitions over the past 30 years, starting with Act III Broadcasting (in 1994-96, a total of 5 stations across 5 DMAs), and ending with Bonten Media Group (in 2017, a total of 18 stations across 8 DMAs) to build a unique and detailed dataset. We hand collect these data from SBG company filings, archives of the acquired companies' websites, and confirmations from independent media reports. In addition to acquisitions of the large companies, we track SBG's acquisition of 13 independent stations acquired in 13 different DMAs between 2012-16. SBG is also linked to other broadcasting companies, such as Cunningham Broadcasting Corporation and Deerfield Broadcasting corporation, through Local Market Agreements (LMAs), which allow SBG to bypass the FCC's local duopoly rule because as per laid-down rules the official owner of the station is a company different from SBG. The inclusion of LMAs in our dataset is, to the best of our knowledge, unique to our paper and allows us to remove potential confounding effects from stations indirectly owned by SBG. Our final data set includes the station name, the corresponding channel (if any), the DMA in which it is located, and the date SBG entered each DMA. We match the DMAs with the respective counties using publicly available data. With this combined information, we can identify the year in which SBG initiated media coverage in each county.

Banking data come from the FDIC Summary of Deposits and HMDA mortgage loan applications. The FDIC Summary of Deposits provides the geographic location of bank branches and the total deposits held at each branch. We use the FDIC Call Reports to determine if the institution of that branch is a member of a bank holding company (BHC). The HMDA mortgage loan data provide individual loan application-level information which includes the bank, county, and year of the loan application, demographic information about the loan applicant, and whether the loan was rejected, approved, and ultimately originated. We use survey data from RateWatch, a division of Standard and Poor's, for branch-level deposit rates and mortgage rates. Responding banks comprise the largest banks, accounting for roughly 80% of total domestic deposits (Morelli, Moretti, and Venkateswaran, 2024). We construct bank-county-year averages of the deposit and mortgage data.[23] We compute average deposit rates across five deposit products: money market, savings account, and 12, 24, and 60 month certificate of deposits (CDs). Mortgage rates are the average of 10, 15, 20, and 30 year fixed rate mortgages.

We use the Gallup Confidence in Institutions Survey to analyze patterns in public trust over the period from 2000 to 2024, during which Gallup surveyed at least 1,000 U.S. adults in regions throughout the country. This survey is part of the Gallup Poll Social Series, and it aims to monitor public opinion among U.S. adults aged 18 and older across all 50 states and the District of Columbia on various topics, including trust in a range of institutions including banks, both large and small businesses, churches, and the police force. Gallup categorizes responses as "a great deal," "quite a lot," "some," or "very little." We define an indicator variable for trust that equals 1 for responses of either "a great deal" or "quite a lot," and zero otherwise. To compare individuals in counties with SBG entry to those without, we match respondents using demographic characteristics including gender, region, education, race, ideological identification, and income.

Finally, we build a dataset of demographic characteristics recovered from the 2000 and 2010 census at the census tract level and with the Regional Economic Accounts from the Bureau of Economic Analysis. Using these data, we define county-level variables such as total population share, the shares of the population that are female, black, Hispanic, Asian, native American, between 25 and 34 year old, between 35 and 44 years old, between 45 and 54 years old, between 55 and 64 years old and over, rural, high school graduates, college graduates, veterans, employed, labor aged population employed in agriculture and manufacturing, below the poverty line, using Medicare, receiving social security, and crime rates, average household income, number of housing units, infant mortality deaths, and the water use per capita. We also measure growth in county-level GDP. We use these data to measure county-level observable characteristics and to account for potential

[23] When RateWatch reports no interest rate information available for a particular year we interpolate or extrapolate the data to complete missing information. We follow linear interpolation using the information about the interest rate in each county, that is we assume a linear relationship and estimate the value of the missing data for each individual county. The value at $year_t$ of interest rate r_{cst} will be $\frac{r^1_{cst} - r^0_{cst}}{year^1_t - year^0_t} * (year_t - year^0_t) + r^0_{cst}$. Where $year^1_t > year_t$ and $year^0_t < year_t$ and both interest rates are observed. When there is no information for these, we choose the average within the state to estimate the closest points with information r^1_{cst} and r^0_{cst}.

differences between counties in which SBG operates and those in which it does not.

Table 1 column 1 reports that there are 3,114 U.S. counties with deposit data over our time series. The majority of these (2,584) have both local and national banks. About 15% of counties (418) have only local banks and about 5% (93) have only national banks. There are 19 counties in the U.S. with neither local nor national banks. Our setting includes about 40% of total U.S. counties (1,304), the majority of which have both national and local banks. The distribution of counties with different banking structures is similar to the total population of U.S. counties. Columns 2 - 4 summarize the subsample of these counties that are in our analysis.

[TABLE 1 ABOUT HERE]

In Figure IA.1 we show the distribution of local banks (Panel A) and national banks (Panel B) in counties throughout the U.S. Areas without local banks are in the Northwestern U.S. and areas without national banks are concentrated in the central U.S.[24]

3 Methods

In this section, we outline our general empirical strategy and the steps that we take to construct credible counterfactuals for our treatment group. Finally, we discuss how we overcome the limitations of a naive two-way fixed effects estimator by using the Local Projections Approach to Difference-in-Differences Estimation (Dube et al., 2023). Because this approach is relatively new to the empirical literature, we provide a detailed description of how it should be implemented.

3.1 General Strategy

In our empirical analysis, we estimate the effect of SBG entry on the local banking markets in which it enters. Our general strategy is to compare the change in the banking market (i.e., consumer deposits, branching, rate setting, and lending) before and after SBG acquired a TV station and compare it with changes in the banking market in those places where SBG did not operate.

[24] We present summary statistics for the counties in Table IA.I. The level differences are absorbed in the DiD design.

There is heterogeneity in the counties where SBG does not operate, and it might be the case that some of these counties are not fully comparable to the areas where SBG operates. To rule out the possibility of a non-observable shock affecting the control areas that could contaminate our empirical results, we limit our comparison. For each cohort (county-year pair), the comparison groups are those counties where SBG was not able to operate due to the failed acquisition of Tribune Media. This strategy ensures we are comparing each cohort to counties in which SBG was interested in expanding and therefore takes care of the selection problem. For example, SBG may target counties with unobservable characteristics, such as a more risk-averse population or a community with fewer social connections. If this is the case, the counties where the failed acquisitions occurred should also share these attributes.

Moreover, SBG's gradual expansion led to staggered entry in counties over time. Standard empirical methods designed to identify causal effects based on the difference-in-difference model are not well suited in these cases, especially in the presence of heterogeneous treatment effects (Sun and Abraham, 2021; Callaway and Sant'Anna, 2021; de Chaisemartin and d'Haultfoeuille, 2021; Roth, 2022; Goodman-Bacon, 2021; Dube et al., 2023). The problem with a naive two-way fixed effects (TWFE) model arises in the presence of heterogeneous treatment effects over cohort and across units. In this case, the estimator uses forbidden comparisons (i.e., using early treated units as controls for units treated later). Practically speaking, these models are uninformative about pretrends or anticipatory behavior, and, in our setting, coefficients do not capture the outcome dynamics produced by the entry of SBG.

Ideally, we would estimate an event-study two-way fixed effects (TWFE) model with the following equation:

$$Y_{cst} = \alpha_c + \alpha_{st} + \sum_{l=-T, l \neq -1}^{T} \theta_l D^l_{cst} + \epsilon_{cst} \tag{1}$$

Here, Y_{ct} is our outcome of interest at the county level. α_c are county fixed effects, and α_{st} are state-time fixed effects, controlling for state trends affecting financial markets in each county. D^l_{ct} is a dummy variable that takes the value one if SBG operates in county c after l years.

However, with staggered treatment, if treatment effects are dynamic and heterogeneous across adoption cohorts, the coefficient θ_l is biased and does not capture the true effect of SBG.

Table IA.II assesses the extent of this problem based on the decomposition proposed by Goodman-Bacon (2021). We show that using the entire sample, only excluding areas with a long history of SBG operation, the forbidden comparisons would represent 4.9% of all comparisons. Furthermore, using only the Tribune sample, the forbidden comparisons would represent around 15.0%. We arrive at similar conclusions when we estimate the share of ATT comparisons that would enter with negative weights, showing that some ATT would enter with negative weights. This implies that using TWFE in our context would most likely lead to biased estimates.

3.2 Empirical Model: Local Projections Approach to Difference-in-Differences

To account for this bias, we employ the Dube et al. (2023) LP-DiD approach. This method, which subsumes the methods by Callaway and Sant'Anna (2021) and Cengiz et al. (2019), uses local projections to estimate the group-time ATT in the difference-in-difference design, implemented by identifying a cohort of treated counties as the counties in which SBG entered in the same year of operation, regardless of the month. The method is computationally faster than the estimators by Sun and Abraham (2021) and Callaway and Sant'Anna (2021), and allows the weighting scheme for different cohorts to be flexible and extremely transparent. Moreover, it allows us to control for the levels of each outcome variable prior to treatment, which addresses the challenges posed by properties of financial variables, such as complex autocorrelation structure, in estimation.[25] Since the Dube et al. (2023) approach is relatively new to the literature, we offer a step-by-step guide to its implementation, which we hope will be useful in other finance settings.

As a pre-processing stage, we follow Borusyak, Jaravel, and Spiess (2024) and residualize the outcomes from the state-time fixed effects, using only the control observations. We denote these

[25] Importantly, our results are robust to using these estimators as well, which we show in Section 7.

outcomes with a tilde, $\tilde{Y}$. However, not all states where SBG entered had Tribune operations. To avoid dropping these states, we use similar counties in neighboring states as a comparison group when there was no Tribune comparison county in the same state. These states are defined as the closest ones with Tribune operations. State assignments are provided in Table IA.III. Results become even stronger when we restrict the analysis to only those states with Tribune presence, as discussed in Section 7.

We estimate the following equation for each time interval period l five years before and after SBG entry, using a sample of pure controls (i.e., counties where SBG never operated but where Tribune operations were present) and new SBG-entry counties. We estimate the following regression equation at each horizon $l \in \{-5, ..., 0, ...5\}$.

$$\tilde{Y}_{cs,t+l} - \tilde{Y}_{cs,t-1} = \delta_t^l + \beta_l^{LP} \Delta D_{cst} + \Delta \tilde{Y}_{c,t-1} + \varepsilon_{cst}^l \tag{2}$$

where $\tilde{Y}_{cs,t}$ is our residualized outcome of interest, differenced with $\tilde{Y}_{cs,t-1}$ to capture the change in our outcome variables; as a result of the differencing there is no need for unit fixed effects; δ^h are time effects.[26] The ΔD_{cst} allows us to capture the idea that if a unit is treated at some time s, then $D_{cst} = 1$ for $t \geq s$, however, $\Delta D_{cst} = 1$ for $t = s$, and $\Delta D_{cst} = 0$ for $t \neq s$. Each β_l^{LP} can be interpreted as the DiD coefficient at different leads and lags. We choose this method because of its simplicity in directly controlling for pre-treatment values of the outcomes. This is an advantage in our setting given that financial variables often have a time series component, and therefore, it allows us to include $\Delta \tilde{Y}_{c,t-1}$, a direct control for the pre-treatment period, $\Delta \tilde{Y}_{cs,t-1} = \tilde{Y}_{cs,t-1} - \tilde{Y}_{cs,t-2}$.

Under the standard DiD assumptions of no conditional anticipation and conditional parallel trends this method consistently estimates a convex combination of all group-specific effects (τ_g^l).

$$\mathbb{E}(\hat{\beta}_l^{LP}) = ATT(l) = \sum_{g \in G} \omega_g^l \tau_g^l \tag{3}$$

[26]The left hand side would be familiar to those who work with local projections in macroeconomics and finance.

By default, this method recovers a variance-weighted ATT, where the cohort weights ω_g^l are non-negative and depend on the subsample size and treatment variance for each group. We estimate Equation (2) using regression adjustments to calculate an equally weighted average effect, that is numerically equivalent to Callaway and Sant'Anna (2021) when not controlling for the pre-treatment values of the outcomes. This readjustment is directly done using the steps provided by Dube et al. (2023). In sum, the LP-DiD approach allows us to use a weighting scheme that maintains the maximum comparability between treatment and control counties.

The validity of our estimation relies on two key assumptions. First, the set of never-treated counties, i.e. those where Tribune operated but the SBG acquisition attempt failed, could plausibly have been treated. Second, the conditional parallel trends assumption holds; that is, treated and never-treated counties followed similar trends prior to the start of SBG's operations. We present several exercises in Section 7 that support the plausibility of these assumptions and examine how our estimates respond to small deviations from them.

4 Results

This section presents our main findings of the effects of media slant on the consumer preferences for local and national banks (Sections 4.1 and 4.2) and on the actions of local and national banks (Section 4.3). We discuss the mechanism driving these results in Section 5.1.

4.1 Main results: Reallocation of Consumer Deposits

In this section, we test our first hypothesis that media slant influences how consumers use the local banking system by examining two primary banking decisions: deposits and mortgage loan applications. We use the county deposit (loan) share, which is the fraction of total county-level deposits (loan applications) that are held by each bank type in the county and year, to measure whether consumers change how they allocate these activities between local and national banks. The estimated effects represent shifts across bank types in the counties where SBG entered relative to the control counties.

In Figure 2 Panel A, the results indicate that the county-level deposit share at local banks increases by approximately one percentage point (p.p.) per year in years one and two in counties where SBG entered the media market. In event time, the entry year is t=0 such that this shift responds to at least a full year of exposure to media slant. Panel B shows a corresponding reduction in the deposit share at national banks per year over this same time period.[27]

[FIGURE 2 ABOUT HERE]

Our primary deposit measure captures the aggregate allocation of deposits across local and national banks. Because the Summary of Deposits (SOD) reports total branch-level deposits, this measure establishes whether the media shock affects the allocation of bank deposits overall but does not identify which types of depositors account for the reallocation. Thus, our main deposit results establish that deposits shift from national to local banks following SBG entry, but do not allow us to determine which depositors account for the reallocation. The aggregate shift is economically important in its own right: it shows that the effects of media slant extend to the allocation of deposits across financial institutions. Moreover, because SOD deposits include deposits from businesses, municipalities, and other entities in addition to households, the aggregate response could potentially reflect a broader response to the media shock among other types of depositors. To determine whether households themselves respond to the shock, we use information from the Call Reports to construct two measures that more directly capture household deposits.

Our first measure uses information on whether a bank offers household deposit products. All banks in this sample report whether they offer these products. We restrict the SOD data in each year to banks that report offering household deposit products and reconstruct our county-level deposit shares using deposits at branches of these banks. Specifically, we aggregate SOD deposits across branches of household-service banks within each county and calculate the fraction held at local and national banks. This measure does not identify which deposits at these institutions are held by households; rather, it restricts our main deposit measure to institutions that actively serve

[27] Throughout the paper our figures report 95% confidence intervals.

household depositors. Figure 3 shows that, within this sample, deposit shares shift from national to local banks following SBG entry. Thus, the main reallocation result is present among banks that provide household deposit products.

[FIGURE 3 ABOUT HERE]

Our second measure uses the dollar value of household deposits reported in the Call Reports. Reporting of these balances is required only for banks above the applicable reporting threshold, resulting in a more restricted sample of institutions. For reporting banks, we calculate the fraction of the institution's total deposits attributable to household deposit products. Because households may also hold deposits in products that are not separately identified as household deposits in the Call Reports, this measure provides a conservative estimate of the dollar value of deposits attributable to households. Because the Call Reports provide this information at the institution rather than branch level, we assume that the household-deposit fraction is constant across the bank's branches. We apply this fraction to each bank's SOD deposits in a county to estimate the dollar value of household deposits held by that bank in the county. We then aggregate these estimated household deposits separately across local and national banks and calculate each bank type's share of total estimated household deposits in the county.

The results using this second measure provide more direct evidence that households reallocate deposits following the media shock. After SBG entry, the share of estimated household deposits held at national banks declines while the share held at local banks increases. Figure 3 also reports our standard SOD deposit-share estimates over the same restricted time period, allowing us to verify that the main deposit reallocation remains present in the shorter sample used for the household-deposit analysis. The similarity between the SOD and household-deposit results indicates that the reallocation we document reflects changes in household deposits rather than changes driven solely by other types of depositors.

Although the shorter reporting period prevents us from directly examining household deposits for the earlier SBG entry events, the similarity between the household-deposit and aggregate SOD results in the overlapping sample supports interpreting the broader deposit reallocation as household behavior.

4.2 Main results: Reallocation of Credit Demand

In terms of loan application shares, Figure 4 Panel A shows an increasing share of loan applications at local banks. Specifically, the loan application share begins shifting three years after SBG entry, with statistically significant increases of roughly 1 p.p. per year in years four and five. Hence, these shifts lag the changes in deposits that occur immediately following the entry of SBG media. The loan application share at national banks (panel B) exhibits the opposite pattern consistent with the shift in the shares.

[FIGURE 4 ABOUT HERE]

We explore heterogeneity in the loan application results by income, gender, and race.[28] For example, in each county we identify individuals with income above (below) the median income and sum the loan applications of these individuals by bank type. Our analysis then compares the loan application share of high (low) income individuals at local banks. Figure 5 shows a statistically significant increase in the share of loan applications by low income and high income individuals at local banks. The fact that this occurs across income groups suggests a broader change in households' banking preferences rather than a response specific to a particular income group. This pattern is consistent with our model, presented in Section 6. In analyses reported in Section 7, we explore heterogeneity in these results by gender and race and find no differences within these groups.

[FIGURE 5 ABOUT HERE]

In sum, the results from this analysis accord with our primary hypothesis that the change in media slant induced by SBG entry led consumers to shift their banking activity away from national

[28]This heterogeneity by consumer type is available in the HMDA loan data but not in the Summary of Deposits (SOD) data.

banks to local banks. We find this is so, both for deposits and loan applications. These results are robust to different matching, subsample, and estimation choices, which we discuss in detail in Section 7.

4.3 Banking Market: Lending, Branching, and Pricing

In this section we test whether SBG entry affects how banks react to the media shock by examining banks' loan approvals, entry and branching decisions, and deposit and mortgage rates.

4.3.1 Loan Approval Rates and Shares

Loan approval rates are the fraction of total loan applications at local (national) banks that were approved in the county and year. We examine the share of total loan approvals across bank types and find that local banks account for a higher share of loan approvals, which is especially pronounced four years after SBG entry (Figure 6). There is a corresponding decline in the share of loan approvals that occur at national banks. The results show that banks do not change loan approval rates.

[FIGURE 6 ABOUT HERE]

We explore heterogeneity in the loan approval rates by borrower demographics and find no discernible differences at local or national banks based on borrower income (Figure 7), gender, or race (see Section 7 for these results). When we disaggregate the loan approval shares by borrower demographics, the results are statistically and economically significant for both high and low income individuals. Local banks increase their share of loan approvals for these individuals at the same time that national banks reduce their approval shares. Section 7 presents results by gender and race.

[FIGURE 7 ABOUT HERE]

Taken together, these results suggest that local and national banks did not change the ease or difficulty that consumers faced when applying for loans. The number of loan approvals increased at local banks, which matched the increase in loan applications such that loan approval rates remained constant. In addition, these results suggest that, although the media shock may have altered lenders' trust, it did not affect approval rates (Jiang and Lim, 2018).

4.3.2 Pricing Effects

We examine loan and deposit rates to determine whether banks use pricing to attract depositors and borrowers. To measure changes in lending rates, we focus on the average rate for fixed rate mortgages. To measure changes in deposit rates, we focus on the average of the combination of money market, savings account, and 12, 24, and 60 month CDs paid by local and national banks. Figure 8 Panel A shows that mortgage rates increase at local banks and remain unchanged at national banks. Panel B shows that local banks reduce deposit rates by up to 2 percentage points per year in the three years following SBG entry, while national banks do not change their rates. Figure IA.14 shows that when we replace missing observations with zeros, the reduction in deposit interest rates is more muted, but the decline is still visible albeit less significant economically and statistically.

[FIGURE 8 ABOUT HERE]

The results suggest that banks are not using prices to attract local depositors or borrowers. To the extent that banks adjust prices, local banks appear to be taking advantage of the surge in loan demand to increase the mortgage rates they charge to consumers. They may also use the surge in demand as an opportunity to reduce deposit interest. At the same time, we do not see pricing adjustments at national banks which suggests that rates are not increasing in the area overall. It is important to note that national level policies, such as the implementation of several banking regulations in 2011, do not drive our results as these policies apply to both treatment and control counties and hence get differenced out. We explore the effects of these potential confounders in more detail in Section 7.

4.3.3 Banking Networks

We examine whether banks change their presence in the local banking market on the extensive and intensive margins following the entry of SBG. On the extensive margin, we estimate the probability that a bank enters or exits a local banking market in treated counties. Bank entry is defined as opening a branch in a county where the bank did not operate before. Exit is closing all branches in a county where the bank previously operated. Figure (IA.2) shows that neither national nor local banks exhibit a higher propensity to enter or exit a county where SBG entered.

On the intensive margin, we estimate the probability that a bank expands or reduces its branching network within treated counties. Figure IA.3 shows that the probability that local banks open a new branch does not change (Panel A). In Panel B, the probability that national banks open a new branch increases in the first year following SBG media entry, but falls four years after SBG media entry. The magnitude of these effects is small relative to the magnitudes in the pre-treatment period. The bottom panels show that there is no change in the probability that local and national banks close branches.

5 Mechanisms

5.1 Mechanism: Trust in Financial Institutions

In this section, we explore how SBG entry is associated with public trust, which we hypothesize is the mechanism through which uncertainty influences banking choices. Using the Gallup Confidence in Institutions Survey, our analysis spans the period between 2000 and 2024 and covers U.S. adults aged 18 and older across all 50 states and the District of Columbia on various topics, including trust in a range of institutions. We analyze respondents' trust in banks, both large and small businesses, churches, and police. Because this is a cross-sectional survey that is not representative at the county level, we match each individual living in an area exposed to SBG-driven uncertainty to a control respondent living in a Tribune area with the same demographic characteristics such as gender, region, education, race, ideological identification, and income.

Figure 9 reports the results. Panel A shows a reduction in trust of financial institutions among respondents after SBG entry. Trust in big businesses also declines (Panel B), while trust in small businesses does not change (Panel C). Trust in police and churches did not change (Panels D and E, respectively). The survey does not distinguish between bank types. We extrapolate the loss of trust in big business to indicate that individuals would also lose trust in other large institutions. Hence, the decline in confidence in banks and big businesses, together with the absence of a decline for small businesses and other locally observable institutions, is consistent with the mechanism in which SBG erodes trust in more distant institutions.

[FIGURE 9 ABOUT HERE]

Our primary definition of a local bank is based on its geographic footprint. This definition captures an important dimension of local banking relationships. However, although geographic proximity fosters the social links that build trust, alone it may not encompass the organizational characteristics that support relational trust. An essential characteristic of a local bank is the ability of bank decision makers to act on behalf of their customers. In other words, a local bank is partly defined by giving local bankers the authority to act on local information. For some banks, a geographically local bank may belong to a larger organizational structure in which decision authority is less local and more centralized.

We use bank holding company (BHC) structure as a proxy for decision authority outside of the local environment. BHCs can own multiple banking institutions and impose the values of the larger organization on what would otherwise look like a geographically local bank. Within our sample of local banks, we distinguish banks that are not part of a BHC or belong to a BHC that owns only one bank (local organizational form) from those that belong to multi-bank BHCs (nonlocal organizational form). We calculate county-level shares of deposits and loan applications accounted for by these two groups of local banks separately.

Figure 10 shows that the shift toward local banks is concentrated among local banks with local organizational forms. Deposit shares increase following SBG entry for these banks, while there is little corresponding increase for local banks with nonlocal organizational forms. The results are similar for loan applications: the increase in local-bank loan application shares is concentrated among banks with local organizational forms.

[FIGURE 10 ABOUT HERE]

These results help distinguish the relational-trust mechanism from a simple preference for geographically local banks. Geographic proximity proxies for organizational characteristics that allow banks to develop but also sustain relationships with customers. Multi-bank BHC ownership weakens the link because decision authority may be more centralized and less local. The results show that households shift their banking activity toward the subset of geographically local banks in which local relationships and decision authority are more likely to remain closely connected.

Next, we explore whether our results are robust to our primary geographic definition of local banks. Our baseline definition classifies banks operating within a single state as local, but state boundaries do not necessarily reflect the geographic concentration of a bank's operations and relationships. We construct an alternative measure, which classifies banks according to the geographic concentration of their branch networks around the deposit-weighted center of the bank's operations. Figure 11 shows that our results hold using this alternative definition. Deposit shares and loan application shares shift away from non-local banks toward banks with more geographically concentrated branch networks. The results are consistent with geographic proximity capturing characteristics that support local banking relationships.

[FIGURE 11 ABOUT HERE]

The value households place on a bank's discretion should depend not only on their current income but also on the uncertainty they face about future financial needs. Households exposed to greater income uncertainty are more likely to need a bank to take discretionary action on their behalf at some future point in time. We therefore examine whether our results are stronger in areas where households face greater income uncertainty. We construct a county-level measure of wage volatility based on the average within-year standard deviation of quarterly average weekly wages in the private sector and divide counties according to whether this measure is above or below the mean across all counties from 2006 through 2010. We then separately estimate the effects of SBG entry on local-bank deposit and loan-application shares in the two groups.

Figure 12 shows that the reallocation toward local banks is stronger in counties with greater pre-treatment wage volatility. The increase in local-bank deposit shares is more pronounced in high-wage-volatility counties, and the loan-application results exhibit a similar pattern. These results are consistent with households placing greater value on local banking relationships when uncertainty increases the potential need for discretionary actions.

[FIGURE 12 ABOUT HERE]

6 A Simple Model of Relational Trust

Our model is based on the idea of relational contracting. While there are contractible aspects of a banking relationship, trust is a self-enforcing agreement between a household and a bank, sustained by repeated interaction and by the bank's stake in the relationship continuing. Appendix II develops the model in full and derives the implications for pricing, bank responses, and welfare that this version omits. The core result and its intuition are presented here.

6.1 Setup

Two banks, local L and national N, serve a continuum of households in a county over an infinite horizon. Each household i banks with one of them. Both sides discount at $\beta \in (0, 1)$. Following the relational-contract literature we read β as an effective discount factor that combines time preference with the chance that the relationship ends for outside reasons, such as the household moving away. Bank j posts a spread σ_j over its outside return, household i holds a balance b_i, and the bank's rent from the relationship is $\pi_i = \sigma_j b_i$ per period.

The bank provides two things. The first is the posted terms, which are contractible. The second is not. With probability λ each period a *discretionary state* arises in which the household needs something no contract can specify. She has missed a payment and needs forbearance. A fee has been charged that could be reversed. She needs a loan renewed on a signal that would not survive a credit committee. Or she simply needs not to be steered into a product that is good for the bank and bad for her. Let h_i be the value to household i of being accommodated in that state. The banker's choice is unverifiable. If she exploits instead of accommodating, the household gets nothing and the bank captures γh_i, with $\gamma < 1$.

Banks differ in how far the banker's interests diverge from the household's. The banker at bank j weights the household's payoff by $1 - \delta_j$, where $\delta_j \in [0, 1]$ is the *divergence parameter*. We do not read this as altruism. It is the reduced form of a wider relationship between the same people. The officer sits on the same school board as the depositor, the directors are local business owners, and the authority to act on soft information sits with the person who holds those ties rather than with a credit committee elsewhere (Stein, 2002). Each channel lowers δ_j. Throughout, we shall assume that $\delta_L < \delta_N$, which is what our geographic definition of local banks is intended to proxy for.

Given δ_j, the banker's temptation to exploit household i is

$$T_i(\delta_j) \;=\; \gamma h_i - (1-\delta_j)h_i \;=\; h_i\,\Delta_j, \qquad \Delta_j \equiv \delta_j - (1-\gamma). \tag{4}$$

If $\delta_j < 1 - \gamma$ the temptation is negative. The banker chooses to accommodate. We call this *structural* trust. If $\delta_j > 1 - \gamma$ the banker would rather exploit and accommodates only to protect the future. We call this *relational* trust.

6.2 Trust as a relational contract

In the relational case the household has one lever. She can leave. Suppose she leaves for good the first time she is exploited. Then in a discretionary state the banker weighs the gain from exploiting today against the rent stream she gives up, $\beta\pi_i/(1-\beta)$.[29] She accommodates if and only if

$$\boxed{\frac{\beta}{1-\beta}\pi_i \;\geq\; h_i\,\Delta_j} \qquad \Longleftrightarrow \qquad \chi_i \equiv \frac{h_i}{\pi_i} \;\leq\; \frac{\beta}{(1-\beta)\,\Delta_j} \equiv \mathscr{H}_j. \tag{5}$$

The threat to leave is never carried out in equilibrium. A household who expects to be exploited leaves before it happens whereas one who is accommodated has no reason to go. The threat exists to make accommodation credible.

We call χ_i the household's *trust intensity* and, $\mathscr{H}_j$ the bank's *trust capacity*. Trust intensity is the household's stake in discretion per dollar of rent she generates. Trust capacity is the largest such stake the bank can credibly promise to honor. It rises with patience and falls with divergence, and because the discount factor is common, the ordering $\mathscr{H}_L > \mathscr{H}_N$ follows from $\delta_L < \delta_N$ alone.

On the household's side, the expected flow payoff from bank j is

$$u_{ij} \;=\; -\sigma_j b_i \;+\; \lambda h_i\,\mathbf{1}\{\chi_i \leq \mathscr{H}_j\} \tag{6}$$

She pays the spread and, if the bank can credibly promise it, receives accommodation worth λh_i in expectation. She chooses the bank with the higher u_{ij}. Her problem is the same every period and switching is free, so discounting does not change the comparison.

Equation (5) restricts what a bank can promise but not whom it serves. A household with $\chi_i > \mathscr{H}_j$ still has her deposit accepted and her mortgage application scored on hard information. What she does not get is accommodation, and it is the loss of that that sends her to another bank. The model predicts sorting on trust and no credit rationing, which is what Figures 6 and 7 show.

The households closest to the constraint are those with large h_i relative to π_i, that is, those for whom discretion matters most per dollar of business they bring. That ratio varies across households for reasons that cut across income. Stakes scale with exposure, since forbearance on a large loan is worth more than on a small one, so what remains is variation in how much of a household's finances

[29] She also gives up the payoff she gets from accommodating in future discretionary states, $\lambda(1-\delta_j)h_i$ per period. This adds a second-order term to the constraint and changes none of the comparative statics. Appendix II.2 includes it.

runs through the banker's judgment, which depends on income volatility, self-employment, and the availability of substitutes more than on the level of income. We treat χ_i as heterogeneous and do not assume it varies with income.

6.3 The media shock

Households do not observe δ_j. They infer it from a private local signal z_{ij}, with precision τ_{ij}, and from a public signal m carried by the news media about how far institutions are aligned with ordinary people, with precision τ_m. The posterior mean is

$$\hat{\delta}_{ij} \;=\; \omega_{ij}\, m + (1-\omega_{ij})\, z_{ij}, \qquad \omega_{ij} = \frac{\tau_m}{\tau_m + \tau_{ij}}. \tag{7}$$

A household can see how a local bank behaves. She cannot see how a national bank behaves toward people like her in other places. So $\omega_{iL} \ll \omega_{iN}$. This is the mechanism in Gentzkow and Shapiro (2006a). Slant is disciplined where readers can check and undisciplined where they cannot.

SBG's entry raises m. The county's news spends more time on national affairs and presents national institutions as dysfunctional and indifferent to ordinary people. By (7), $d\hat{\delta}_N = \omega_{iN}\, dm \gg d\hat{\delta}_L$. Households revise their view of the national bank and barely revise their view of the local bank.

Proposition 1 (Reallocation)**.** *A rise in $\hat{\delta}_N$ lowers the national bank's trust capacity from $\hat{\mathscr{H}}_N$ to $\hat{\mathscr{H}}'_N < \hat{\mathscr{H}}_N$. Households with $\chi_i \in (\hat{\mathscr{H}}'_N, \hat{\mathscr{H}}_N]$ lose the national bank's trust while retaining the local bank's, and shift toward it. Hence* (i) *the local share rises and the national share falls by the same amount;* (ii) *aggregate county deposits and applications are unchanged;* (iii) *the shift is concentrated among high-χ_i households.*

Parts (i) and (ii) are Figures 2 and 14. Part (iii) identifies the movers as the households for whom (5) was closest to binding at the national bank. Trust intensity is not observed, and Figure 5 shows that the reallocation does not differ across income brackets. That is what the model implies if stakes scale with exposure, and it rules out the reading in which low-income households simply believe the news more. Everyone revises the same belief. What differs across households is how much they have at stake in the bank's discretion. The lag between deposits and mortgage applications follows the same way. A household moves her deposits when her belief changes and her mortgage when she next applies for one (Appendix II.3).

Coverage that makes the world feel more dangerous may also raise a household's belief that she will need accommodation, without changing what she believes about the bank. That raises the value of trust, λh_i, at both banks, and pushes households who were staying at the national bank for its amenities toward the local one, which could already accommodate them. It does not lower trust in anything, so it cannot account for the fall in confidence in banks in Figure 9. That result says beliefs about alignment moved. The two channels are complementary. Appendix II.3.3 explains how they differ.

6.4 Predictions and evidence

The model was built to explain the reallocation. However, it is rich enough to pin down several further features of the results. We list them here.

Prediction	**Evidence**
Local share rises and national share falls one-for-one	Fig. 2
Aggregate county deposits and GDP do not move	Fig. 14
Deposits respond immediately, applications with a lag	Figs. 2 vs. 4
Approval *rates* unchanged at both banks	Figs. 6, 7
Approval *shares* track application shares	Fig. 6
Confidence falls for banks and big business, not small business, churches, or police	Fig. 9
Effect concentrated in local banks outside multi-bank holding companies	Fig. 10
Reallocation stronger where households more often need discretion	Fig. 12

The first three rows come from Proposition 1. The remaining five are each a consequence that the model imposes.

No rationing. The approval decision uses hard information, such as credit score, loan-to-value, and debt-to-income, and is made before any discretionary state arises. The trust constraint plays no role in it. A household the national bank cannot credibly promise to accommodate still has her application scored the same way as any other applicant with her characteristics. Approval rates should therefore not change at either bank, and Figures 6 and 7 show that they do not. Figure 7 reports rates within income groups, which rules out a flat aggregate concealing a shift in who applies.

Approval shares are different. Applications move to the local bank, the local bank approves the same fraction of them as before, and so its share of county originations rises by the same amount as its share of applications, as shown in Figure 6. Had distrust worked on the bank's side instead, with national banks tightening on borrowers they expected to lose or local banks loosening to absorb the inflow, approval rates would have moved in opposite directions at the two banks.

Which local banks gain. What matters is δ_j, and geography is only a proxy for it. A local bank owned by a multi-bank holding company may not have direct decision authority. Instead decisions may be made higher in the organizational structure by individuals with no residual claim on the bank and less social exposure to its customers. That raises δ within the class of banks our geographic definition calls local (Stein, 2002). The model predicts that the shift toward local banks is concentrated in those outside such holding companies. Figure 10, which we report as a robustness check is under the model a direct test and it goes the predicted way.

Where discretion matters more. The value of trust is λh_i, so the more often a household needs the banker's judgment, the larger the gap between a bank that can accommodate her and one that cannot, and the more of the households who lose the national bank's trust move. Counties with more volatile wages are counties where households more often need forbearance, a fee reversed, or a renewal on judgment, so the model predicts a larger reallocation there. Figure 12 shows it, for both deposits and applications. Volatile income may raise the stake h_i as well as the frequency λ; both enter through the product, and the prediction is the same.

7 Robustness

7.1 Confounding Factors and Alternative Methods

In this section, we report the robustness of our results to potential confounding factors. We use alternative estimators, truncated samples, and violations of the parallel trends assumption to explore the robustness of our findings.

A potential concern is that our results coincide with the widely publicized misconduct at Wells Fargo during our sample period. Because Wells Fargo is a large national bank, households' responses to the scandal could generate a shift from national to local banks that is unrelated to the change in media slant induced by SBG entry. To examine this possibility, we exclude Wells Fargo from the construction of our deposit and loan-application measures and re-estimate our main results. Figure 13 shows that our results hold after excluding Wells Fargo in our sample of national banks.

Post-financial-crisis regulatory changes resulted in large banks significantly reducing their provision of mortgage credit over the 2011 – 2015 period, leaving a gap that was filled by smaller banks.[30] It is possible that these concurrent regulatory changes affect our results. To address this concern, we identify bank holding companies that were affected by Federal Reserve stress tests over this period.[31] We identify banks that were stress-tested as of 2010 and estimate county-wide mortgage market shares of stress-tested banks over our sample period. Affected counties are those with high exposure (above-median). If the stress-test regulations drive our results, the shift in loan applications and deposits to local banks should be particularly pronounced in high-exposure areas. Figure IA.4 Panels A and B show that both high and low-exposure counties exhibit an increase in deposit shares at local banks. Panels C and D show that the loan application shares increase at local banks in low-exposure counties rather than high-exposure counties.

[30] This could also affect deposits via deposit requirements for mortgages.

[31] As of 2010, stress testing was formally integrated into the Federal Reserve's supervisory assessment of BHC capital adequacy on an on-going basis. This integration occurred through two separate, though related, channels: the Dodd-Frank Act stress tests (DFAST) and the Comprehensive Capital Analysis and Review (CCAR). The Federal Reserve publishes an annual report of the assessment framework, which lists bank holding companies that underwent stress tests in a given year. We track the list of banks from 2010 to 2019.

Finally, we analyze whether SBG entry is correlated with changes in the overall local economy. To do so, we examine local GDP per capita and the total bank deposits per capita. Figure 14 reports that overall deposits and GDP did not change in the counties where SBG entered relative to control counties.

[FIGURE 14 ABOUT HERE]

For our main analysis, we use the Dube et al. (2023) estimator. In this section, we employ three alternative estimators to estimate causal effects in difference-in-difference settings with staggered adoption. The first is the Callaway and Sant'Anna (2021) (CS) procedure, which is the standard estimator for staggered differences-in-differences analysis. It estimates group-time specific ATT, avoiding forbidden comparisons and aggregating them as averages for each period.[32] The second is the Sun and Abraham (2021) estimator, which captures the cohort-specific average difference in outcomes relative to never being treated and not yet being treated, in other words, the cohort average treatment effects on the treated (CATT). The third is the de Chaisemartin and d'Haultfoeuille (2021) (CDH) estimator, where the ATT measures the instantaneous treatment effect of transitioning from being untreated to treated.

Figure IA.5 reports the deposit share results using the LP-DiD method (dotted line), the AS method (diamond line), the CS method (triangle line), and the CDH method (square line). Regardless of which estimator we use, both the magnitude and statistical significance of our results are persistent for both local and national deposit shares.

Our estimation relies on the fundamental assumption that the set of never-treated counties, i.e., counties where Tribune operated but the SBG attempted acquisition of Tribune failed, could have been treated. However, these areas might differ from those where SBG successfully entered, particularly since the planned acquisition would have occurred later, potentially leading to discrepancies in county characteristics. To evaluate this possibility, we analyze the overlap in observable characteristics between the two types of counties. First, we estimate a LASSO model following

[32] Dube et al. (2023) show that the local projections estimation with reweighting is numerically equivalent to this procedure. Thus, this robustness check involves estimating the effect without controlling for the lag of the outcome variable.

Belloni, Chernozhukov, and Hansen (2014), where the dependent variable indicates whether the county was affected by SBG's entry. We then identify the variables that best predict treatment, use these variables to estimate the propensity score, and follow Crump, Hotz, Imbens, and Mitnik (2009) to truncate the sample, thereby increasing overlap. Lastly, we re-estimate our baseline model on the common support.

Figure (IA.6) reports these results. Figure IA.6 Panels (a) and (b) repeat our main analysis on a propensity score matched sample of treatment and control counties. Here, the magnitude of the treatment effect, roughly a 1% increase (decrease) in local (national) deposit share per year, is consistent with the main results, but the effects persist and are statistically significant five years following SBG entry. In Panel B, the national deposit share declines by almost 2% per year over the five year treatment window. When we limit the sample of treatment and control counties to those located in states with both Tribune and SBG media, the magnitude of the treatment effect is almost double the unconditional treatment effect (roughly 1.8% per year) and persists for five years after SBG media entry (Figure IA.6, Panels (c) and (d)). The results in both panels are statistically significant in the five years following SBG entry.

Finally, despite the graphical evidence that there do not appear to be parallel trend violations, this may be due to the fact that the coefficients for banking market outcomes before the entry are around zero and not significant. To assess the validity of our main identifying assumption (that potential outcomes after treatment are the same for treated and never-treated cohorts), we evaluate the robustness of our findings to the presence of moderate linear and non-linear deviations from the parallel trends assumption. We follow the partial identification method proposed by Rambachan and Roth (2023).

Figure IA.7 reports the results. These graphs report the 90% confidence intervals for our parameters of interest after accounting for potential deviations from the parallel trends assumption. They display the original confidence intervals from our estimation, followed by adjustments that incorporate possible violations of parallel trends. Specifically, we present results that allow for a linear deviation (M = 0) based on pre-treatment estimates, as well as deviations that permit the trend to vary in both magnitude and direction across consecutive periods (M>0). We allow the maximum change in the trend between successive periods to be as large as the estimated pre-trend that has an 80% probability to detect such changes given the precision of pre-treatment estimates. These graphs demonstrate that our conclusions remain robust to these deviations and that the estimated effects are significantly different from zero.

Lastly, we extend our analysis of loan applications and approval rates to different borrower demographics which include the male and the white populations in counties. In Figures IA.8 and IA.9, all panels show that the magnitude and direction of loan applications by gender and by race exhibit similar patterns at local and national banks although they are statistically weaker.

When we disaggregate the results by gender and race, there are no discernible differences in loan approval rates at local and national banks. These results are reported in Figures IA.10 and IA.11, respectively.

8 Conclusion

This study examines whether media slant affects how households use banks. The banking sector allows us to document a connection between media, trust, and households' choice of depository and lending institutions. Exploiting the staggered expansion of SBG and the failed Tribune acquisition, we find that households reallocate their banking activity from national to local institutions following SBG entry. Deposit shares shift starting one year from entry and measures constructed from Call Reports data indicate that this reallocation reflects household deposits. Mortgage applications subsequently shift in the same direction. These changes reflect household demand rather than changes in banks' credit supply. Banks do not respond to the shock by entering (exiting) banking markets, expanding (contracting) their branching footprint, or changing loan approval rates.

Our results suggest that changes in relational trust are a mechanism underlying this reallocation. Following SBG entry, survey respondents report lower confidence in banks and large businesses, while confidence in small businesses and other locally oriented institutions does not decline. The reallocation occurs across income groups, suggesting a broader change in households' banking preferences rather than a response specific to a particular income group. The reallocation is stronger in counties with greater pre-treatment wage volatility, consistent with households placing greater value on banking relationships when uncertainty increases the potential need for discretionary interactions. Moreover, the effects are concentrated among geographically local banks with organizational structures that preserve local decision-making authority and are strongest for banks with geographically concentrated branch networks. Together, these results suggest that households respond to media-driven changes in trust by shifting toward institutions for which local information, relationships, and decision authority can support discretionary interactions with customers.

These findings highlight a broader economic role for trust in household finance. Media slant can alter financial relationships even when the information households receive is not directly about the financial institutions themselves and even when the contractible terms offered by those institutions do not improve. The resulting reallocation can therefore have welfare consequences: if media slant causes households to revise their beliefs about institutions without changing those institutions' underlying behavior, households may accept less favorable financial terms in exchange for relationships they perceive as more trustworthy. More broadly, our results demonstrate that information intermediaries can affect not only beliefs but also the way that households use the banking system. While our findings primarily pertain to the U.S. broadcast media and the banking system, they offer valuable insights into the effects of information intermediaries on fundamental consumer decisions.

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Table 1: County Banking Structure - Local and National Banks

	Complete sample	Tribune sample		
		Treated	Control	Total
Both (National and Local)	2584	714	356	1070
Local only	418	148	29	177
National only	93	43	7	50
Neither (National and Local)	19	7	0	7
Total	3114	912	392	1304

Table 1 summarizes the banking market of counties in our sample as of 2011. Local banks are those operating in only one state and national banks are those operating in more than one state. The complete sample is all counties in the U.S. with available deposit data. The "Tribune Sample" consists of counties where SBG either entered the media market or attempted to enter between 2012 and 2017. Treated counties are those where SBG entered and control counties are those where entry was blocked by regulators.

Table 2: Effect of SBG on deposit and loan application shares

	Deposit Shares			Loan Application Shares		
	Local Banks	National Banks	N	Local Banks	National Banks	N
	(1)	(2)	(3)	(4)	(5)	(6)
Before SBG entry						
SBG $\times \mathbb{I} \cdot (t-5)$	-0.001	-0.001	6001	-0.003	0.004	6001
	(0.008)	(0.007)		(0.007)	(0.007)	
SBG $\times \mathbb{I} \cdot (t-4)$	0.001	-0.003	6393	-0.007	0.008	6393
	(0.006)	(0.006)		(0.007)	(0.007)	
SBG $\times \mathbb{I} \cdot (t-3)$	0.002	-0.003	6785	-0.008	0.004	6785
	(0.005)	(0.005)		(0.006)	(0.007)	
SBG $\times \mathbb{I} \cdot (t-2)$	0.002	-0.003	7177	-0.006	0.005	7177
	(0.003)	(0.003)		(0.005)	(0.005)	
After SBG entry						
SBG $\times \mathbb{I} \cdot (t=0)$	0.004	-0.005	7569	-0.002	-0.002	7569
	(0.003)	(0.003)		(0.005)	(0.005)	
SBG $\times \mathbb{I} \cdot (t+1)$	0.009^{**}	-0.010^{**}	7177	0.005	-0.013^{*}	7177
	(0.004)	(0.004)		(0.006)	(0.007)	
SBG $\times \mathbb{I} \cdot (t+2)$	0.012^{**}	-0.013^{**}	6785	0.017^{**}	-0.021^{***}	6785
	(0.006)	(0.006)		(0.008)	(0.008)	
SBG $\times \mathbb{I} \cdot (t+3)$	0.011	-0.010	6393	0.023^{***}	-0.026^{***}	6393
	(0.007)	(0.008)		(0.009)	(0.009)	
SBG $\times \mathbb{I} \cdot (t+4)$	0.016^{**}	-0.014	6001	0.028^{***}	-0.031^{***}	6001
	(0.008)	(0.009)		(0.009)	(0.009)	
SBG $\times \mathbb{I} \cdot (t+5)$	0.015	-0.013	5525	0.031^{***}	-0.032^{***}	5525
	(0.009)	(0.010)		(0.010)	(0.010)	
Average pre SBG entry	0.001	-0.002	6001	-0.006	0.005	6001
	(0.005)	(0.005)		(0.005)	(0.005)	
Average post SBG entry 0 to 4 years	0.010^{**}	-0.011^{*}	6001	0.015^{**}	-0.019^{***}	6001
	(0.005)	(0.006)		(0.006)	(0.006)	
Average Dep. Var.	0.56	0.44		0.28	0.72	
Std. Dev. Dep. Var.	0.337	0.337		0.204	0.207	
State-Year FE	✓	✓		✓	✓	

This table reports coefficient estimates from an event study analysis of the effects of SBG entry on the loan applications received by local and national banks. We use the Dube, Girard, Òscar Jordà, and Taylor (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Columns 1 and 2 report deposit shares as the fraction of total dollar deposits held at branches. Columns 4 and 5 report the loan application shares as the fraction of the total number of loan applications received by branches. The shares are relative to all branches of local banks (columns 1 and 4) and national banks (columns 2 and 5). Columns 3 and 6 report the total number of observations used on the local estimation of the effects. The observation count differs due to the projection method that optimizes the estimate for each event time individually. Event time zero denotes the first non-complete year of SBG entry in a county. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Effects on local banks

	Deposit (Millions)		Loan Application	
	Average	Total	Average	Total (Th.)
	(1)	(2)	(3)	(4)
SBG $\times \mathbb{I} \cdot (t = 0)$	0.007	6.737	5.236	4.738
	(0.049)		(13.887)	
SBG $\times \mathbb{I} \cdot (t + 1)$	0.021	18.686	10.417	9.428
	(0.147)		(25.679)	
SBG $\times \mathbb{I} \cdot (t + 2)$	0.030	27.336	13.078	11.836
	(0.229)		(32.030)	
SBG $\times \mathbb{I} \cdot (t + 3)$	0.030	26.891	11.838	10.714
	(0.238)		(30.114)	
SBG $\times \mathbb{I} \cdot (t + 4)$	0.047	42.443	17.239	15.601
	(0.384)		(41.565)	
SBG $\times \mathbb{I} \cdot (t + 5)$	0.043	35.338	18.362	15.075
	(0.311)		(45.600)	
Totals (Year 1 to 5)	0.030	157.430	12.606	67.392
	(0.250)		(33.183)	

This table reports coefficient estimates from an event study analysis of the effects of SBG entry on the dollar value of deposits and the total number of loan applications received by local banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as level changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Columns 1 and 3 report coefficient estimates. Columns 2 and 4 report the total dollar value of deposits and total number of loan applications. The observation count differs due to the projection method that optimizes the estimate for each event time individually. Event time zero denotes the first non-complete year of SBG entry in a county. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

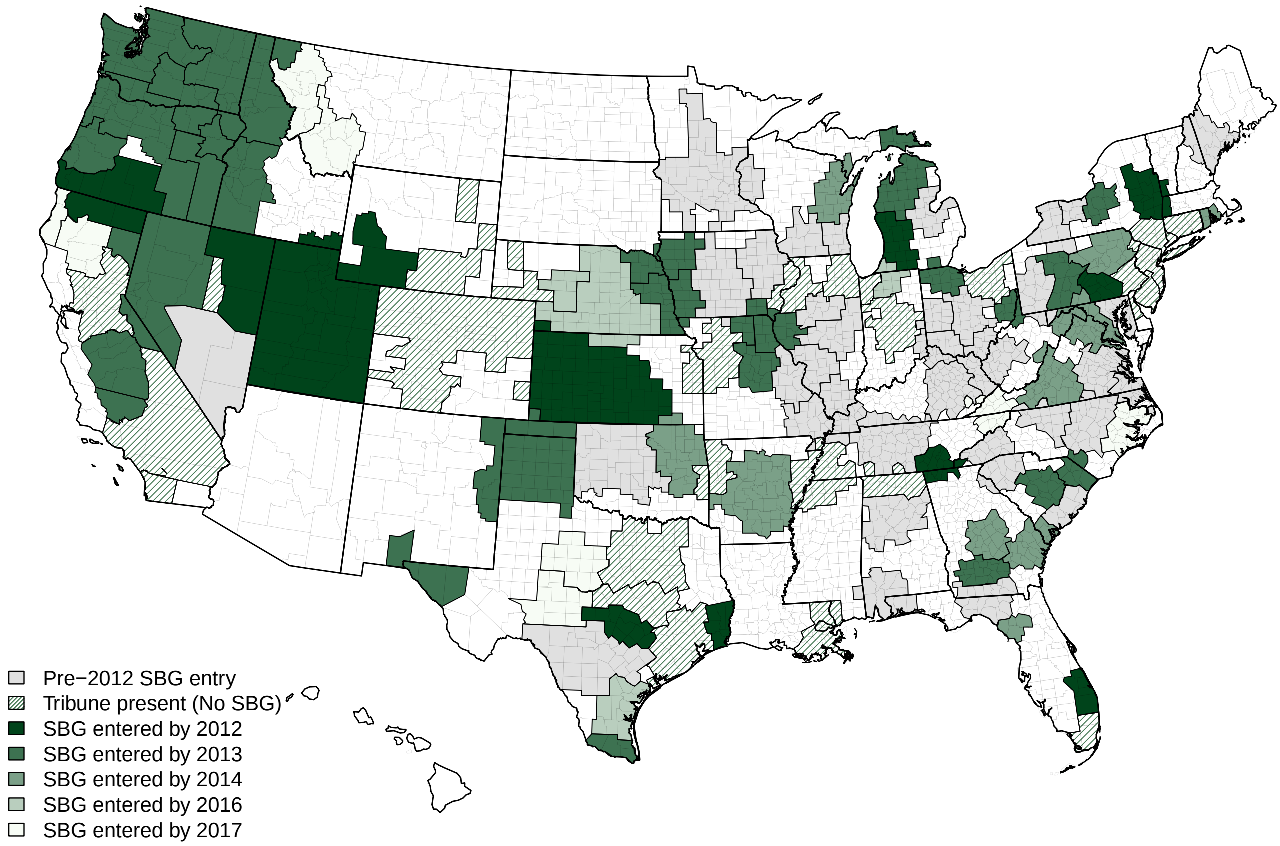
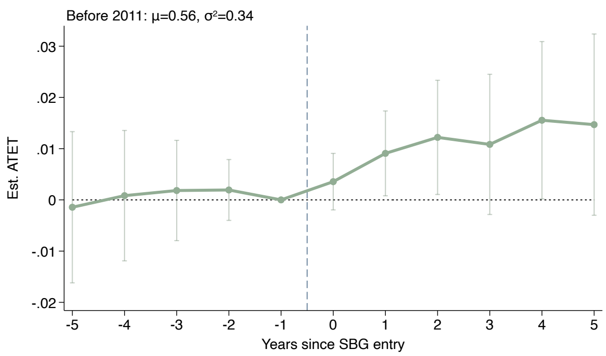


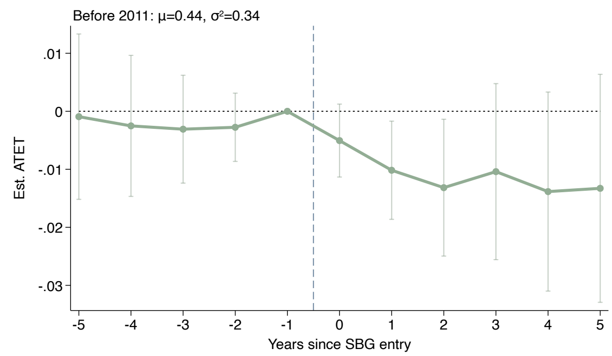
Figure 1: SBG Acquisition History

Figure 1 presents the distribution of SBG operations and its acquisitions over time and across regions of the U.S. in solid shaded areas. Areas with lines denote regions where Tribune Media operated and Sinclair was unable to enter through acquisition.

Figure 2: Deposit Shares



(a) Local Banks

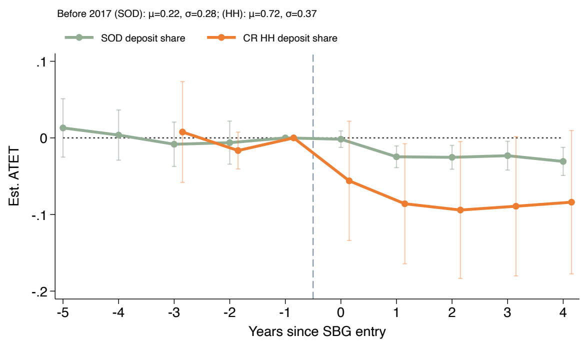


(b) National Banks

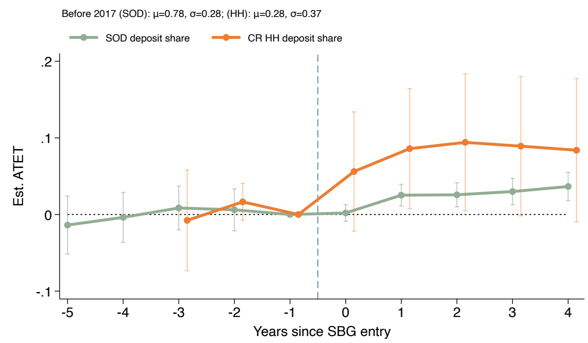
Figure 2 plots coefficient estimates from an event study analysis of the effects of SBG entry on the deposits held by local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Deposit shares are the fraction of total dollar deposits held at branches of local banks (Panel A) and national banks (Panel B). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 3: Deposit Shares: Household Deposits (Call Reports)

Panel A: Household Deposit Balances

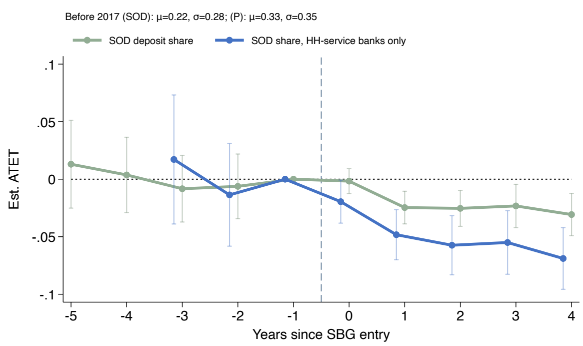


Local Banks

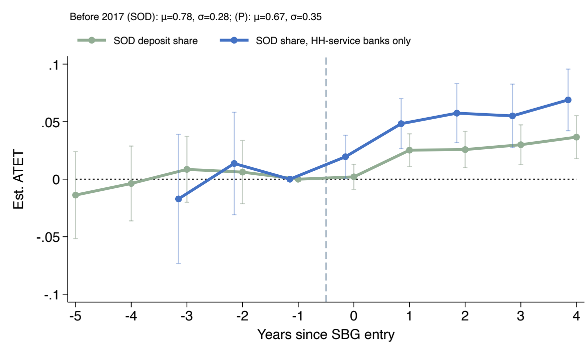


National Banks

Panel B: Banks Offering Household Deposit Products



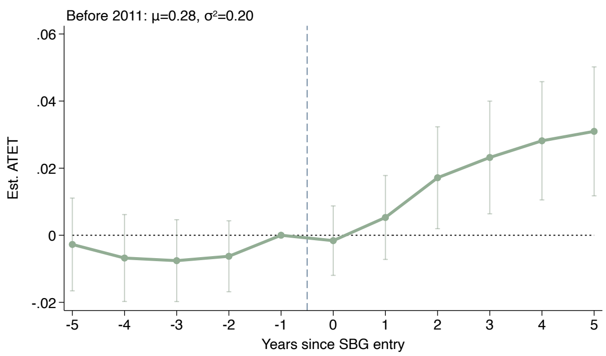
Local Banks



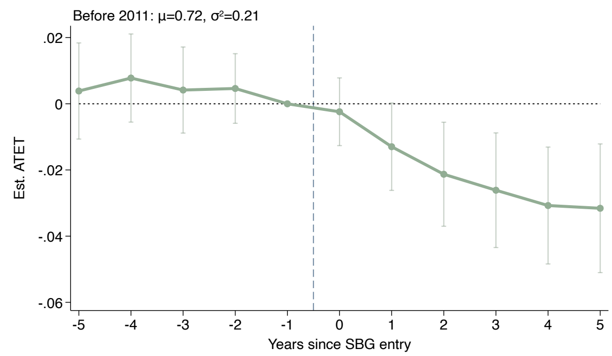
National Banks

Figure 3 plots coefficient estimates from an event study analysis of the effects of SBG entry on household deposits held at local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. We use two measures to identify household deposits. The first uses household deposits reported in the Call Reports to calculate the share of household deposits held at local and national banks (Panel A). The second identifies banks that offer household deposit products and calculates local and national deposit shares using FDIC Summary of Deposits (SOD) deposits only at these banks (Panel B). Household deposit shares are the fraction of estimated county-level household deposits held at local banks (left) and national banks (right). Because the Call Report household-deposit measure is available for a more limited period, the analysis covers a shorter sample than our main deposit analysis. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.]

Figure 4: Loan Application Shares



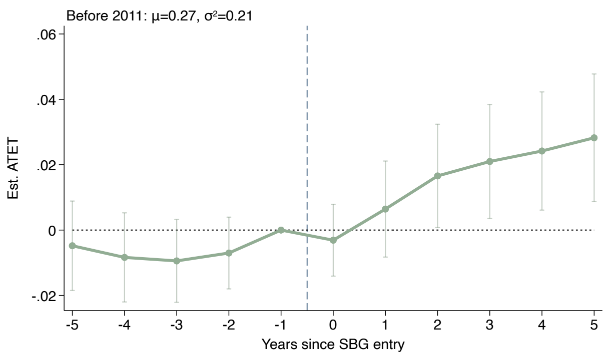
(a) Local Banks



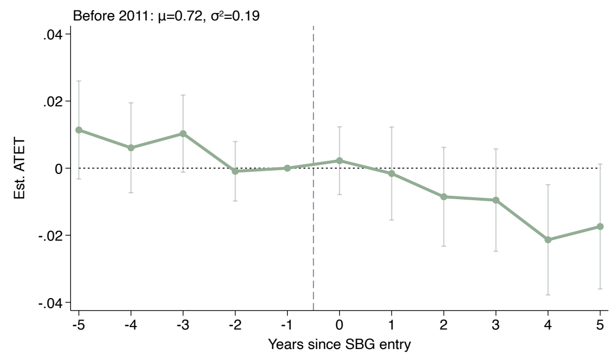
(b) National Banks

Figure 4 plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan applications received by local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Loan application shares are the fraction of the total number of loan applications received by branches of local banks (Panel A) and national banks (Panel B). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

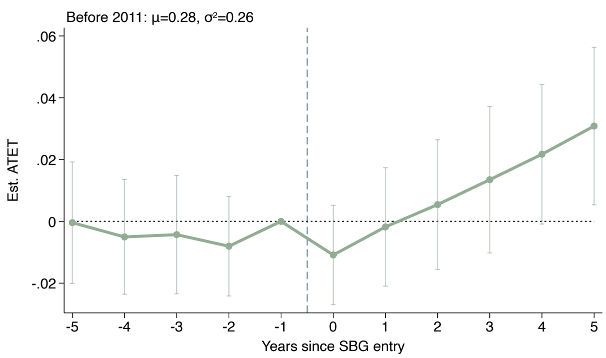
Figure 5: Loan Application Shares by Income



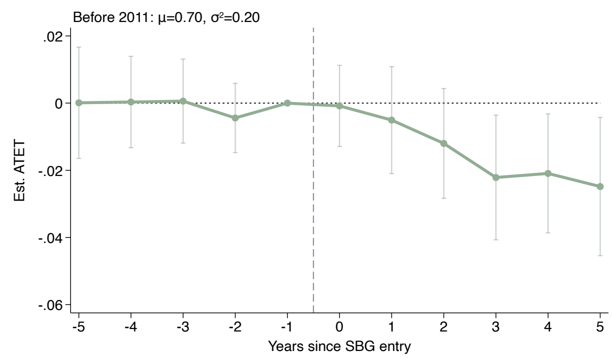
(a) Local Banks – High Income



(b) National Banks – High Income



(c) Local Banks – Low Income

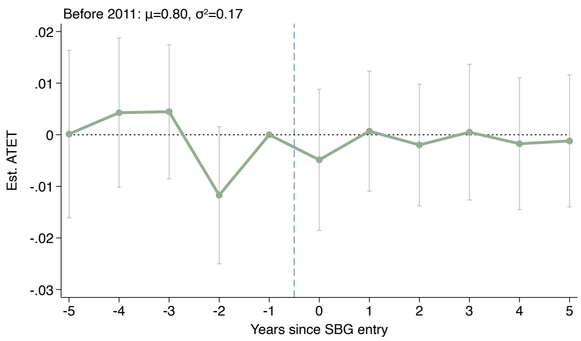


(d) National Banks – Low Income

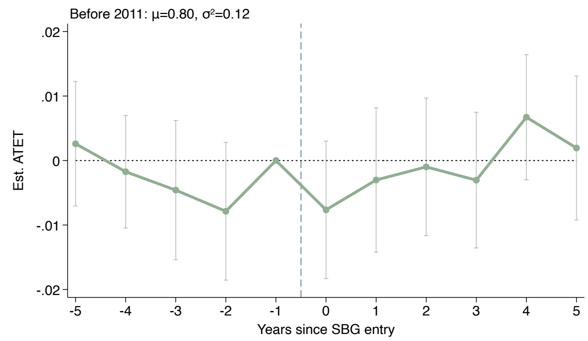
Figure 5 plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan applications received by local and national banks based on an applicant's income. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. High (low) income applicants are those with above (below) median income at the county level. Loan application shares are the fraction of the total number of loan applications received by branches of local banks (Panel A – high income and Panel C – low income) and national banks (Panel B – high income and Panel D – low income). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 6: Loan Approval Rates and Shares

Panel A: Loan Approval Rates

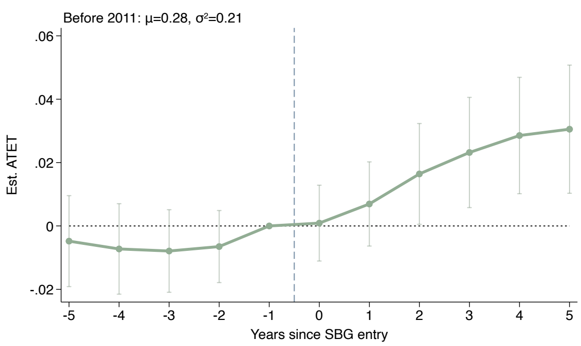


Local Banks

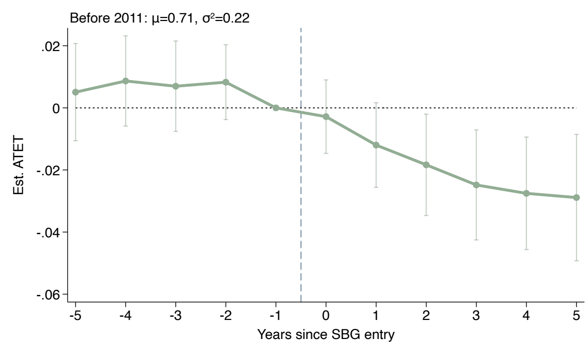


National Banks

Panel B: Loan Approval Shares



Local Banks

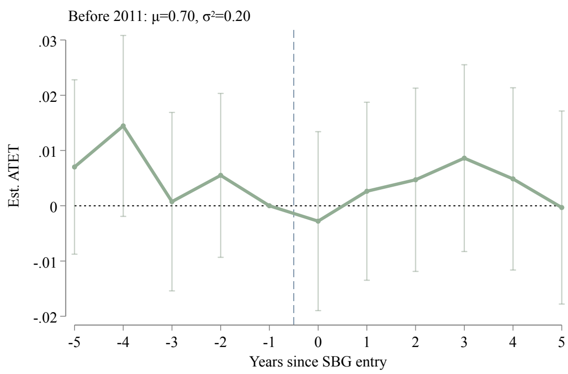


National Banks

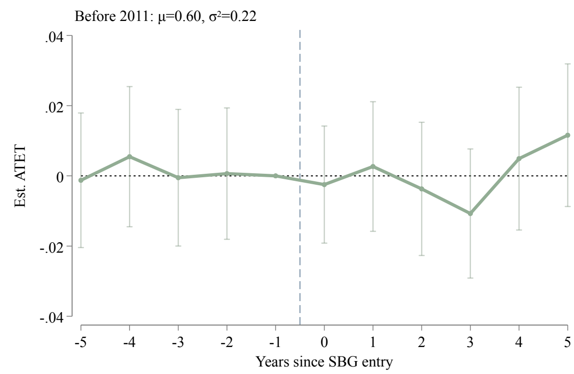
Figure 6 plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan approval rates of local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. The loan approval rate is the fraction of loan applications that are approved by local banks and national banks (Panel A). The share of approved loans is the fraction of total loan approvals by local and national banks (Panel B). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 7: Loan Approval Rates and Shares by Income at Local Banks

Panel A: Loan Approval Rate

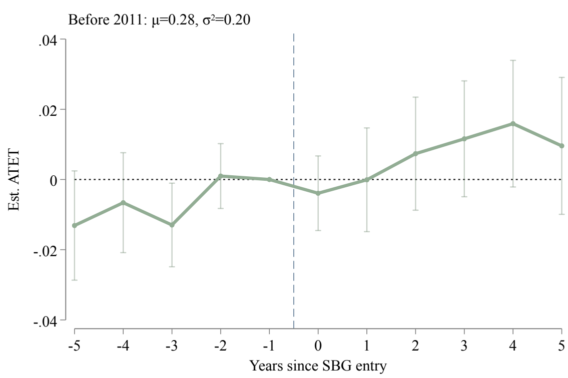


High Income

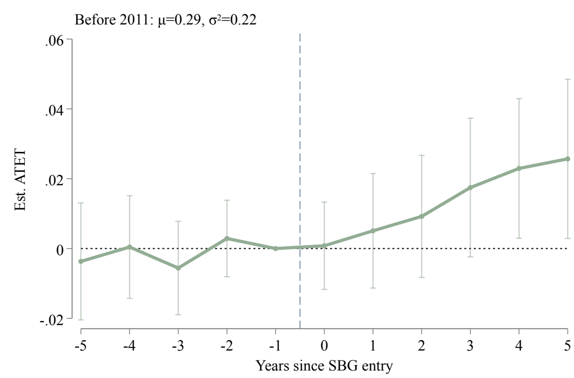


Low Income

Panel B: Loan Approval Shares



High Income

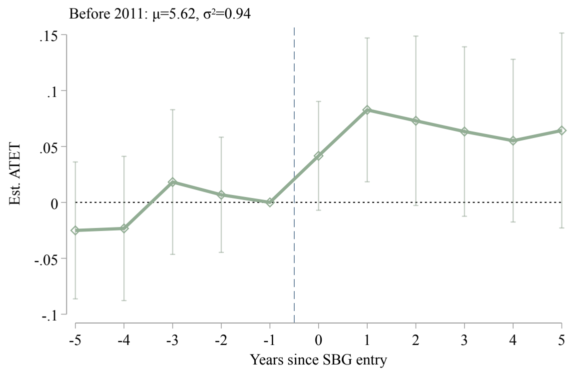


Low Income

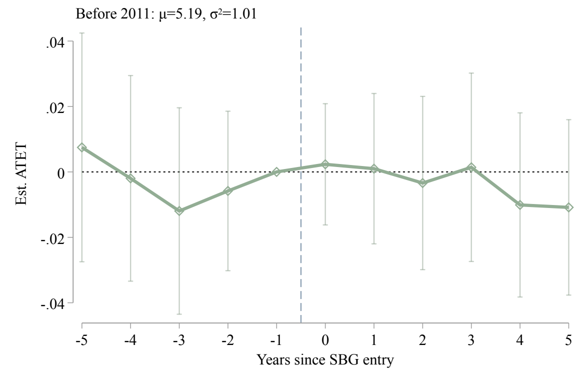
Figure 7 plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan approval rates of local banks based on an applicant's income. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. High (low) income applicants are those with above (below) median income at the county level. The loan approval rate is the fraction of loan applications received that are approved by local banks (Panel A). The share of approved loans is the fraction of total loan approvals by local banks (Panel B). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 8: Bank Pricing: Mortgage Rates and Deposit Rates (Interpolated)

Panel A: Mortgage Rate

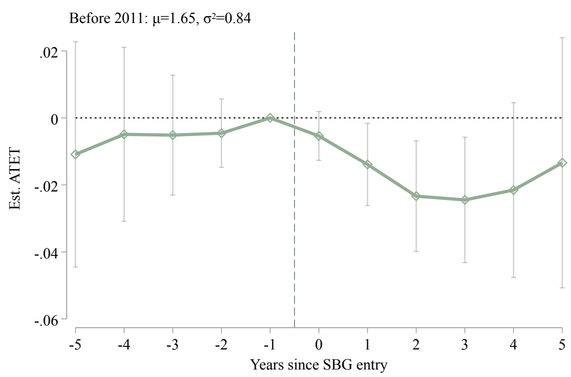


Local Banks

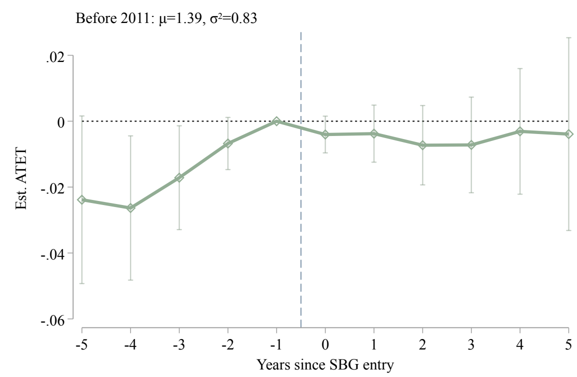


National Banks

Panel B: Deposit Rate



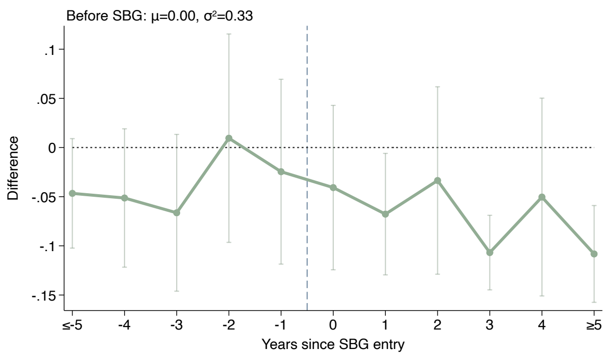
Local Banks



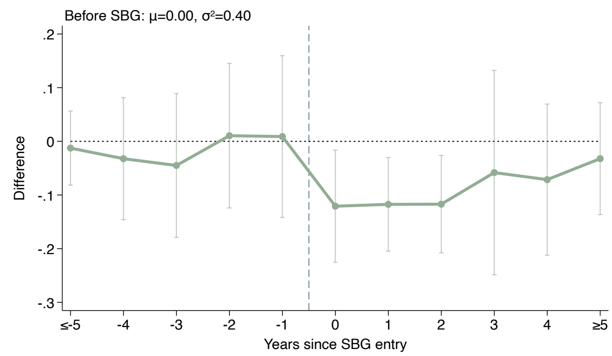
National Banks

Figure 8 plots coefficient estimates from an event study analysis of the effects of SBG entry on the average mortgage rates charged and deposit rates paid by local and national banks. Mortgage rates are the average of 10-, 15-, 20-, and 30-year fixed-rate mortgages. Deposit rates are the average across money market, savings account, and 12, 24, and 60 month CDs. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. To account for county-years with missing mortgage data, the figure presents results with the mortgage rate interpolated at the county then state-levels and include an indicator variable for missing county-year pairs. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

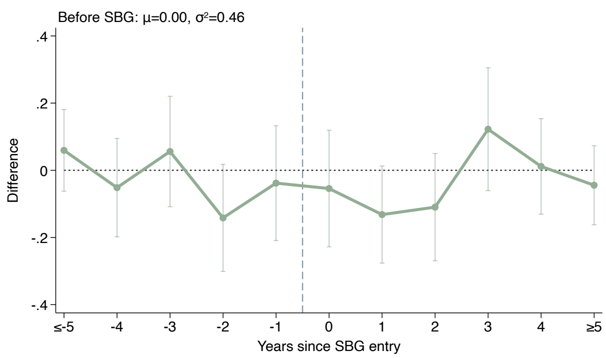
Figure 9: Trust: Gallup Confidence in Institutions Survey



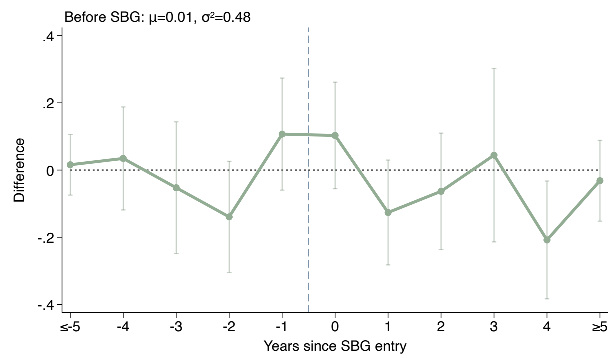
(a) Banks



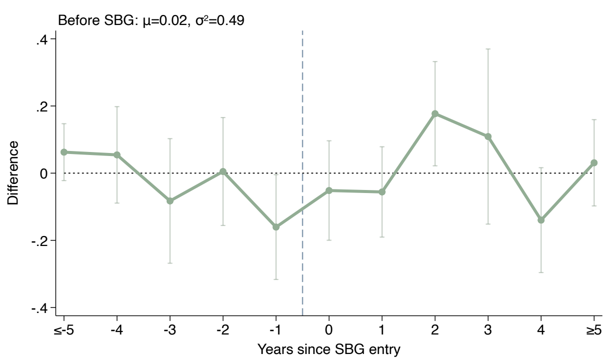
(b) Big Business



(c) Small Business



(d) Police

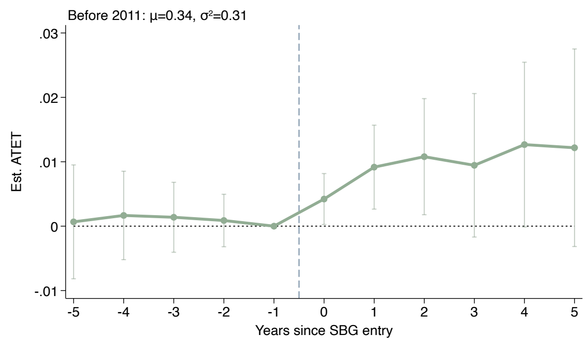


(e) Church

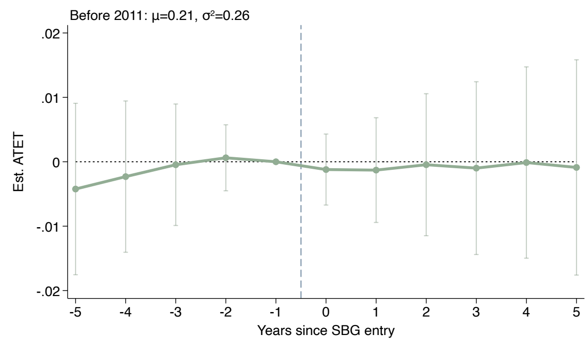
Figure 9 plots pseudo-event study of the effect of SBG entry on respondents' trust in institutions, following Kleven (2026). We match each Gallup respondent living in a treated DMA to respondents in control counties where the Tribune acquisition failed. We assign these counties a counterfactual entry year of 2017. Matching is exact on gender, education, income, race, ideology, Census region, and event time. The inverse of the number of matches for each treated respondent weights control observations. Respondents report trust in a range of institutions including banks (Panel A), both large and small businesses (Panels B and C), the police force (Panel D), and churches (Panel E). Gallup categorizes responses as "a great deal," "quite a lot," We define an indicator variable for trust that equals 1 for responses of either "a great deal" or "quite a lot," and zero for responses of either "some," or "very little." Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 10: Effect on Local Banks based on BHC structure

Panel A: Deposit Shares

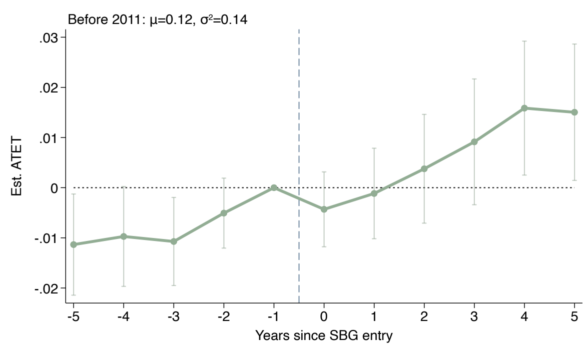


Local Organizational Form

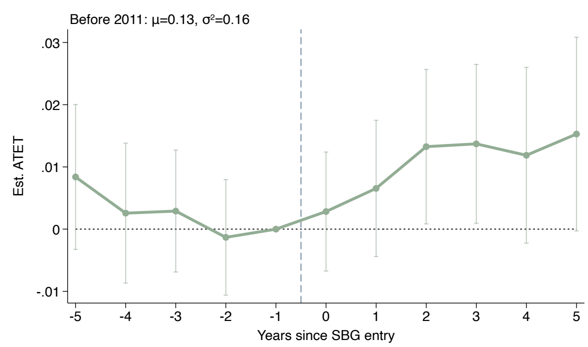


Non-Local Organizational Form

Panel B: Loan Application Shares



Local Organizational Form

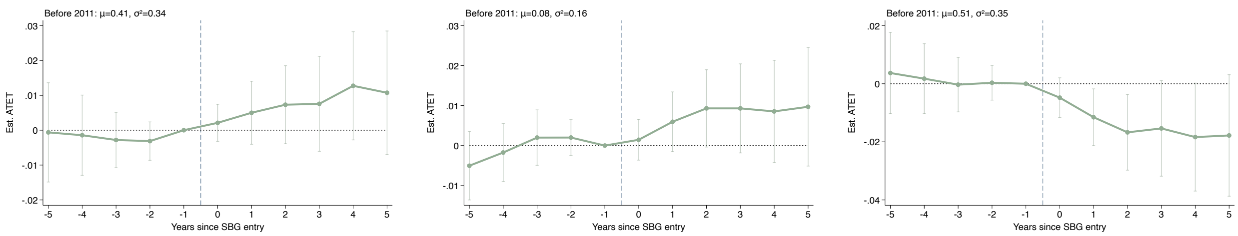


Non-Local Organizational Form

Figure 10 plots coefficient estimates from an event study analysis of the effects of SBG entry on deposits and loan applications at local banks according to bank holding company (BHC) structure. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state. We divide local banks into those that are not part of a BHC or belong to a BHC that owns only one bank, and those that belong to a multi-bank BHC. Deposit shares are the fraction of total county-level deposits held at each type of local bank, and loan application shares are the fraction of total county-level loan applications received by each type of local bank. Panel A reports deposit shares for local banks outside and within multi-bank BHCs, respectively. Panel B reports the corresponding loan application shares. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

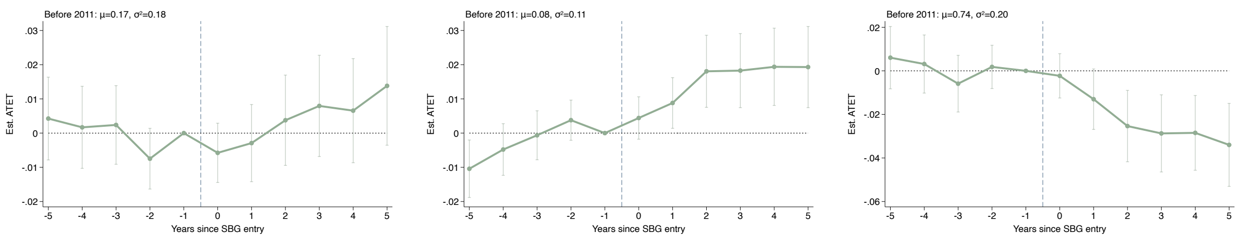
Figure 11: Alternative Definition of Local Banks - Distance

Panel A: Deposit Shares



0–100 km | 100–200 km | Non-local

Panel B: Loan Application Shares

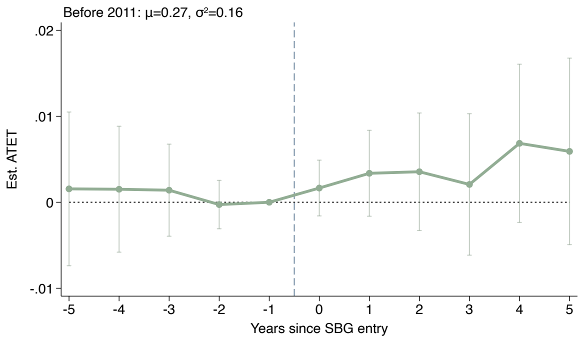


0–100 km | 100–200 km | Non-local

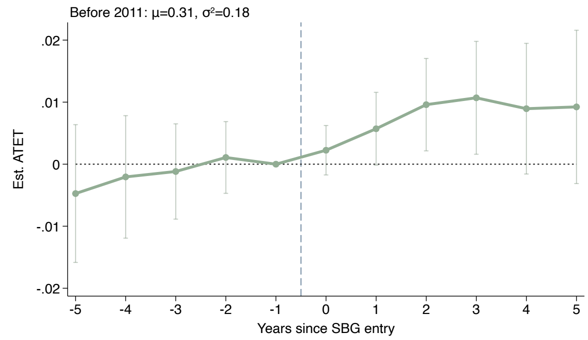
Figure 11 plots coefficient estimates from an event study analysis of the effects of SBG entry on deposits and loan applications using a distance-based definition of local banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. We define banks according to the geographic concentration of their branch networks, measured relative to the deposit-share-weighted geographic center of each bank's network. Banks with branches located within 100 km of this center are classified as local; we separately classify banks with branches located between 100 and 200 km, while national banks have branches located more than 200 km from the center. Deposit shares are the fraction of total county-level deposits held at each bank type, and loan application shares are the fraction of total county-level loan applications received by each bank type. Panel A reports deposit shares and Panel B reports loan application shares. Within each panel, the columns report results for banks with branch networks spanning 0–100 km, 100–200 km, and more than 200 km, respectively. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 12: Heterogeneity by Wage Volatility

Panel A: Deposit Shares

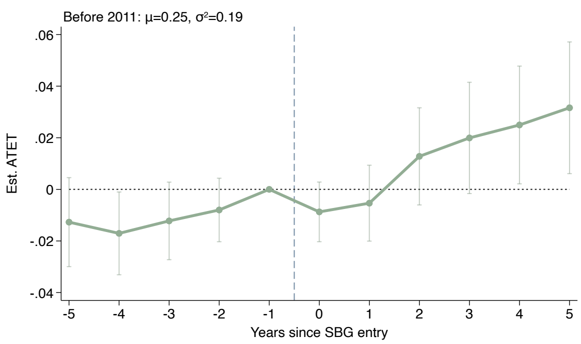


Below Mean

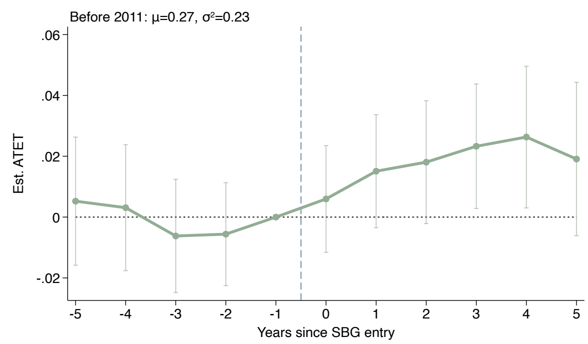


Above Mean

Panel B: Loan Application Shares



Below Mean

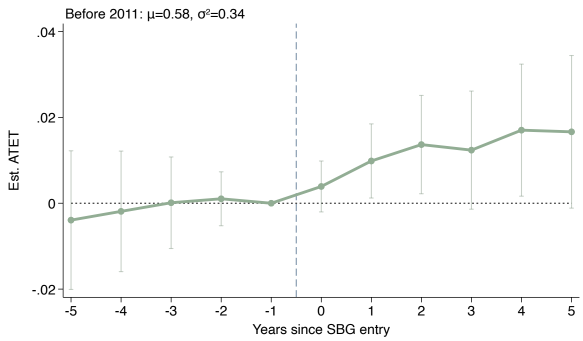


Above Mean

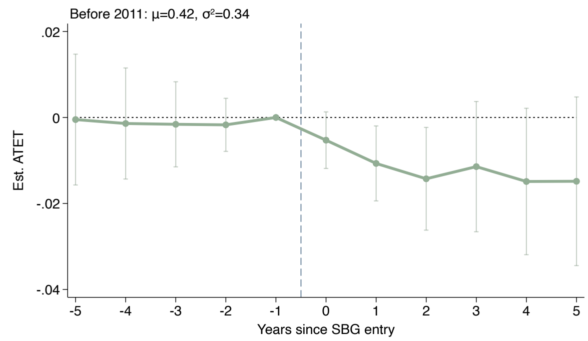
Figure 12 plots coefficient estimates from an event study analysis of the effects of SBG entry on deposits and loan applications according to county-level wage volatility. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state. We divide counties into high- and low-wage-volatility subsamples based on pre-treatment wage volatility. County wage volatility is measured as the average from 2006 through 2010 of the within-year standard deviation of quarterly average weekly wages in the private sector, using data from the BLS Quarterly Census of Employment and Wages. Counties are classified as having high or low wage volatility based on whether this pre-treatment measure is above or below its cross-county mean in 2011. Deposit shares are the fraction of total county-level deposits held at local banks, and loan application shares are the fraction of total county-level loan applications received by local banks. Panel A reports deposit shares for counties with below mean (left) and above mean wage volatility (right). Panel B reports the corresponding loan application shares. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 13: Outcomes without Wells Fargo Banks

Panel A: Deposit Shares

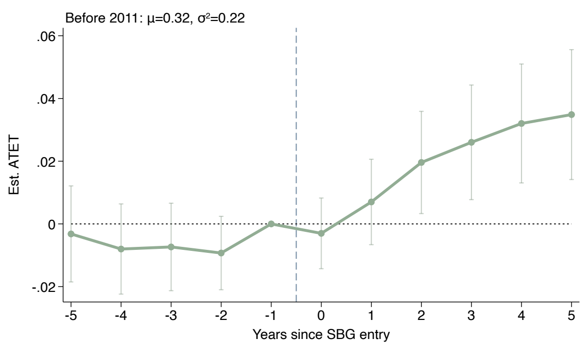


Local Banks

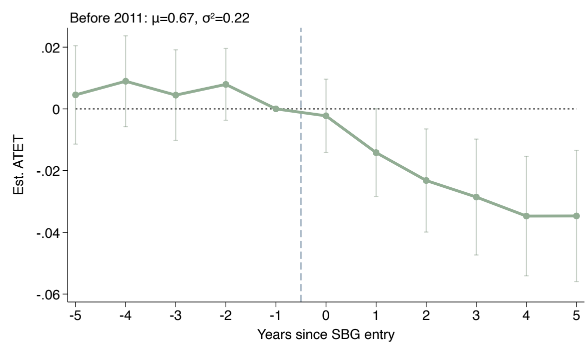


National Banks

Panel B: Loan Application Shares



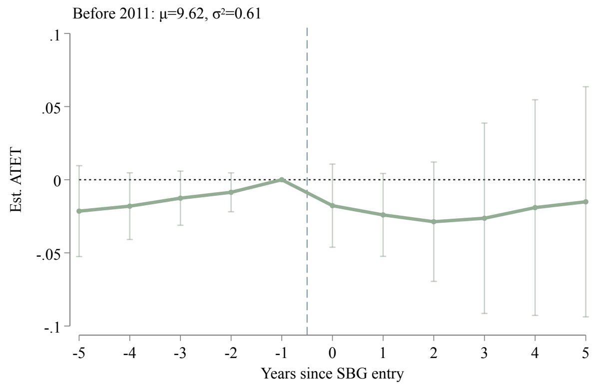
Local Banks



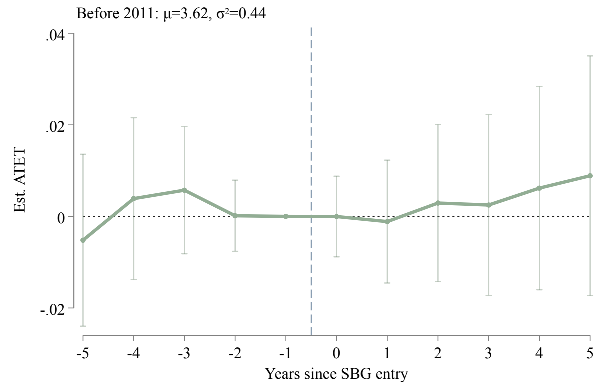
National Banks

Figure 13 plots coefficient estimates from an event study analysis of the effects of SBG entry on deposits and loan applications at local and national banks, excluding Wells Fargo banks from the analysis. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Deposit shares are the fraction of total county-level deposits held at local and national banks, excluding deposits held at Wells Fargo banks. Loan application shares are the fraction of total county-level loan applications received by local and national banks, excluding applications received by Wells Fargo banks. Panel A reports deposit shares for local and national banks without Wells Fargo, respectively. Panel B reports the corresponding loan application shares. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure 14: Trends in County-Level Deposits and GDP per capita



(a) Ln (Total Deposits per capita)



(b) Ln (Local per capita GDP)

Figure 14 plots coefficient estimates from an event study analysis of the effects of SBG entry on the log of county-level deposits per capita (Panel A) and GDP per capita (Panel B). We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

I Appendix

Gallup Survey Matching Method

We follow a strategy similar to (Kleven, 2026) to estimate the changes in trust indices using data from the Gallup Survey. The objective is to compare the answers provided by individuals in areas with SBG operations with those from areas without SBG presence. The main challenge of using this cross-sectional data for event studies is that, for individuals residing in areas without SBG operations, we cannot determine their state in the future if SBG were to enter the market, as the negative event times are unobserved. To overcome this problem, we only use data on residents in places where they failed the Tribune acquisition, as we know this would have occurred in 2017. This allows us to index the event time of the possible treatment. We matched each observed person at the event time (relative to the SBG entry) to a person in the control group with the same demographic characteristics, obtaining a synthetic observation for each treated respondent.

We use a set of demographic characteristics that include the respondent's gender, education level (above or below a completed high school education), income level (high vs. low), race (white vs. non-white), self-reported ideological status (conservative vs. non-conservative), region of residence (East, Midwest, South, West), and age (grouped in two-year bins). For instance, in this setup, we match a white, high-income, conservative man living in an area with SBG operations to someone with the same characteristics and in the same age range, but living in a county where the Tribune acquisition failed. The matching is done at the same event time relative to when SBG began operations, assuming that the control treatment would have occurred in 2017.

We then reported the average difference in trust reported by both those groups for each relative time based on a regression model using the sample of respondents who have a match. In case of a person with multiple matches, we weighted their synthetic observation by the inverse of the total number of matches. Finally, we report confidence intervals based on standard errors clustered at the demographic group level.

Interpolation

Because participation in RateWatch is voluntary and reflects each bank's competitive presence in a given product market, the resulting panel is highly unbalanced. A county-year-by-bank-type-by-product cell is observed only if at least one branch belonging to the corresponding bank type reports a rate for that product in that year.

We use a two-stage linear interpolation procedure to obtain a balanced panel by imputing missing cells. In the first stage, for each county-by-bank-type-by-product series, we interpolate missing years along a straight line connecting the nearest preceding and subsequent observations in the same series. This approach assumes that interest rates evolve smoothly over short intervals, allowing gaps of one or two years to be reasonably bridged by a linear path. We do not extrapolate observations beyond the support of each series. In the second stage, we apply an analogous interpolation procedure at the state level and use the resulting values as a fallback for county-years that remain missing after the first stage, provided that the county has at least one observed year within the sample period. Counties that are never covered by RateWatch remain missing and are excluded from the estimation sample, ensuring that we do not construct county-level series in the absence of any county-specific signal.

Alternative Local definition based on network structure

For every bank in the Summary of Deposits, we calculate the deposit-weighted centroid of its branches and measure the distance between each branch and that centroid. The maximum of these distances provides a summary measure of the geographic reach of the bank's branch network. We then classify banks into three mutually exclusive categories: "hyper-local" banks, whose most distant branch lies within 100 kilometers of the centroid; "medium-local" banks, whose most distant branch lies more than 100 but no more than 200 kilometers from the centroid; and "non-local" banks, whose branch networks extend beyond 200 kilometers. We assign all single-county banks to the hyper-local category to preserve their classification under our baseline definition.

We apply the distance-based thresholds only to banks operating within a single state. Any bank with branches in more than one state is classified as non-local, regardless of the geographic concentration of its branch network. This conservative restriction reflects regulatory and competitive differences across state boundaries, although it excludes a small number of geographically concentrated banks operating in border areas. Also, we construct the classification using a fixed snapshot of each bank's branch network during the pre-treatment period, 2004–2011. Banks therefore retain their initial classification throughout the panel, even if they subsequently expand or contract geographically.

Table IA.I: Descriptive Statistics by County Banking Structure

Variable	Local Without (1)	Local With (2)	Local Diff (3)	National Without (4)	National With (5)	National Diff (6)
Log(Population)	8.914	10.399	1.295***	8.625	10.613	1.291***
	(1.223)	(1.570)		(0.892)	(1.496)	
Share female population	0.494	0.500	0.001	0.492	0.501	0.007**
	(0.016)	(0.021)		(0.030)	(0.019)	
Share white population population	0.880	0.835	0.002	0.851	0.835	−0.011
	(0.125)	(0.147)		(0.148)	(0.147)	
Share population age 25-34 yo	0.105	0.116	0.015***	0.108	0.117	0.008***
	(0.021)	(0.022)		(0.022)	(0.022)	
Share population age 35-44 yo	0.109	0.122	0.009***	0.114	0.122	0.004*
	(0.015)	(0.016)		(0.017)	(0.016)	
Share population age 45-54 yo	0.151	0.149	−0.009***	0.151	0.149	−0.005***
	(0.020)	(0.015)		(0.015)	(0.015)	
Share population age 55-64 yo	0.150	0.131	−0.018***	0.139	0.131	−0.010***
	(0.029)	(0.022)		(0.024)	(0.022)	
Share population age over 65 yo	0.176	0.158	−0.022***	0.180	0.155	−0.018***
	(0.044)	(0.042)		(0.044)	(0.041)	
Share urban population	0.266	0.463	0.238***	0.163	0.501	0.275***
	(0.275)	(0.324)		(0.248)	(0.311)	
Share population above 25 year with high education	0.035	0.011	−0.022*	0.033	0.008	−0.020***
	(0.048)	(0.022)		(0.043)	(0.017)	
Share population above 25 year with some college	0.110	0.125	0.026***	0.108	0.127	0.013***
	(0.038)	(0.052)		(0.043)	(0.052)	
Share of agriculture employment	0.116	0.061	−0.036**	0.131	0.052	−0.047***
	(0.072)	(0.067)		(0.100)	(0.055)	
Share of construction employment	0.082	0.075	−0.000	0.076	0.075	−0.007**
	(0.030)	(0.029)		(0.038)	(0.027)	
Share of manufacturing employment	0.069	0.116	0.017*	0.086	0.119	0.017**
	(0.045)	(0.071)		(0.068)	(0.070)	
Share of public employment	0.058	0.048	−0.008**	0.052	0.048	−0.004**
	(0.025)	(0.026)		(0.028)	(0.026)	
Share of labor force	0.487	0.496	0.013	0.503	0.494	0.001
	(0.074)	(0.065)		(0.089)	(0.061)	
Share of employment	0.898	0.910	0.008	0.924	0.908	−0.001
	(0.038)	(0.032)		(0.032)	(0.032)	
Crimes per 10000 inhabitants	17.912	25.836	4.538	18.715	26.608	7.602***
	(25.220)	(23.191)		(18.509)	(23.813)	
Log(Average household income)	10.591	10.684	0.105***	10.550	10.701	0.073***
	(0.199)	(0.251)		(0.198)	(0.251)	
Log(Federal expenditure +1)	11.148	12.491	1.218***	10.849	12.690	1.214***
	(1.224)	(1.719)		(0.905)	(1.686)	
Share population under poverty line	0.153	0.145	−0.016***	0.163	0.143	−0.013**
	(0.047)	(0.053)		(0.060)	(0.051)	
Share of population with medicare	0.156	0.144	−0.016***	0.165	0.141	−0.015***
	(0.046)	(0.043)		(0.046)	(0.042)	
Share of population with no health insurance	0.117	0.120	0.006	0.140	0.117	−0.010***
	(0.029)	(0.037)		(0.046)	(0.033)	
Housing unites per 1000 inhabitants	533.207	478.023	−41.613**	529.561	472.342	−55.155***
	(141.506)	(122.333)		(155.327)	(115.886)	
Share of population receiving social security benefits	0.233	0.209	−0.028***	0.226	0.207	−0.017***
	(0.069)	(0.054)		(0.052)	(0.054)	
Share of veteran population	0.100	0.086	−0.007	0.085	0.087	−0.000
	(0.031)	(0.022)		(0.024)	(0.023)	
Infant under 1 year mortality rate	6.966	7.410	−0.653	8.845	7.163	−0.091
	(11.020)	(12.452)		(27.394)	(7.718)	
Water use per capita	16.165	5.800	−6.458**	12.170	5.257	−5.694**
	(21.269)	(15.406)		(27.948)	(12.622)	
Preference Democrats	0.341	0.406	0.025	0.320	0.417	0.023**
	(0.141)	(0.142)		(0.136)	(0.139)	
Preference Democrats in House 2000	0.342	0.336	−0.011	0.273	0.346	−0.003
	(0.172)	(0.178)		(0.195)	(0.173)	

Table IA.I presents county characteristics according to banking market structure. Columns 1, 2, 4, and 5 show the mean and standard deviation (in parentheses). Columns 3, and 6 present the difference in comparison with the control groups taking into account state fixed effects and DMA fixed effects. Robust standard errors. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table IA.II: Two-way Fixed Effects Decomposition and Weights

	All Sample (1)	Tribune (2)
Panel A: Bacon Decomposition		
Treated (T) vs Never Treated (C)	0.915	0.741
Early Treated (T) vs Late Treated (C)	0.036	0.109
Late Treated (T) vs Early Treated (C)	0.049	0.150
Panel B: Negative Weights		
Share of Negative Weights (County)	0.000	0.000

Table IA.II presents the decomposition of a naive two-way fixed effects model. Column 1 shows the results using the complete sample of the entire United States (Without areas where SBG operated before 2004). Column 2 shows the results using only the sample of Tribune operating areas and the areas with SBG expansion after 2012. In Panel A, we present the Goodman-Bacon (2021) decomposition, where T represents treated units and C represents the comparison groups. In Panel B, we present the share of negative weights following de Chaisemartin and d'Haultfoeuille (2021)) for the estimation, using counties as the unit of analysis.

Table IA.III: Comparison States: by Tribune Media Presence

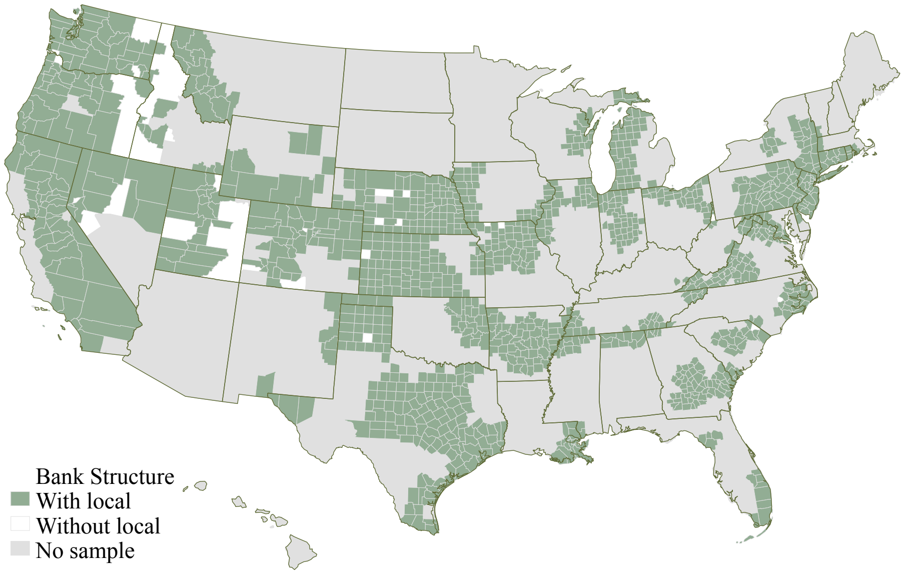
Original State (1)	Assigned (2)
MD	PA
GA	AL
KY	TN
WI	IL
ID	WY
MT	WY
MI	IN
NC	TN
SC	TN
VA	TN
WV	TN
NM	CO
UT	CO
OR	CA
WA	CA
RI	CT
SD	NE
VT	NY
MA	NY
DC	PA

This table shows the assignment of states without Tribune operations to neighboring states with operations. Column 1 lists the original states, and column 2 shows their assignment.

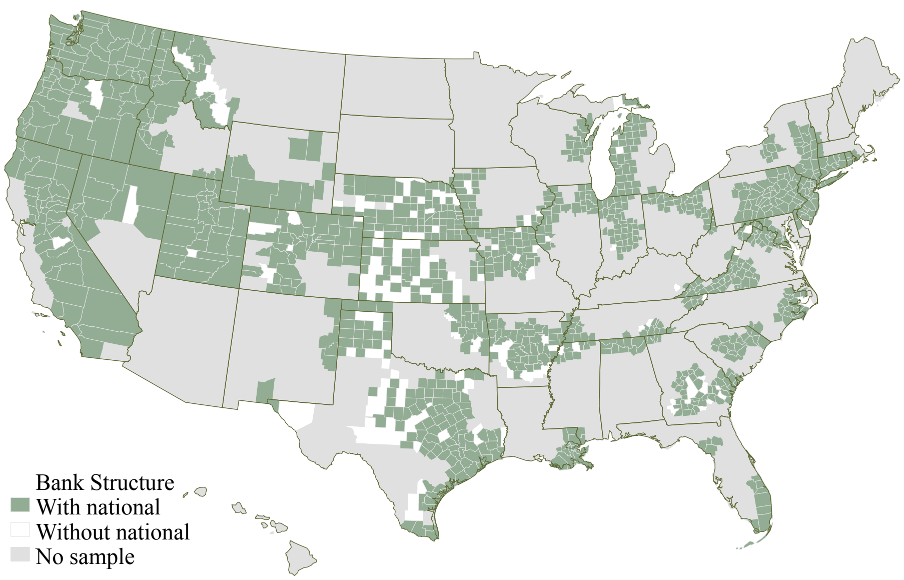
Table IA.IV: Distribution of Banks by BHC Status

	BHC except 1			**BHC**		
Local bank	No	Yes	Total	No	Yes	Total
Uni county	3,842	2,001	5,843	1,435	4,408	5,843
Uni State	3,182	2,419	5,601	748	4,853	5,601
National	472	622	1,094	145	949	1,094
Total	7,496	5,042	12,538	2,328	10,210	12,538

Figure IA.1: Local and National Banks



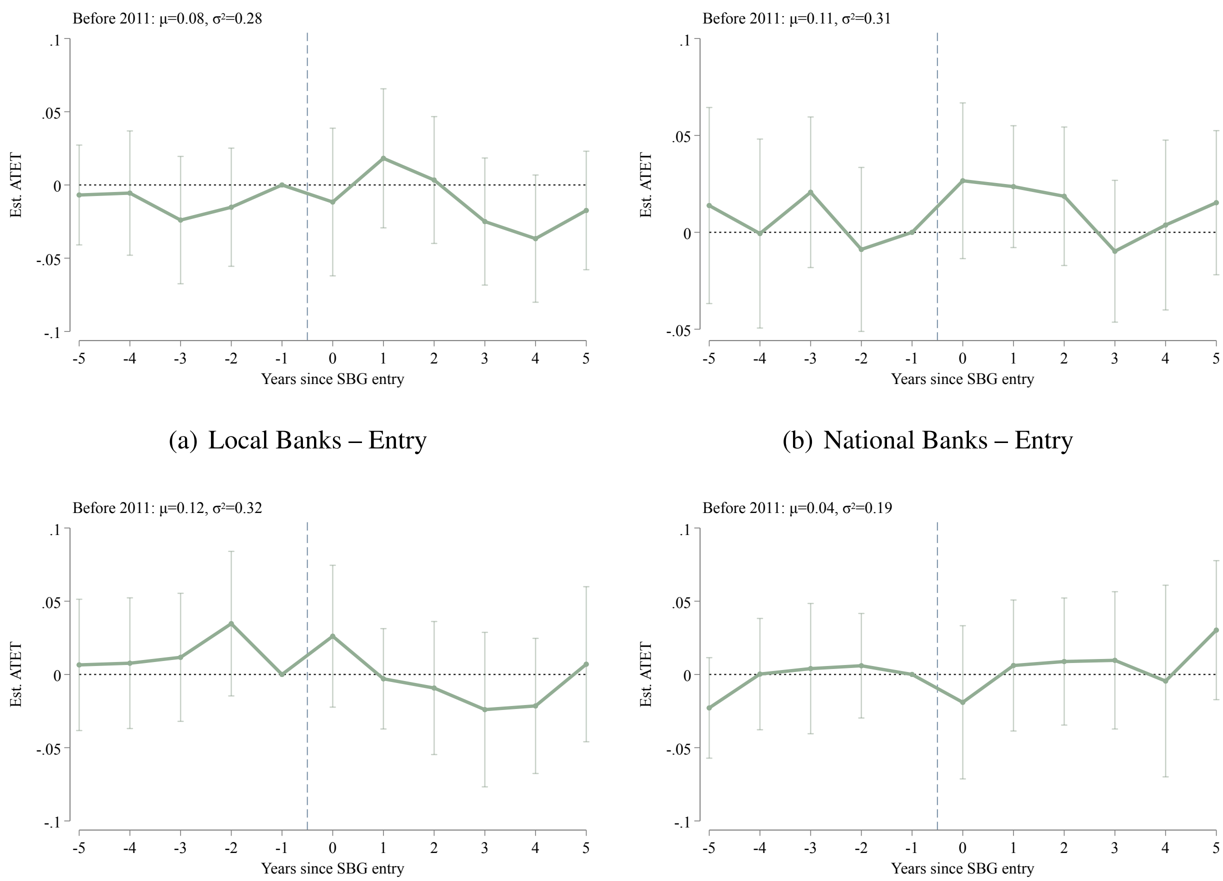
(a) Local Banks



(b) National Banks

Figure IA.1 presents the distribution of local (Panel A) and national (Panel B) banks across counties in the U.S. as of 2010. Local banks are those operating in only one state and national banks are those operating in more than one state. In Panels A and B, dark shaded areas have local (national) banks and light shaded areas do not have local (national) banks, respectively. Grey shaded areas are not in our sample.

Figure IA.2: Bank Entry and Exit



(a) Local Banks – Entry

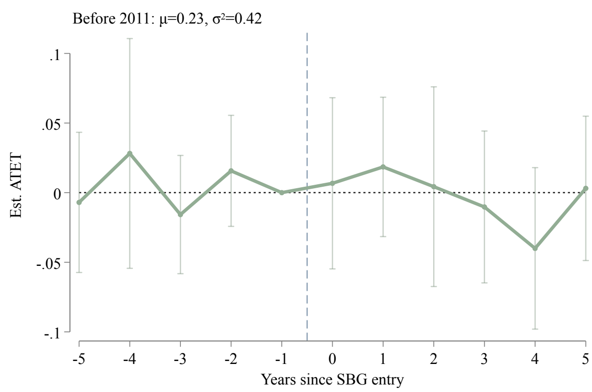
(b) National Banks – Entry

(c) Local Banks – Exit

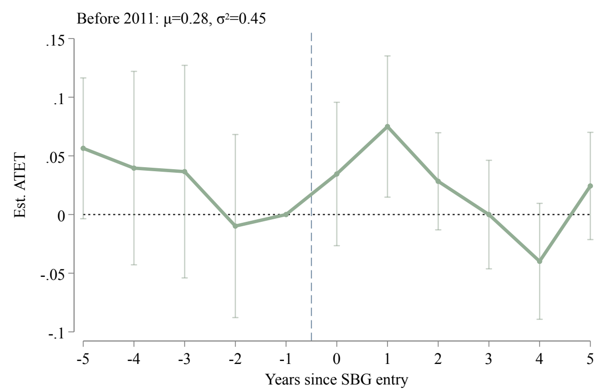
(d) National Banks – Exit

Figure IA.2 plots coefficient estimates from an event study analysis of the effects of SBG entry on the probability that a bank begins or ceases operations in a county. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage probability of the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Bank entry is an indicator variable equal to one when a bank establishes a branch in a county where it did not operate previously (Panel A – local banks and Panel B – national banks). Bank exit is an indicator variable equal to one when a bank closes all branches in a county such that the bank no longer operates in the county (Panel C – local banks and Panel D – national banks). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

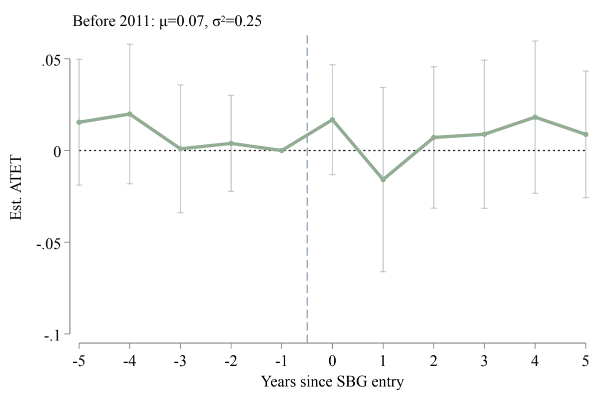
Figure IA.3: Branch Entry and Closures



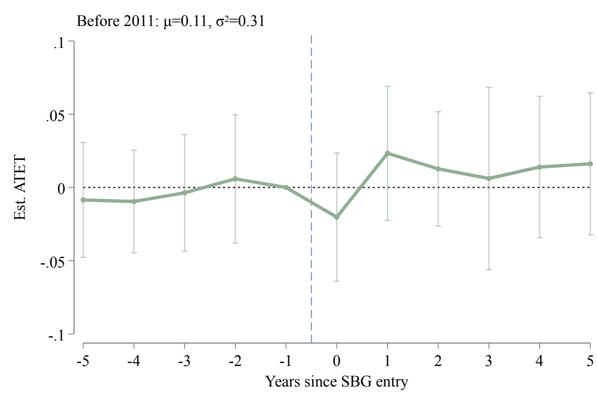
(a) Local Banks – Branch Openings



(b) National Banks – Branch Openings



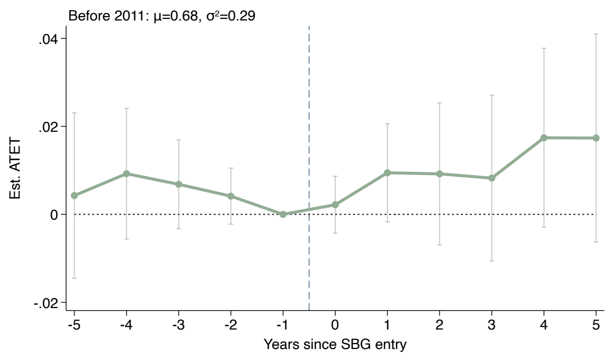
(c) Local Banks – Branch Closures



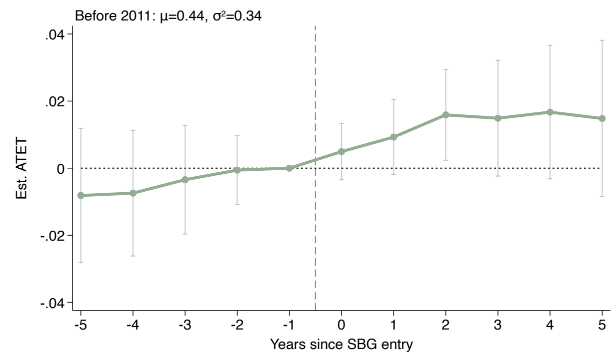
(d) National Banks – Branch Closures

Figure IA.3 plots coefficient estimates from an event study analysis of the effects of SBG entry on the probability that a bank expands or reduces operations in a county. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage probability of the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Branch opening is an indicator variable that equals one when a bank opens a branch in a county where it currently operates (Panel A – local banks and Panel B – national banks). Branch closure is an indicator variable that equals one when a bank closes a branch in a county where the bank currently operates and will continue to operate (Panel C – local banks and Panel D – national banks). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

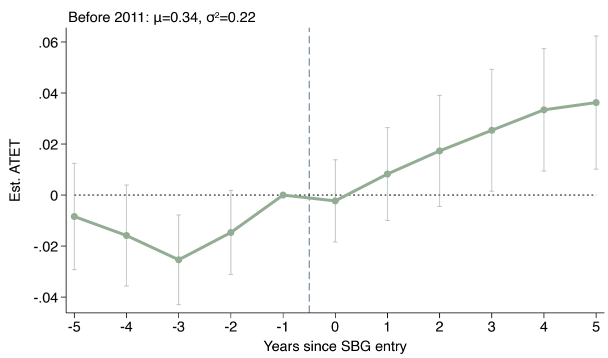
Figure IA.4: Heterogeneous Effect on Local Banks: Federal Reserve Stress Tests (2010-2019)



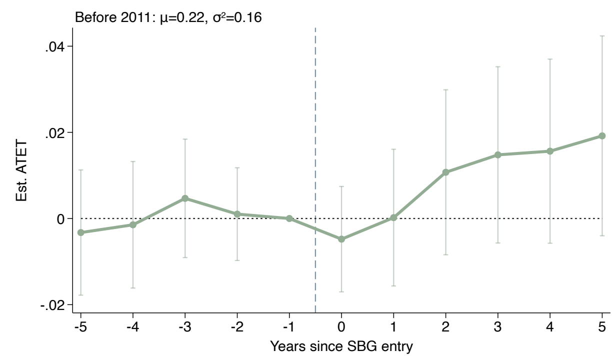
(a) Deposit Shares - Below Median



(b) Deposit Shares - Above Median



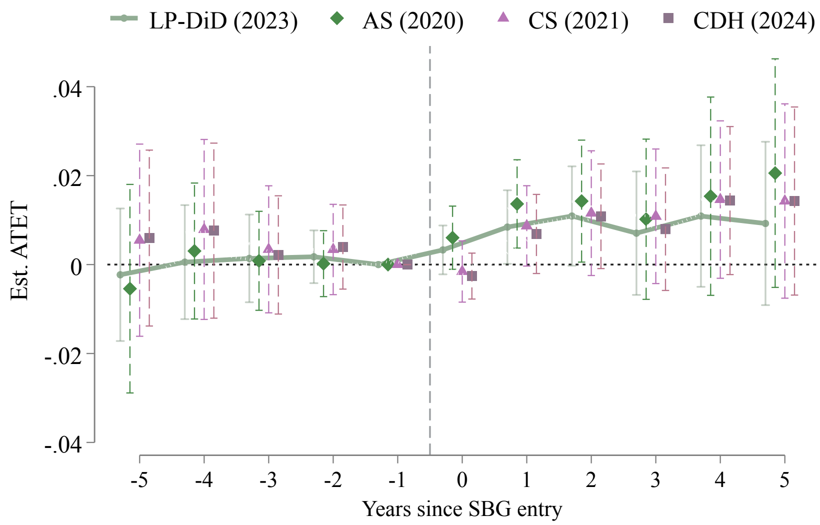
(c) Loan Application Shares - Below Median



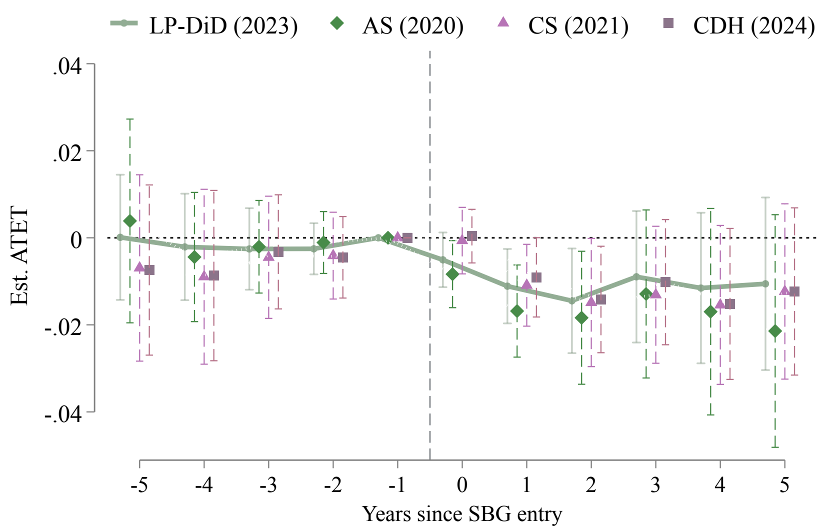
(d) Loan Application Shares- Above Median

Figure IA.4 plots coefficient estimates from an event study analysis of the effects of SBG entry on deposits and loan applications at local banks according to county exposure to banks subject to Federal Reserve stress tests over the 2010–2019 period. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state. We identify bank holding companies subject to Federal Reserve stress tests in each year from 2010 through 2019 and measure county exposure using the mortgage market share of banks belonging to these stress-tested bank holding companies. Counties are classified as having high or low exposure based on whether their exposure to stress-tested banks is above or below the sample median. Deposit shares are the fraction of total county-level deposits held at local banks, and loan application shares are the fraction of total county-level loan applications received by local banks. Panels A and B report deposit shares for counties with low and high exposure to stress-tested banks, respectively. Panels C and D report the corresponding loan application shares. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure IA.5: Alternative Estimators



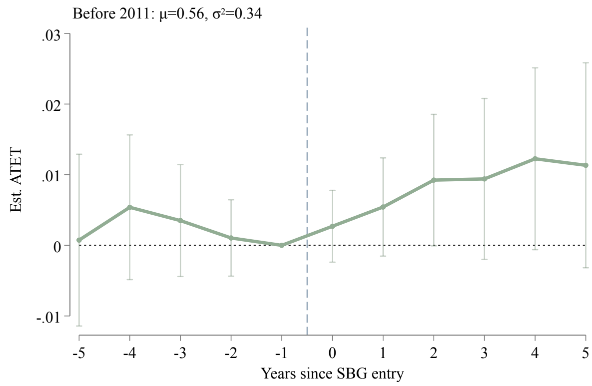
(a) Local Banks



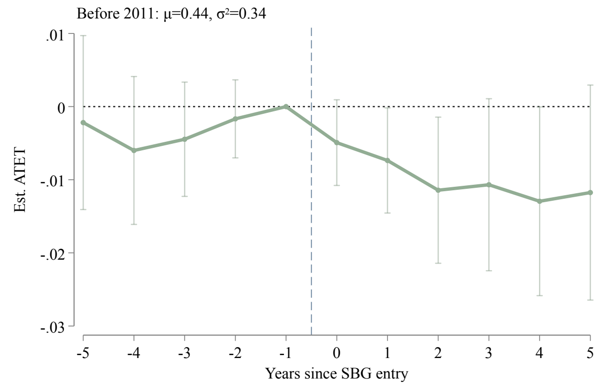
(b) National Banks

Figure IA.5 presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry and three different models for the treatment of the entry of Sinclair. We present the model suggested by Callaway and Sant'Anna (2021) (CS), the regression model suggested by Sun and Abraham (2021) (AS), and the model suggested by de Chaise-martin and d'Haultfoeuille (2021) (CDH). Panel (A) reports the main results for local banks and Panel (B) reports the main results for national banks. Local banks are those operating in only one state and national banks are those operating in more than one state. Brackets represent a 95% confidence interval using cluster standard errors at the CZ level as defined in 2000.

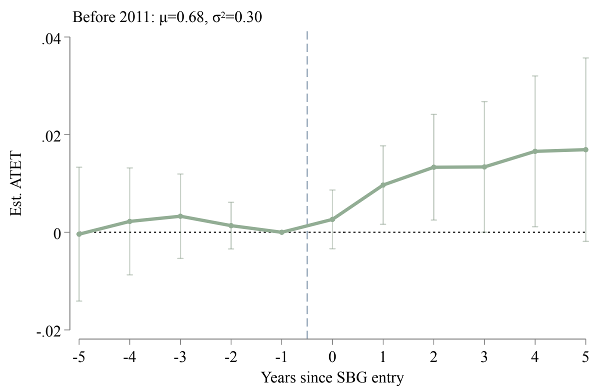
Figure IA.6: Propensity Score Matched Sample and Tribune Subsamples



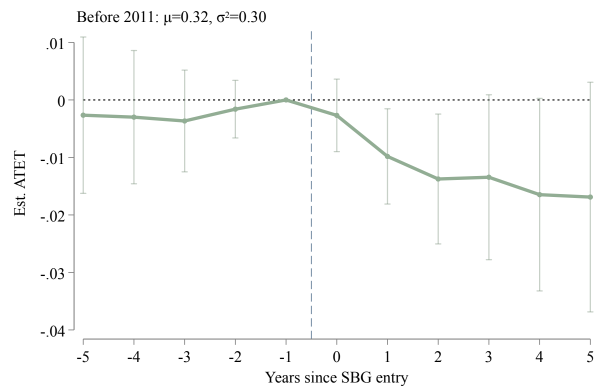
(a) Local Banks – Matched Sample



(b) National Banks – Matched Sample



(c) Local Banks – Tribune Sample

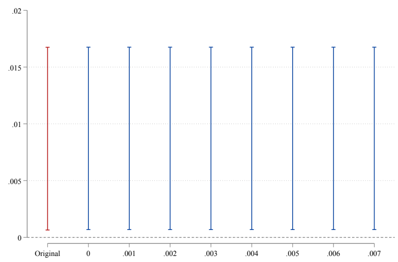


(d) National Banks – Tribune Sample

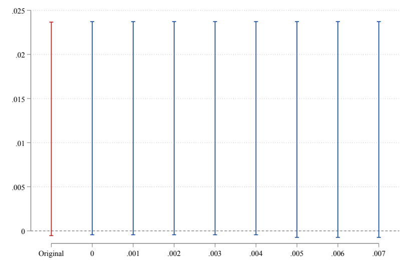
Figure IA.6 presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry. In panels (A) and (B), the sample is restricted to the optimal selection rule from Crump et al. (2009) over the propensity score, probability of observing the entry of SBG. The covariates used to predict the probability were selected following Belloni et al. (2014) machine learning algorithm, which selects the best covariates predicting the entry of SBG and each one of the outcomes. In panels (C) and (D), the sample is restricted states with both operation of Tribune and SBG. Brackets represents a 95% confidence interval using cluster standard errors at the CZ level as defined in 2000.

Figure IA.7: Parallel Trends Violations

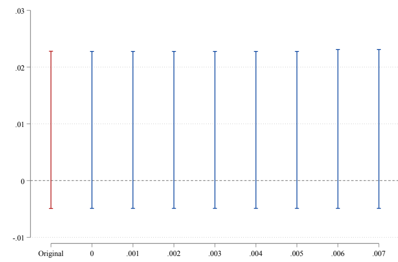
Local Banks



(a) 1 Year

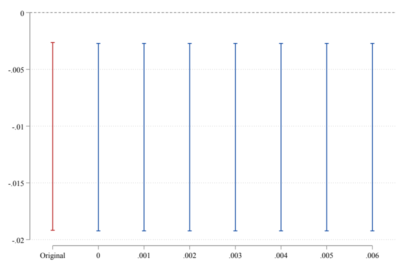


(b) 2 Year

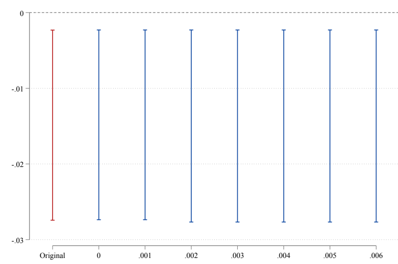


(c) 3 Year

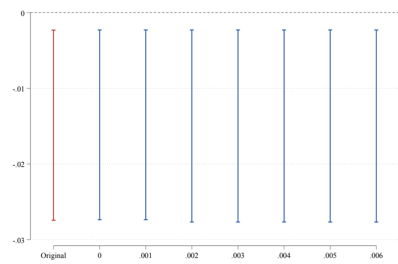
National Banks



(d) 1 Year



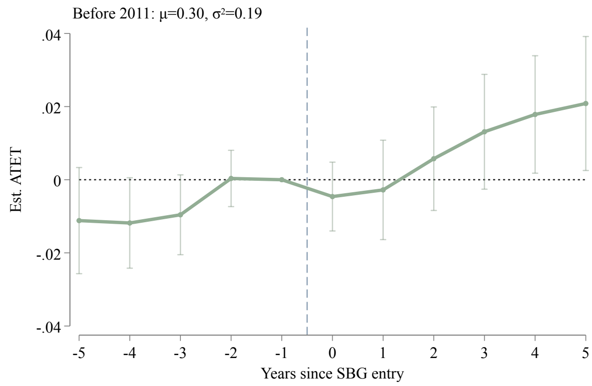
(e) 2 Year



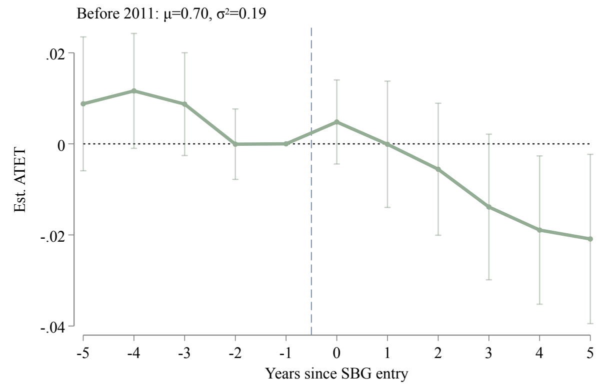
(f) 3 Year

Figure IA.7 presents the 90% confidence interval for both linear and non-linear violations of the parallel trends assumption, following Rambachan and Roth (2023) for estimations in Figure 2. The figure displays the coefficient for deposit shares following the Sinclair entry, with the first row representing the local banks and the second row representing the national banks. Local banks are those operating in only one state and national banks are those operating in more than one state. The parameter M measures the magnitude of the change in trend between consecutive periods. M=0 indicates a linear violation of the assumption of parallel trends. The maximum value of M corresponds to the trend that has an 80% probability of being detected, given the precision of the pre-period estimates (Roth, 2022)

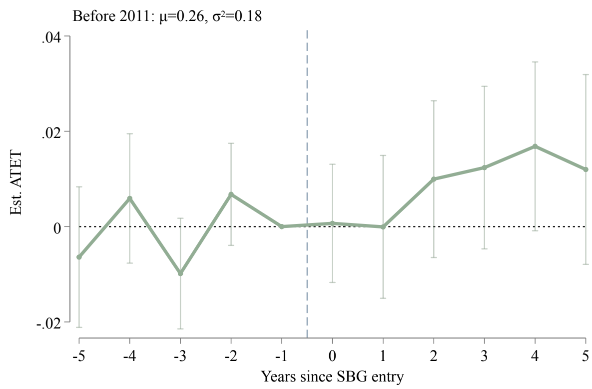
Figure IA.8: Loan Application Shares by Gender



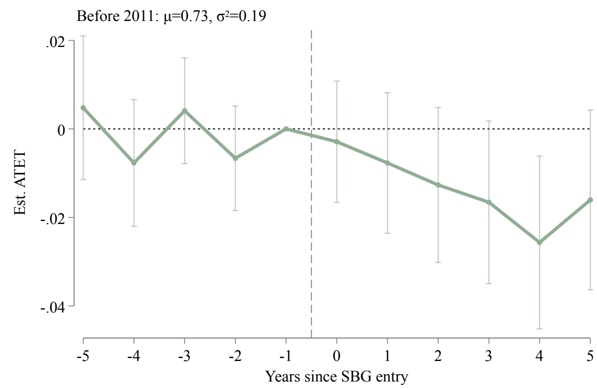
(a) Local Banks – Male



(b) National Banks – Male



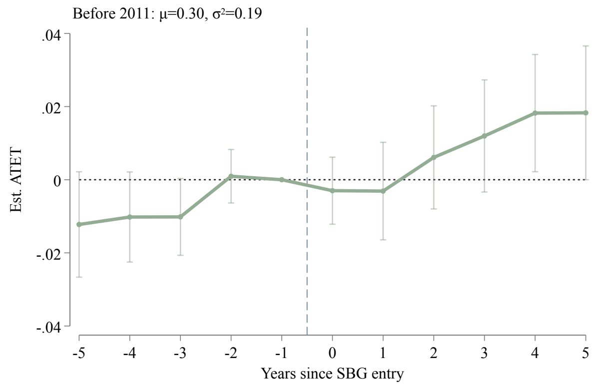
(c) Local Banks – Female



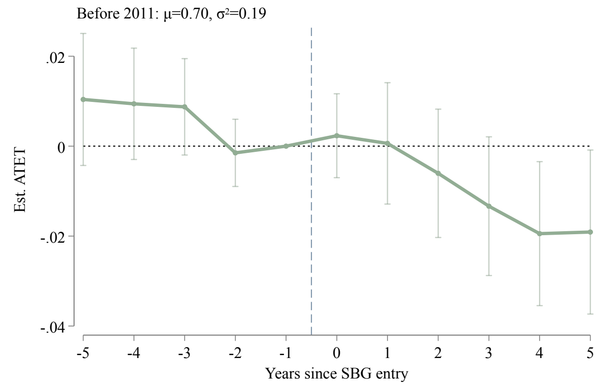
(d) National Banks – Female

This figure plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan applications received by local and national banks based on an applicant's gender. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Loan application shares are the fraction of the total number of loan applications received by branches of local banks (Panel A – male and Panel C – female) and national banks (Panel B – male and Panel D – female). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

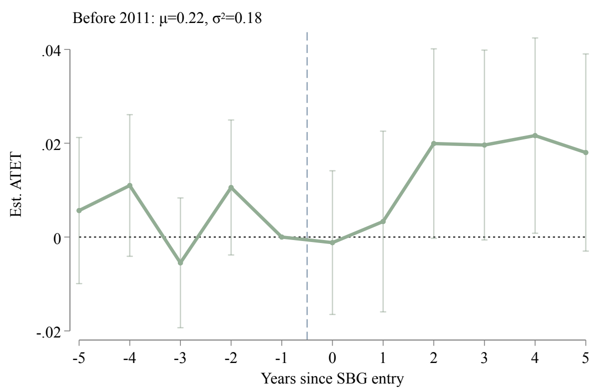
Figure IA.9: Loan Application Shares by Race



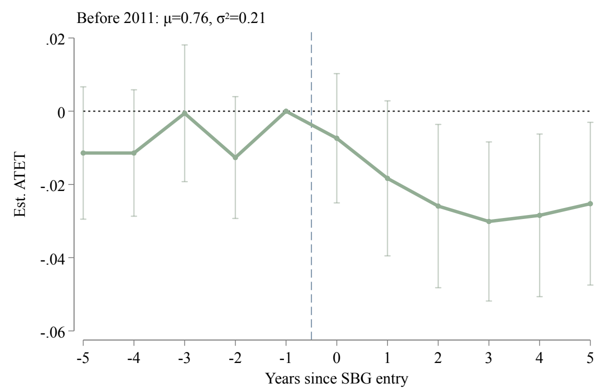
(a) Local Banks – White



(b) National Banks – White



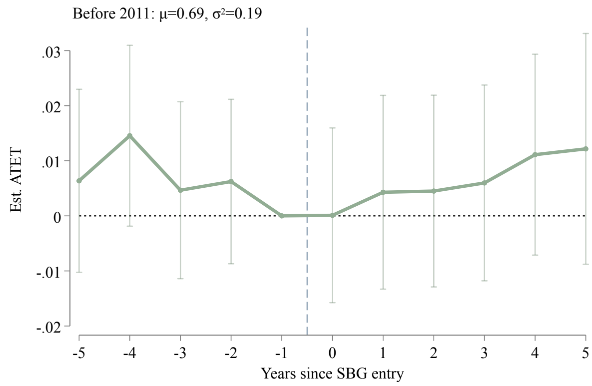
(c) Local Banks – Non-White



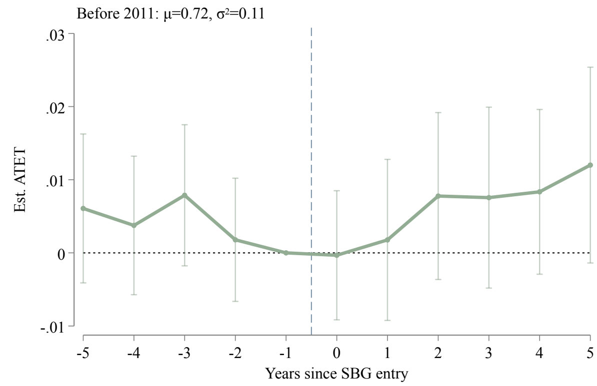
(d) National Banks – Non-White

This figure plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan applications received by local and national banks based on an applicant's race. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. Loan application shares are the fraction of the total number of loan applications received by branches of local banks (Panel A – white and Panel C – non-white) and national banks (Panel B – white and Panel D – non-white). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

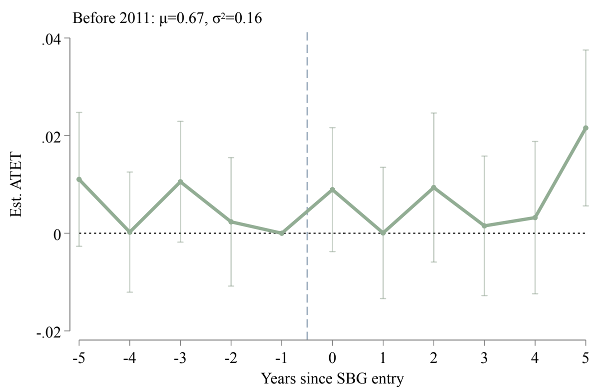
Figure IA.10: Loan Approval Rate by Gender



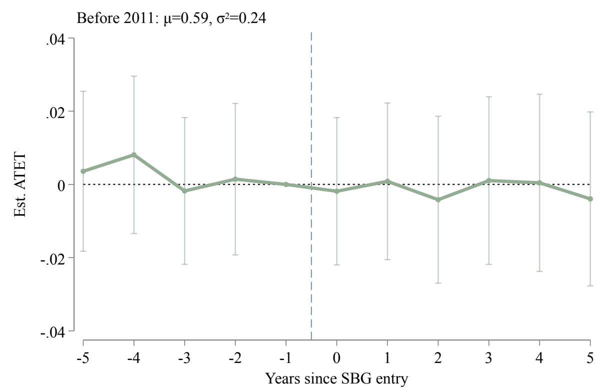
(a) Local Banks – Male



(b) National Banks – Male



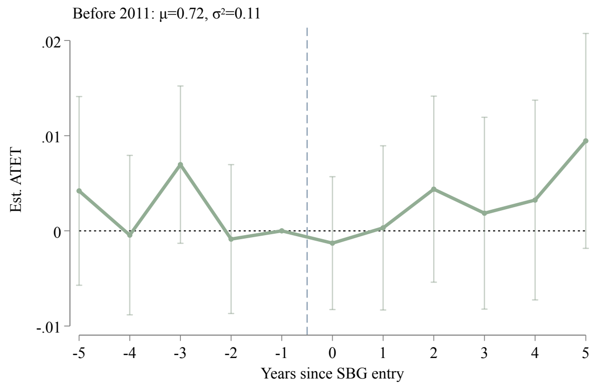
(c) Local Banks – Female



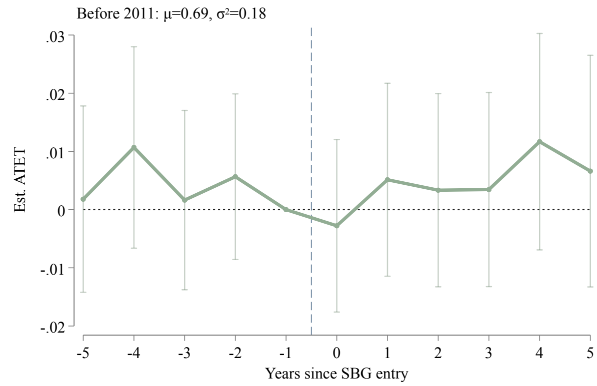
(d) National Banks – Female

This figure plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan approval rates of local and national banks based on an applicant's gender. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. The loan approval rate is the fraction of loan applications received that are approved by local banks (Panel A – male and Panel C – female) and national banks (Panel B – male and Panel D – female). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

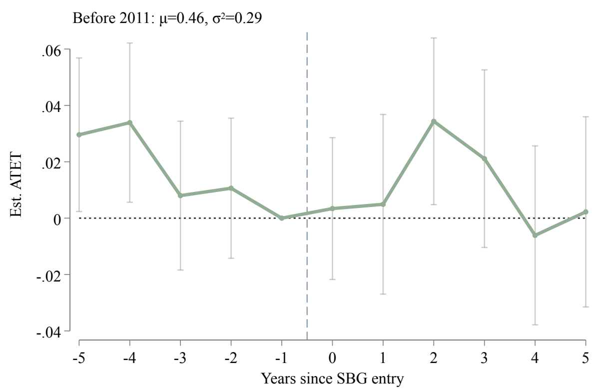
Figure IA.11: Loan Approval Rate by Race



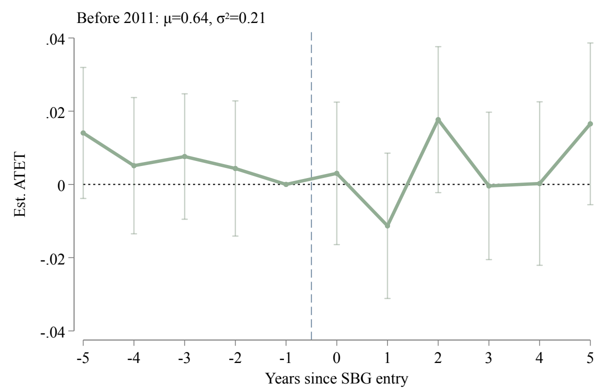
(a) Local Banks – White



(b) National Banks – White



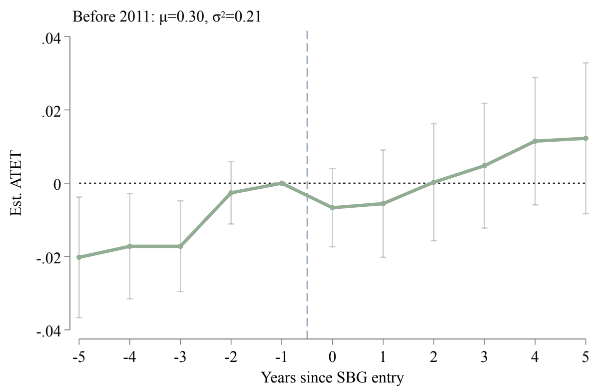
(c) Local Banks – NonWhite



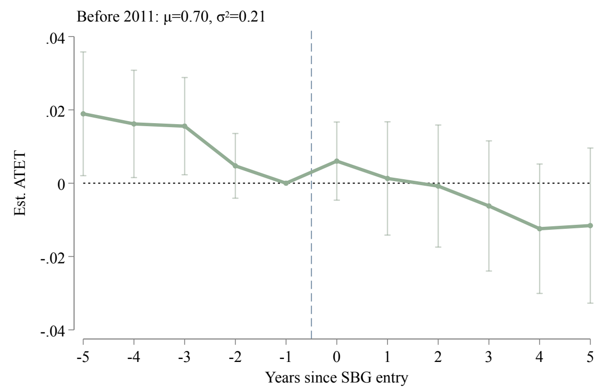
(d) National Banks – NonWhite

This figure plots coefficient estimates from an event study analysis of the effects of SBG entry on the loan approval rates of local and national banks based on an applicant's race. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. The loan approval rate is the fraction of loan applications received that are approved by local banks (Panel A – white and Panel C – non-white) and national banks (Panel B – white and Panel D – non-white). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

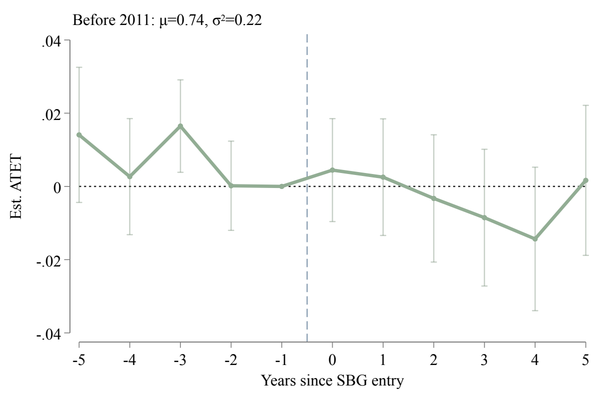
Figure IA.12: Loan Approval Shares by Gender



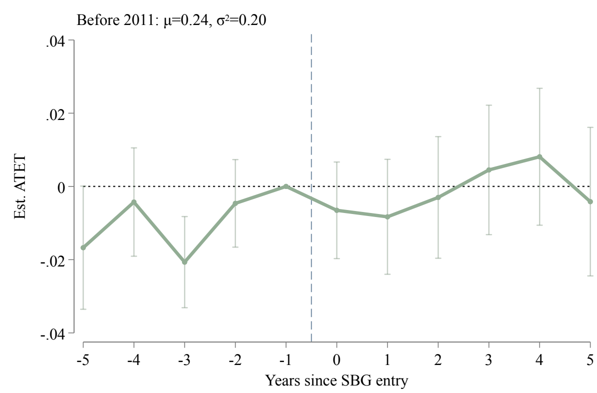
(a) Local Banks – Male



(b) National Banks – Male



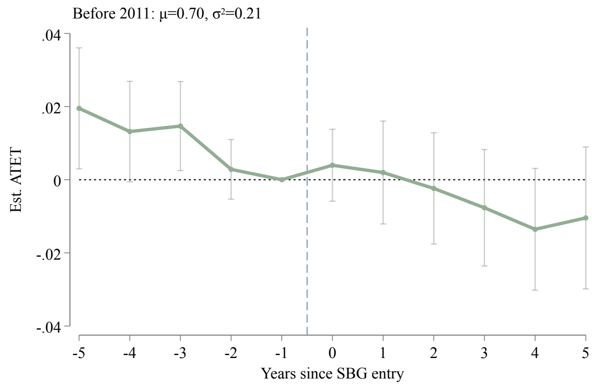
(c) Local Banks – Female



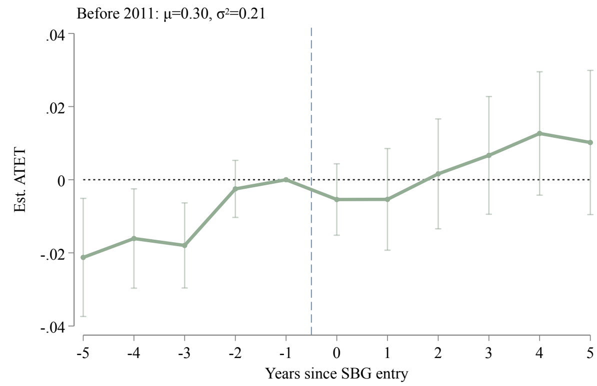
(d) National Banks – Female

This figure plots coefficient estimates from an event study analysis of the effects of SBG entry on the shares of approved loans by local and national banks based on an applicant's gender. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. The share of approved loans is the fraction of total loan approvals by local banks (Panel A – male and Panel C – female) and national banks (Panel B – male and Panel D – female). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

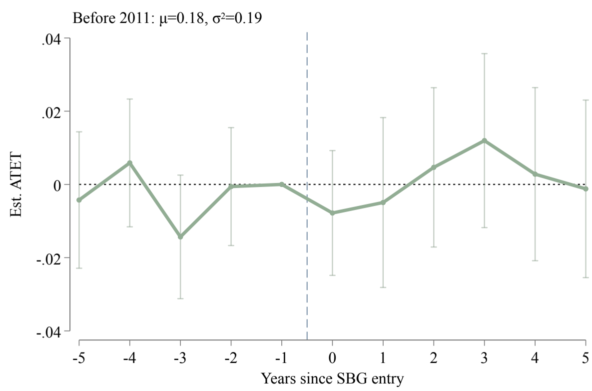
Figure IA.13: Loan Approval Shares by Race



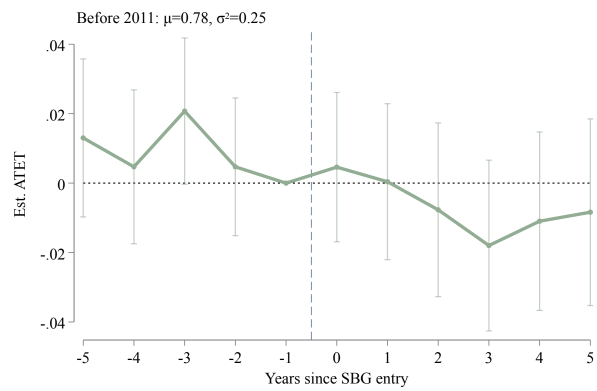
(a) Local Banks – White



(b) National Banks – White



(c) Local Banks – Non-White

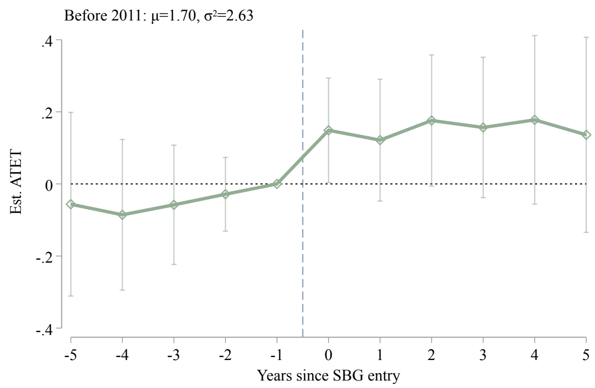


(d) National Banks – Non-White

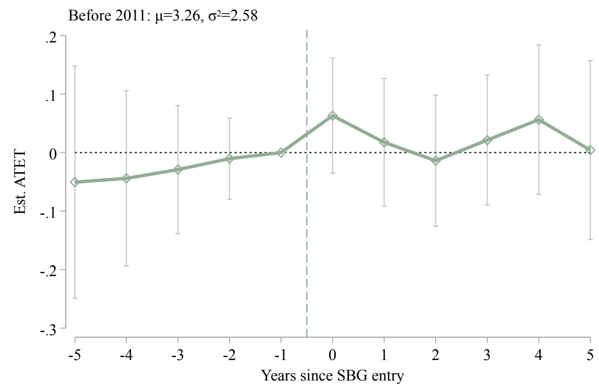
This figure plots coefficient estimates from an event study analysis of the effects of SBG entry on the shares of approved loans by local and national banks based on an applicant's race. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. The share of approved loans is the fraction of total loan approvals by local banks (Panel A – white and Panel C – non-white) and national banks (Panel B – white and Panel D – non-white). Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

Figure IA.14: Bank Pricing: Mortgage Rates and Deposit Rates (Modified)

Panel A: Mortgage Rate

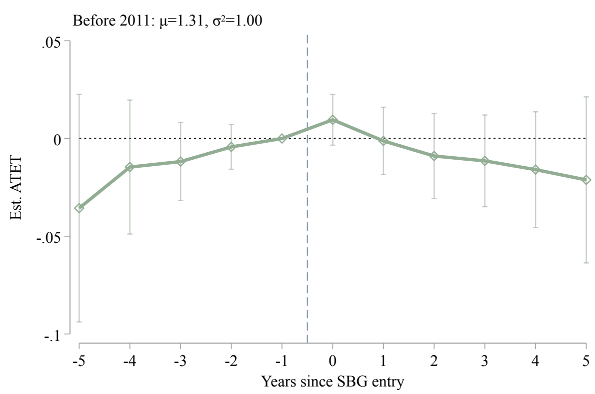


(a) Local Banks - Modified

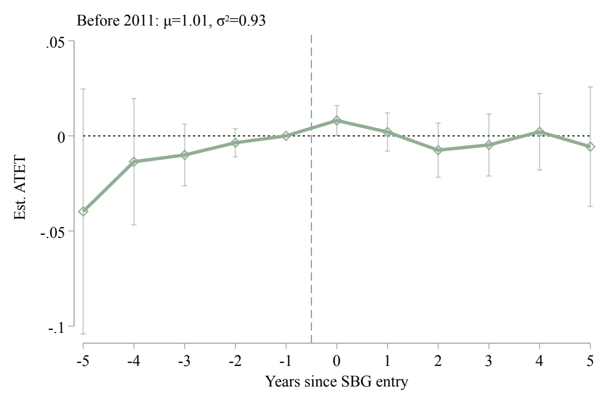


(b) National Banks - Modified

Panel B: Deposit Rate



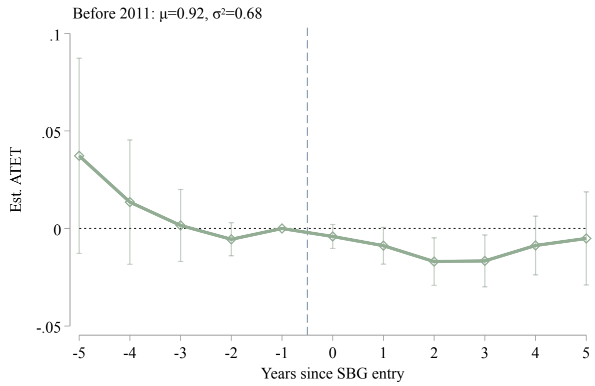
(c) Local Banks - Modified



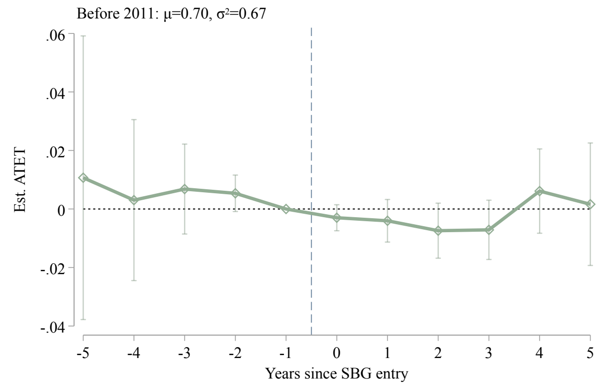
(d) National Banks - Modified

Figure IA.14 plots coefficient estimates from an event study analysis of the effects of SBG entry on the mortgage rates charged on single-family homes by local and national banks and on the average deposit rates on the combination of money market, savings account, and 12, 24, and 60 month CDs paid by local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. To account for county-years with missing mortgage data, the table reports results using modified mortgage rates in which missing observations are set to zero and an indicator variable denotes missing county-year pairs. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

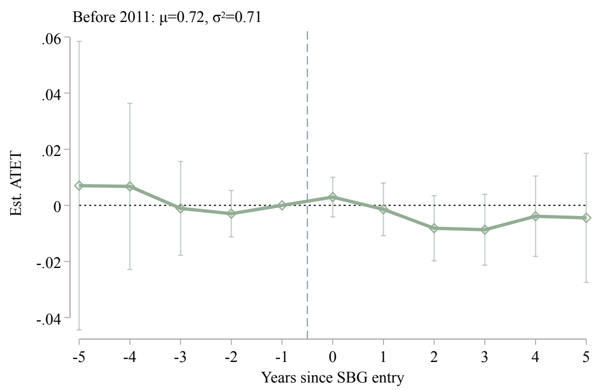
Figure IA.15: Deposit Rates - Money Market



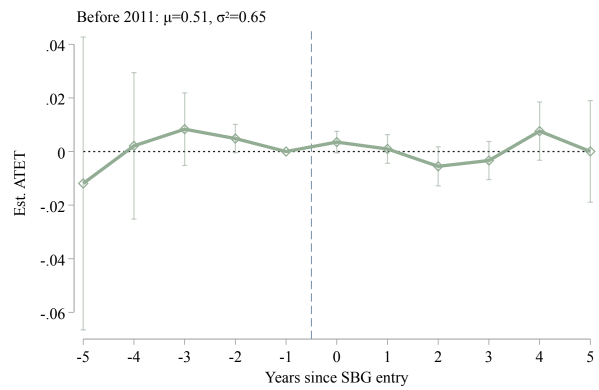
(a) Local Banks - Interpolated



(b) National Banks - Interpolated



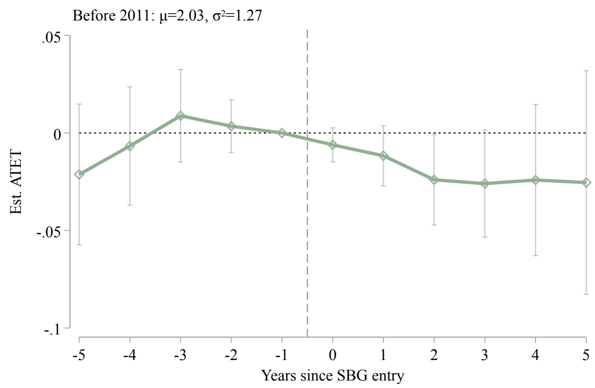
(c) Local Banks - Modified



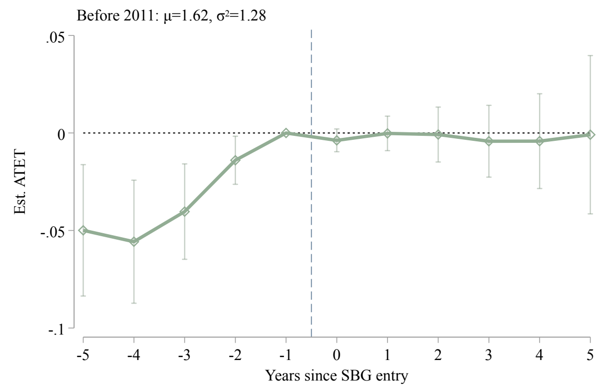
(d) National Banks - Modified

Figure IA.15 plots coefficient estimates from an event study analysis of the effects of SBG entry on the money market interest rates paid by local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. To account for county-years with missing money market rate data, Panels A and B present results with the money market rate interpolated at the county then state-levels and include an indicator variable for missing county-year pairs. Panels C and D modify the money market rate by setting missing observations to 0 and include an indicator variable for missing county-year pairs. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

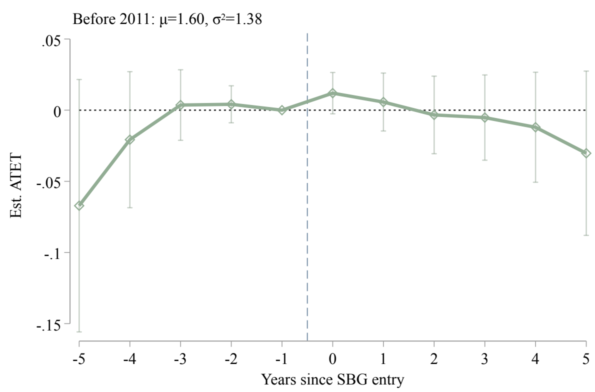
Figure IA.16: Deposit Rates - 12-month CDs



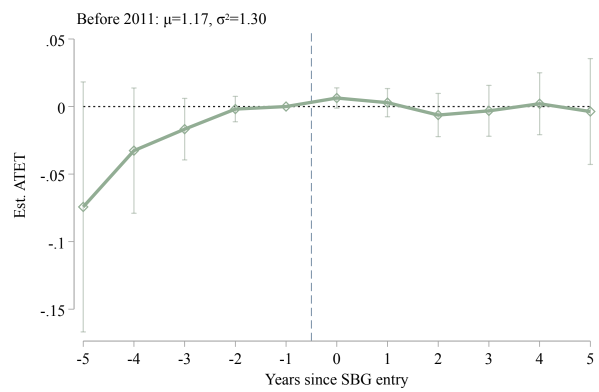
(a) Local Banks - Interpolated



(b) National Banks - Interpolated



(c) Local Banks - Modified



(d) National Banks - Modified

Figure IA.16 plots coefficient estimates from an event study analysis of the effects of SBG entry on the 12-month CD rates paid by local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects, and calculate variance-weighted average treatment effects (ATT) for each period. Coefficients are measured as percentage point changes in the outcome. Local banks are those operating in only one state and national banks are those operating in more than one state. To account for county-years with missing 12-month CD rate data, Panels A and B present results with the 12-month CD rates interpolated at the county then state-levels and include an indicator variable for missing county-year pairs. Panels C and D modify the 12-month CD rates by setting missing observations to 0 and include an indicator variable for missing county-year pairs. Event time zero denotes the first non-complete year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level as defined in 2000.

II The Relational Model in Full

This appendix develops in full the framework summarized in Section 6 of the main text.

II.1 Environment

II.1.1 Players, timing and preferences

Time is discrete and infinite, $t = 0, 1, 2, \dots$, and all agents discount at the common factor $\beta \in (0, 1)$. Following the relational-contract literature we read β as an effective discount factor that folds together time preference and the exogenous hazard that a relationship ends through migration, death, bank failure.[1] A county contains two banks, indexed $j \in \{\mathrm{L}, \mathrm{N}\}$ for local and national, and a unit continuum of households indexed by i. Each household maintains a banking relationship with exactly one bank in each period. We take the extensive margin of banking participation as fixed, consistent with the evidence in Figure 14 that county-level deposits per capita do not move. This means that any reallocation we derive is one-for-one between bank types.

It is convenient to write the *enforcement multiplier*

$$\Theta \;\equiv\; \frac{\beta}{1-\beta}, \tag{IA1}$$

which is the discounted expected number of future periods of a relationship and is strictly increasing in β. Because Θ is common to both banks, every cross-bank difference in enforcement below operates through a difference in alignment for soft requests from a customer to the bank.

II.1.2 Discretion and the non-contractible margin

The services a bank provides to a household divide into a contractible and a non-contractible component. The contractible component is the posted price, meaning the deposit rate paid, the mortgage rate charged, and the approval decision, all of which are verifiable and enforceable and all of which we observe in RateWatch and HMDA.

The non-contractible component makes the relationship worth more than the sum of its posted terms. In each period, with probability $\lambda \in (0, 1)$, a *discretionary state* arrives in which the household needs something the contract does not and cannot specify. Examples include forbearance on a missed payment, a fee reversed, funds made available before a deposit clears, a loan renewed on a soft signal that would not survive a credit committee, or simply not being steered into a product that is profitable for the bank and unsuitable for the household. Let $h_i \geq 0$ denote household i's *discretionary stake*, which is the value to i of being accommodated rather than exploited, conditional on the discretionary state arising. Heterogeneity in h_i is central to what follows.

In a discretionary state the banker takes an unverifiable action $a \in \{A, X\}$. Under accommodation ($a = A$) the household receives h_i and the bank receives nothing beyond its contractual return. Under exploitation ($a = X$) the household receives nothing and the bank captures γh_i, where $\gamma \in (0, 1)$.

[1] Allowing that hazard to differ across banks is a natural extension that we do not pursue here.

Remark II.1 (Exploitation is inefficient). Because $\gamma < 1$, exploitation destroys $(1-\gamma)h_i$ of surplus. Trust is therefore not merely distributive. An economy in which relational agreements are sustained produces more than one in which they are not.

II.1.3 Divergence

The object at the center of the model is the extent to which the banker's objective diverges from the household's. Formally, the banker at bank j maximizes the bank's own payoff plus $(1-\delta_j)$ times the household's payoff, where $\delta_j \in [0,1]$ is the *divergence parameter*. At $\delta_j = 0$ the banker is a perfect fiduciary, and at $\delta_j = 1$ she is a pure profit center.

The term $1-\delta_j$ is not to be read as altruism. It is the reduced form of a broader and longer relationship between the same two parties, of a kind that the institutional literature on community banking describes directly. The officer sits on the same school board as the depositor, the bank's directors are local business owners who will encounter the household in other settings, ownership and residual claims are held locally, and the decision authority to act on soft information sits with the person who holds those ties rather than with a credit committee in a different time zone (Stein, 2002; Berger and Udell, 2002). Each of these channels lowers δ_j, because each attaches a private cost to expropriating a customer.

Given δ_j, the banker's static temptation to exploit household i is the gain γh_i net of the internalised loss $(1-\delta_j)h_i$,

$$T_i(\delta_j) \;=\; \gamma h_i - (1-\delta_j)h_i \;=\; h_i\big(\delta_j - (1-\gamma)\big). \tag{IA2}$$

Define the *structural-trust threshold* $\underline{\delta} \equiv 1-\gamma$ and the *net divergence*

$$\Delta_j \;\equiv\; \delta_j - \underline{\delta} \;=\; \delta_j - 1 + \gamma, \tag{IA3}$$

so that $T_i = h_i \Delta_j$.

Lemma II.1 (Structural versus relational trust)**.** *If $\delta_j < \underline{\delta}$ then $T_i < 0$ for all $h_i > 0$, so that accommodation is statically dominant and the household is accommodated in every discretionary state regardless of the value of the relationship. If $\delta_j > \underline{\delta}$ then $T_i > 0$ and accommodation requires dynamic enforcement.*

Proof. The sign of T_i in (IA2) is the sign of $\delta_j - (1-\gamma)$. If $T_i < 0$ then $a = A$ is optimal in the stage game, hence in every period irrespective of continuation values. If $T_i > 0$ then $a = X$ is optimal in the stage game and $a = A$ can be supported only by continuation payoffs. □

The distinction determines which institutions a public signal about alignment can reach. Section II.8 uses it to account for the Gallup placebos.

II.1.4 Contractible terms

Bank j posts a spread $\sigma_j \geq 0$. On the deposit side, $\sigma_j = \bar{r} - r_j$ where $\bar{r}$ is the bank's outside return on funds and r_j the posted deposit rate. On the lending side $\sigma_j = \rho_j - \bar{\rho}$ where ρ_j is the posted mortgage rate. In both cases σ_j is the per-dollar rent the bank earns on the relationship, and in both cases a higher σ_j is worse for the household. Posted rates are uniform within a bank-county-year, which matches the structure of the RateWatch data and which implies that a bank cannot price-discriminate across customers on the basis of their unobserved discretionary stake.

Let $b_i > 0$ denote the size of household i's balance or loan. The bank's per-period rent from the relationship is then

$$\pi_i \;=\; \sigma_j\, b_i. \tag{IA4}$$

Two normalized household characteristics are useful here,

$$\psi_i \;\equiv\; \frac{h_i}{b_i} \qquad \text{and} \qquad \chi_i \;\equiv\; \frac{h_i}{\pi_i} \;=\; \frac{\psi_i}{\sigma_j}. \tag{IA5}$$

We call ψ_i the household's *stake intensity*, the value of discretion per dollar of business, and χ_i its *trust intensity*, the value of discretion per dollar of rent the household generates for the bank. ψ_i is a primitive while χ_i depends on the price the bank posts.

Finally, households differ in a horizontal taste ℓ_i for the amenities of the national bank, such as branch and ATM networks outside the county, digital services, and the ability to bank while traveling. The stake intensity $\psi_i \equiv h_i/b_i$ is continuously distributed with strictly positive density on a bounded support, and is independent of ℓ_i, which has distribution F_ℓ, continuous and strictly increasing on its support. The positive density guarantees that every band of χ we consider has positive mass while continuity rules out atoms. We use bounded support for integrability of the aggregates in Sections II.5 and II.7. Note that independence is a simplification. If households with low stakes also value national amenities more, the two are correlated.

Assumption II.1 (Alignment ordering)**.** $\delta_{\mathrm{L}} < \delta_{\mathrm{N}}$.

This is the model's substantive statement about what "local" means. It motivates the geographic definition of local banks as a proxy in the paper.

Trust intensity varies across households for reasons that cut across income. Stakes scale with exposure, since forbearance on a large loan is worth more than on a small one, so $\psi_i = h_i/b_i$ need not vary systematically with the level of income. What remains is variation in how much of a household's finances runs through the banker's judgment, which depends on income volatility, self-employment, and the availability of substitutes for discretion. We treat χ_i as heterogeneous and do not assume it is ordered by income.[2]

II.2 Trust as a self-enforcing agreement

Consider a relationship between household i and bank j. The relational agreement consists of two strategies. The banker accommodates in every discretionary state, and the household maintains the relationship as long as she has never been exploited and terminates permanently if she has. Termination is the only instrument the household has, since the discretionary action is unverifiable and therefore not actionable.

Let $W_j(h_i)$ denote the banker's continuation value, evaluated in her own objective, at the start of a period in which the relationship is intact and play is on path. Collecting the rent π_i each period,

[2] Allowing the frequency λ to vary across households changes nothing below, since the incentive constraint is evaluated conditional on the state arriving and the value of accommodation becomes $\lambda_i h_i$.

receiving $(1-\delta_j)h_i$ in each discretionary state under accommodation, and discounting the future at β,

$$W_j(h_i) \;=\; \pi_i + \lambda(1-\delta_j)h_i + \beta W_j(h_i) \;\;\Longrightarrow\;\; W_j(h_i) \;=\; \frac{\pi_i + \lambda(1-\delta_j)h_i}{1-\beta}. \tag{IA6}$$

In a discretionary state, the current period's rent having already been collected, the banker compares accommodation, worth $(1-\delta_j)h_i + \beta W_j(h_i)$, against exploitation, worth γh_i followed by termination. The incentive constraint is therefore

$$(1-\delta_j)h_i + \beta W_j(h_i) \;\geq\; \gamma h_i \quad\Longleftrightarrow\quad \beta W_j(h_i) \;\geq\; h_i \Delta_j. \tag{IA7}$$

Substituting (IA6) and (IA1) and rearranging gives the constraint in the form we use throughout,

$$\boxed{\Theta\,\pi_i \;\geq\; h_i\,\mu_j} \qquad \text{where} \qquad \mu_j \;\equiv\; \Delta_j - \lambda\Theta(1-\delta_j). \tag{IA8}$$

We call μ_j the *net temptation intensity*. It is the static net divergence Δ_j less the value of the future stream of accommodation the banker herself enjoys, which is forfeited on deviation and therefore supports current accommodation even absent any rent. In the leading case in which discretionary states are infrequent or divergence is high, $\lambda\Theta(1-\delta_j)$ is small and $\mu_j \approx \Delta_j$, and the reader may carry that simplification through without loss of intuition. Note that $\partial\mu_j/\partial\delta_j = 1+\lambda\Theta > 0$, so μ_j inherits the monotonicity of Δ_j in divergence.

Definition II.1 (Trust capacity)**.** The trust capacity of bank j is

$$\mathscr{H}_j \;\equiv\; \begin{cases} \dfrac{\Theta}{\mu_j}, & \mu_j > 0, \\ +\infty, & \mu_j \leq 0. \end{cases}$$

Proposition II.1 (Trust capacity and the trust margin)**.** *There exists a subgame-perfect equilibrium in which bank j accommodates household i in every discretionary state if and only if*

$$\chi_i \;\leq\; \mathscr{H}_j,$$

that is, if and only if the household's discretionary stake per dollar of rent generated does not exceed the bank's trust capacity. Trust capacity is

(i) strictly increasing in the discount factor β;

(ii) strictly decreasing in divergence δ_j;

(iii) independent of the household's balance b_i and of the posted spread σ_j, both of which enter only through χ_i.

The proof is in Section II.9. We note three features of Proposition II.1.

First, and most importantly for the interpretation of the empirical results, a household with $\chi_i > \mathscr{H}_j$ is *not denied service*. Deposits are contractible and insured, and a mortgage application is evaluated on hard information, so neither is withheld. What she loses is the expectation of accommodation in the discretionary state, worth λh_i per period. The model therefore predicts sorting on trust with no rationing whatever. This is what Panels A of both Figures 6 and 7 show.

Second, the constraint is stated in terms of $\chi_i = h_i/\pi_i$ rather than h_i alone. A household is easy to serve credibly when its stake in discretion is small relative to the business it brings. This ratio, and not the level of either component, is the object that determines who can be trusted.

Third, the condition involves no comparison between banks. Trust capacity is a property of a bank's enforcement technology and alignment, not of the competitive environment.

Lemma II.2 (Feasibility of relational banking)**.** *Trusted service is mutually acceptable, in the sense that the household prefers paying the spread required to make accommodation credible to being served without trust at zero spread, if and only if*

$$\mathscr{H}_j \ \geq \ \frac{1}{\lambda}, \qquad \textit{equivalently} \qquad \lambda\Theta\big(2-\delta_j\big) \ \geq \ \Delta_j.$$

The condition does not depend on the identity of the household.

Proof. See Section II.9. The intuition is a comparison of two per-dollar magnitudes. Making accommodation credible for a household of stake intensity ψ_i requires a spread of at least $\psi_i/\mathscr{H}_j$, by (IA8) and (IA5). The household's willingness to pay for accommodation is $\lambda\psi_i$ per dollar of business. Both scale linearly in ψ_i, so the comparison reduces to $1/\mathscr{H}_j \leq \lambda$ and is common across households. □

Lemma II.2 says that relational banking is viable only when the enforcement technology is good enough that the rent needed to buy credibility is worth less to the household than the accommodation it buys. It is a folk-theorem condition in a familiar form, requiring that patience and relationship durability, scaled by the frequency with which discretion matters, exceed net divergence. The condition is more easily met at a bank with low δ_j, which is the sense in which local banks are the natural home for relational business.

Remark II.2 (Credibility of the punishment). The grim-trigger threat is subject to the usual objection that carrying it out is ex post costly for the household. The standard resolution applies here with an interpretation that is natural in this setting. Suppose a share $\epsilon > 0$ of bankers are behavioral types who exploit in every discretionary state. On path, the strategic type never exploits, so observing $a = X$ raises the household's posterior on the behavioral type to one, and permanent termination is strictly sequentially rational. Because the strategic type's constraint (IA8) is unchanged for any $\epsilon > 0$, all results below hold in the limit $\epsilon \to 0$ and we suppress the type space.

II.3 Beliefs, information, and the media shock

Households do not observe δ_j. They act on their beliefs. The media shock then moves these beliefs. Let $\hat{\delta}_{ij}$ denote household i's posterior mean of bank j's divergence, and let all objects defined above be evaluated at posterior means, which we indicate with a hat.

Household i observes two signals about bank j. The first is a private local signal z_{ij}, capturing whether the loan officer knows her name, whether the bank's directors are people she can identify, and how the bank treated her neighbor when he lost his job. Its precision is τ_{ij}. The second is a public signal m carried by the news media about the alignment of institutions with ordinary people, with precision τ_m, common to all households in the county. With normal signals and a diffuse prior the posterior mean is

$$\hat{\delta}_{ij} \;=\; \omega_{ij}\, m + (1-\omega_{ij})\, z_{ij}, \qquad \omega_{ij} \;=\; \frac{\tau_m}{\tau_m + \tau_{ij}}. \tag{IA9}$$

Assumption II.2 (Differential informativeness)**.** *$\tau_{i\mathrm{L}} \gg \tau_{i\mathrm{N}}$, and hence $\omega_{i\mathrm{L}} \ll \omega_{i\mathrm{N}}$.*

Assumption II.2 is the informational counterpart of Assumption II.1 and has the same institutional basis. A household has direct, verifiable evidence about the conduct of a bank whose decision-makers live in the county, and it has essentially none about the conduct of a national institution, whose behavior toward people like her occurs elsewhere and reaches her only through intermediaries. This is the mechanism Gentzkow and Shapiro (2006b) identify in a different setting, whereby slant is disciplined where consumers can verify and undisciplined where they cannot. The same logic that makes local sports coverage unslanted makes coverage of national institutions slantable.

The shock. Throughout, a prime on a symbol denotes its value after the shock. SBG's entry raises the public signal, $m \to m' > m$, so that the county's local news now devotes more of its time to national affairs and presents national institutions as dysfunctional, captured, and indifferent to ordinary people. By (IA9),

$$d\hat{\delta}_{\mathrm{N}} \;=\; \omega_{i\mathrm{N}}\, dm \;\;\gg\;\; d\hat{\delta}_{\mathrm{L}} \;=\; \omega_{i\mathrm{L}}\, dm \;\geq\; 0. \tag{IA10}$$

Two forces push in the same direction. The first is the informational weight in (IA9), since the public signal moves beliefs most where private information is thinnest, which by Assumption II.2 is the national bank. The second is relevance, since the content of the signal concerns large, impersonal, nationally-scoped organizations and is therefore more diagnostic of δ_{N} than of δ_{L} even holding precisions fixed.

We model only the first. In (IA9) the same signal enters both posteriors and the difference in response comes entirely from the difference in weights, $(\omega_{i\mathrm{N}} - \omega_{i\mathrm{L}})\, dm$. If the signal were instead about δ_{N} specifically, $\hat{\delta}_{\mathrm{L}}$ would not respond at all and the difference would be $\omega_{i\mathrm{N}}\, dm$, which is larger. Omitting the second channel therefore makes the predicted asymmetry smaller than it would otherwise be, and every result below that rests on the asymmetry holds a fortiori.

Note that the shock carries no information about bank balance sheets, deposit insurance, or solvency, and no information about the local bank's conduct.

II.3.1 Sorting

Household i's expected per-period payoff at bank j, normalizing the outside return to zero and measuring the amenity taste relative to the local bank, is

$$u_{ij} \;=\; -\sigma_j b_i \;+\; \lambda h_i\, \mathbf{1}\{\chi_i \leq \mathscr{H}_j\} \;+\; \ell_i\, \mathbf{1}\{j = \mathrm{N}\}. \tag{IA11}$$

The household chooses N if and only if $u_{i\mathrm{N}} > u_{i\mathrm{L}}$, that is if and only if

$$\ell_i \;>\; \bar{\ell}(i) \;\equiv\; \underbrace{(\sigma_{\mathrm{N}} - \sigma_{\mathrm{L}}) b_i}_{\text{price}} + \lambda h_i \Big[\mathbf{1}\{\chi_i \leq \mathscr{H}_{\mathrm{L}}\} - \mathbf{1}\{\chi_i \leq \mathscr{H}_{\mathrm{N}}\}\Big]. \tag{IA12}$$

Proposition II.2 (Sorting on the trust margin)**.** *Suppose $\mathscr{H}_{\mathrm{L}} > \mathscr{H}_{\mathrm{N}}$. Partition households by trust intensity.*

(a) Universally trusted, *$\chi_i \leq \mathscr{H}_{\mathrm{N}}$. Both banks can credibly accommodate. The trust term in* (IA12) *vanishes and the household sorts purely on price and amenities.*

(b) Contested, *$\chi_i \in (\mathscr{H}_{\mathrm{N}}, \mathscr{H}_{\mathrm{L}}]$. Only the local bank can credibly accommodate. The local bank's share among these households exceeds its share among group (a) by $F_\ell(\bar{\ell} + \lambda h_i) - F_\ell(\bar{\ell}) > 0$.*

(c) Universally untrusted, *$\chi_i > \mathscr{H}_{\mathrm{L}}$. Neither bank can credibly accommodate, and the household again sorts purely on price and amenities.*

Consequently the local bank's market share is weakly increasing in χ_i over $(\mathscr{H}_{\mathrm{N}}, \mathscr{H}_{\mathrm{L}}]$ and flat outside it, with a discrete upward jump at $\chi_i = \mathscr{H}_{\mathrm{N}}$ and a discrete downward jump at $\chi_i = \mathscr{H}_{\mathrm{L}}$.

Proposition II.2 isolates where the mechanism can operate. The trust margin is active only on an intermediate band of households, namely those whose stake is too large for the national bank to guarantee but not too large for the local bank. Households on either side of the band are, as far as trust is concerned, indifferent between bank types.

II.3.2 Reallocation

Proposition II.3 (Deposit and application reallocation)**.** *An increase in perceived national divergence, $d\hat{\delta}_{\mathrm{N}} > 0$, lowers the national bank's trust capacity from $\mathscr{H}_{\mathrm{N}}$ to $\mathscr{H}'_{\mathrm{N}} < \mathscr{H}_{\mathrm{N}}$ and widens the contested band. Let $\mathscr{D} \equiv \{i : \chi_i \in (\mathscr{H}'_{\mathrm{N}}, \mathscr{H}_{\mathrm{N}}]\}$ denote the newly contested households. Then*

(i) the local bank's share rises and the national bank's share falls by exactly the same amount,

$$ds_{\mathrm{L}} \;=\; -\,ds_{\mathrm{N}} \;=\; \int_{\mathscr{D}} \Big[F_\ell\big(\bar{\ell}_i + \lambda h_i\big) - F_\ell\big(\bar{\ell}_i\big)\Big]\,di \;>\; 0;$$

(ii) aggregate deposits and aggregate loan applications in the county are unchanged;

(iii) the reallocation is concentrated among households with high χ_i.

Parts (i) and (ii) correspond to Figure 2 and to Figure 14 respectively, with shares moving symmetrically while the level of banking activity does not. Part (iii) identifies the movers as the households with the *highest* trust intensity among those the national bank could previously accommodate, meaning the ones for whom the constraint (IA8) was closest to binding. Trust intensity is not observed. Figure 5 and Panel B of Figure 7 show that the reallocation does not differ across income brackets, which is what the model implies if stakes scale with exposure, and which rules out the reading in which low-income households simply believe the news more. Everyone in the county revises the same belief about the national bank. What differs across households is how much they have at stake in its discretion.

Corollary II.1 (Why deposits move before loan applications)**.** *Suppose a household's need to apply for a mortgage arrives with per-period hazard $\eta \in (0, 1)$, whereas the decision of where to hold deposits can be revisited every period at negligible cost. Then following the shock at $t = 0$ the* *deposit share adjusts immediately and fully, while the cumulative loan-application share adjusts as*

$$\frac{\Delta s_{\mathrm{L}}^{\mathrm{loans}}(t)}{\Delta s_{\mathrm{L}}^{\mathrm{loans}}(\infty)} \;=\; 1-(1-\eta)^{\,t+1},$$

reaching half its long-run value only after $t^* = \ln(1/2)/\ln(1-\eta)-1$ *periods. For an annual mortgage hazard of* $\eta \approx 0.15$, $t^* \approx 3.3$ *years.*

Corollary II.1 accounts for why deposit shares move at $t = 1$ and $t = 2$ (Figure 2) while application shares move only at $t = 3$ through $t = 5$ (Figure 4).

Corollary II.2 (Frequency of discretion)**.** *Holding the displaced set* $\mathscr{D}$ *fixed, the reallocation in Proposition II.3(i) is strictly increasing in* λ.

Proof. The integrand $F_\ell(\bar{\ell}_i+\lambda h_i)-F_\ell(\bar{\ell}_i)$ is strictly increasing in λ because F_ℓ is strictly increasing and $h_i > 0$. The set $\mathscr{D}$ depends on λ only through the correction term in μ_j, which is second-order and which we hold fixed. □

Corollary II.2 is a prediction about counties. Where households more often need the banker's judgment, the value of being trusted is higher and more of the households who lose the national bank's trust act on it. Figure 12 splits counties by pre-treatment wage volatility and finds the reallocation larger in the high-volatility half, for both deposits and applications. This is variation in the true λ across counties, and is distinct from the perceived $\hat{\lambda}$ within a county in Section II.3.3. Volatile income may raise h_i as well as λ. Both enter the reallocation through λh_i in the same way.

II.3.3 A second channel: perceived need for discretion

Coverage that presents the world as more dangerous may raise a household's belief that she will need accommodation, whether or not it changes her belief about the bank's alignment. Let $\hat{\lambda}$ denote the perceived frequency of the discretionary state, and suppose it responds to m alongside $\hat{\delta}_{\mathrm{N}}$.[3] The value of trust in (IA11) becomes $\hat{\lambda}h_i$, and for a household in the contested band the cutoff in (IA12) rises by $(\hat{\lambda}'-\hat{\lambda})h_i$. A rise in $\hat{\lambda}$ therefore moves households toward the local bank with no change in beliefs about alignment. The movers are households who were already contested and were staying at the national bank for its amenities, so the channel amplifies the sorting the local bank's existing trust advantage produces rather than opening a new band. The two shocks move disjoint populations, and their effects on the reallocation add.

The channel matches the reallocation, its concentration among high-χ households, the flat approval rates, and the widening of the local spread. The arrivals under this channel come from the contested band itself rather than from just below $\hat{\mathscr{H}}_{\mathrm{N}}$, so they carry higher ψ_i and raise $\bar{\psi}_{\mathrm{L}}$ by more per household. What separates it from the divergence channel is the survey evidence. A rise in $\hat{\lambda}$ raises the value of being trusted and lowers trust in nothing, so it predicts no change in measured confidence in banks or big business, whereas Figure 9 shows a fall. This reads the survey question as measuring alignment rather than a general sense of security with banks. On that reading, Figure 9 says $\hat{\delta}_{\mathrm{N}}$ moved. It does not rule out $\hat{\lambda}$ moving as well.

[3] $\hat{\lambda}$ also enters the household's assessment of the bank's constraint through $\hat{\mu}_j = \hat{\Delta}_j - \hat{\lambda}\Theta(1-\hat{\delta}_j)$, raising $\hat{\mathscr{H}}_j$ at both banks. The effect is second-order, works against the direct one, and we ignore it.

The two channels differ in the size of the loss, not its sign. The signal is as uninformative about λ as it is about δ_{N}, so $\hat{\lambda}$ overshoots the true value for the same reason $\hat{\delta}_{\mathrm{N}}$ does. Under the divergence channel a switcher gives up an accommodation the national bank would have provided and gains nothing net at the local bank, so her loss is the full amenity differential, at most λh_i. Under the need-for-discretion channel a switcher gains real accommodation at the local bank, since the national bank could not provide it, and the households with $\ell_i - \bar{\ell}_i \in (\lambda h_i,\ \hat{\lambda} h_i]$ switch wrongly, each losing at most $(\hat{\lambda} - \lambda) h_i$. The loss is bounded by the belief error rather than by the value of trust. The welfare analysis in Section II.7 is conducted under the divergence channel and is an upper bound if part of the reallocation runs through the second.

II.4 Why the shock must be to divergence

An alternate reading of the evidence is that SBG's entry did not change what households believe about the alignment of national banks but simply made them gloomier about the future, lowering the common discount factor β and hence Θ. These alternate stories can be investigated through our model.

A shock to $\hat{\delta}_{\mathrm{N}}$ lowers $\mathscr{H}_{\mathrm{N}}$ and leaves $\mathscr{H}_{\mathrm{L}}$ unchanged. The contested band $(\mathscr{H}_{\mathrm{N}}, \mathscr{H}_{\mathrm{L}}]$ widens from below. The flow is one-sided from the national bank to the local bank. Every household who moves retains accommodation at its destination. This is Proposition II.3.

A shock to Θ lowers both capacities in the same proportion, so the ratio $\mathscr{H}_{\mathrm{L}}/\mathscr{H}_{\mathrm{N}} = \Delta_{\mathrm{N}}/\Delta_{\mathrm{L}}$ is preserved but both endpoints of the band fall. Two flows result. Households with χ_i just below the old $\mathscr{H}_{\mathrm{N}}$ enter the band from below and shift toward the local bank. Households with χ_i just below the old $\mathscr{H}_{\mathrm{L}}$ exit the band from above, lose accommodation at both banks, and sort on price and amenities alone. The net change in the local bank's share is therefore ambiguous and depends on where the mass of χ sits. A second implication follows from Section II.7. The departure of the local bank's highest-ψ customers lowers its aggregate stake intensity $\bar{\psi}_{\mathrm{L}}$ and would narrow its minimum credible spread, the opposite of the widening documented in Figure 8.

The observed configuration, a one-sided flow toward the local bank accompanied by a widening of the local spread, is therefore strongly suggestive of a divergence shock and not of a discount shock.

II.5 Rents as collateral

Recall from (IA5) that $\chi_i = \psi_i/\sigma_j$, so that the trust intensity of a household depends on the spread the bank charges it. Substituting into the incentive constraint (IA8), bank j can credibly accommodate household i if and only if

$$\sigma_j \ \geq\ \frac{\psi_i}{\mathscr{H}_j} \ \equiv\ \underline{\sigma}_j(i). \tag{IA13}$$

Equation (IA13) inverts the usual reading of an intermediation spread because the spread is not only what the bank extracts from the household. It is also what the bank stands to lose if it breaks its promise, and so it is what makes the promise credible. If the spread is thin, the rent on the relationship is small, exploitation costs the bank almost nothing, and a household cannot rely on the bank to accommodate her. How wide the spread must be depends on the household's stake per dollar of business, ψ_i. Households with small balances and a large need for discretion have the highest ψ_i. They are the ones for whom the bank needs the widest spread before its promise is worth anything. This is the mechanism of Klein and Leffler (1981) and Shapiro (1983) in a banking setting. Quality that cannot be written into a contract has to be secured by a rent stream and the household who wants the quality pays for the rent.

II.5.1 The binding deviation

Which constraint binds depends on what households can observe. If each household saw only her own treatment and punished only that, (IA13) would have to hold customer by customer, and with uniform posted rates the spread would need to satisfy only the single hardest customer, $\sigma_j \geq \psi_j^*/\mathscr{H}_j$ with ψ_j^* the supremum of ψ_i over the clientele. We instead assume the following.

Assumption II.3 (Aggregate observability)**.** *Households observe the fraction of the clientele that bank j accommodates. Any positive-measure deviation from accommodation is observed by all of bank j's customers and is followed by termination by all of them.*

Assumption II.3 is a simplification of relational contracting under imperfect public monitoring (Levin, 2003), in which households observe a noisy statistic of the bank's conduct and partial deviations are tolerated up to the point of detection. We do not pursue that case. Under the assumption, a deviation on a single customer is measure zero and gains nothing, and a deviation on any positive-measure set costs the entire franchise, so the only deviation that can pay is the one that exploits every customer currently in a discretionary state.

Discretionary states are idiosyncratic, so in any period a fraction λ of the clientele is in one. Writing $\mathscr{C}_j$ for the clientele, the on-path franchise value is $W_j = \big[\int_{\mathscr{C}_j} \pi_i \, di + \lambda(1-\delta_j) \int_{\mathscr{C}_j} h_i \, di\big]/(1-\beta)$. Accommodating this period yields $(1-\delta_j)\lambda \int_{\mathscr{C}_j} h_i \, di + \beta W_j$, deviating yields $\gamma\lambda \int_{\mathscr{C}_j} h_i \, di$ and nothing after, and accommodation is sustained if and only if

$$\Theta \int_{\mathscr{C}_j} \pi_i \, di \;\geq\; \mu_j^P \int_{\mathscr{C}_j} h_i \, di, \qquad \mu_j^P \;\equiv\; \lambda\big[\Delta_j - \Theta(1-\delta_j)\big]. \tag{IA14}$$

The aggregate temptation intensity μ_j^P differs from the individual one, $\mu_j = \Delta_j - \lambda\Theta(1-\delta_j)$, in carrying λ on the net divergence term, because the deviation captures the stake of only those customers currently in a discretionary state while forfeiting the whole franchise. Hence $\mu_j^P < \mu_j$ and the aggregate constraint is the slacker of the two. Define the aggregate trust capacity $\mathscr{H}_j^P \equiv \Theta/\mu_j^P > \mathscr{H}_j$. Substituting $\pi_i = \sigma_j b_i$ into (IA14) and rearranging gives the following inequality.

Proposition II.4 (Minimum credible spread)**.** *Define the clientele's* aggregate stake intensity

$$\bar{\psi}_j \;\equiv\; \frac{\int_{\mathscr{C}_j} h_i \, di}{\int_{\mathscr{C}_j} b_i \, di},$$

the total value of discretion per dollar of business on the bank's books. Under Assumption II.3, accommodation of clientele $\mathscr{C}_j$ is sustainable if and only if the bank posts a spread of at least

$$\sigma_j \;\geq\; \frac{\bar{\psi}_j}{\mathscr{H}_j^P}.$$

If a rival could profitably serve $\mathscr{C}_j$ at a lower spread, the inequality holds with equality, $\sigma_j^* = \bar{\psi}_j/\mathscr{H}_j^P$.

The constraint says that the bank must be earning enough, in total, that abandoning accommodation is unprofitable. What matters is the total stake it guarantees relative to the total business securing it.

Remark II.3 (Cross-subsidy). Because the posted spread is uniform while ψ_i is not, the credibility premium $\bar{\psi}_j/\mathscr{H}_j^P$ is paid by every customer but is worth $\lambda\psi_i$ only to customer i. Households with $\psi_i < \bar{\psi}_j/(\lambda\mathscr{H}_j^P)$ are subsidizing the credibility of the promise to households with higher stakes. This is an independent implication of uniform pricing under an aggregate constraint, and it means that the incidence of the rate movement documented in Figure 8 falls on the bank's entire depositor and borrower base, not only on the households who moved.

II.5.2 Composition and pricing

Proposition II.5 (Composition and pricing)**.** *Let $\mathscr{D}$ be the set of households reallocated from* N *to* L *by the media shock, with aggregate stake intensity $\psi_{\mathscr{D}} = \int_{\mathscr{D}} h_i \, di / \int_{\mathscr{D}} b_i \, di$. Then*

(i) $\bar{\psi}_{\mathrm{L}}$ rises if and only if $\psi_{\mathscr{D}} > \bar{\psi}_{\mathrm{L}}$, in which case the local bank's minimum credible spread rises,

$$\frac{d\sigma_{\mathrm{L}}^*}{d\bar{\psi}_{\mathrm{L}}} = \frac{1}{\mathscr{H}_{\mathrm{L}}^P} > 0,$$

so that its posted deposit rate falls and its posted mortgage rate rises;

(ii) $\bar{\psi}_{\mathrm{N}}$ falls unambiguously, since $\mathscr{D}$ consists of the highest-χ members of the national bank's clientele. The national bank's constraint therefore strictly slackens and its posted spread need not move at all.

The condition in part (i) is that the arriving households have a higher stake per dollar of business than the local bank's existing customers. The arrivals are the highest-ψ households the national bank previously accommodated, and the local bank's existing clientele includes households who chose it on price and convenience and therefore have low ψ_i, by Proposition II.2. The condition holds when the second group is large enough. We take it as holding and note that it is not directly verified.

Proposition II.5 matches Figure 8 in both sign and asymmetry. The local bank's deposit rate falls and its mortgage rate rises, while the national bank's rates are flat in every specification. The asymmetry is not incidental. The constraint binds on the receiving side of the reallocation and slackens on the sending side, so only the local bank is forced to move.

The households who arrive at the local bank are high-stake, low-balance households who need the bank to behave well in circumstances no contract reaches. The bank can promise that only if abandoning them would cost it more than it gains, and the wider spread is what makes the promise credible. The extra rent the local bank earns on the inflow, documented in Section 4.3.2, is the bond behind the accommodation those households came for. A bank that competed the spread away would be cheaper and could not be relied on. The model gives the minimum spread at which the promise holds. A bank with market power may charge more than that minimum, and the data do not separate the credibility floor from a markup above it.

II.6 Why banks do not respond on the branching and approval margins

The evidence shows two nulls. Banks do not change their propensity to enter, exit, open, or close branches (Figures IA.2 and IA.3), and they do not change loan approval rates (Panel A of Figures 6 and 7). Both follow from the structure of the model.

Proposition II.6 (Non-response)**.** *Following a shock to $\hat{\delta}_{\mathrm{N}}$,*

(i) loan approval rates are unchanged at both banks;

(ii) neither bank's entry, exit, branch-opening or branch-closing policy responds at the horizon of the shock.

Proof. (i) Approval is a decision taken on hard, verifiable information before any discretionary state arises, and it is contractible in the sense that it is subject to fair-lending review and is observable to the regulator. It therefore lies outside the relational margin, and δ_j does not enter the approval rule. The composition of applicants at each bank changes, so the *share* of approvals shifts one-for-one with the share of applications, but the *rate* of approval conditional on application is a function of applicant hard characteristics and the bank's credit policy, neither of which the shock moves. This is the pattern in Figure 4 and in Panels A and B of Figure 6.

(ii) The national bank's problem is to restore $\mathscr{H}_{\mathrm{N}}$. By Definition II.1, with Θ common, this requires lowering δ_{N}. Divergence is a stock, accumulated through local ownership, board composition, officer tenure and social embeddedness, and it cannot be adjusted by opening a branch. Since the only argument of $\mathscr{H}_{\mathrm{N}}$ that differs across banks is not adjustable at the frequency of the shock, the national bank's best response on the branching margin is inaction. The local bank, gaining business without needing to alter its footprint, likewise has no reason to move. □

The model says that the asset the national bank has lost is one it cannot buy back with capital expenditure, because the asset is a property of the relationship between particular people rather than of the physical network. That is why the observable response is nothing at all, rather than a slow response. It also explains a result the paper reports as a robustness check but which the model treats as a direct test. The reallocation is concentrated among local banks that are *not* part of multi-bank holding companies (Figure 10). Holding-company affiliation moves decision authority up the hierarchy and weakens the officer's residual claim and social exposure, raising δ_{L} (Stein, 2002). The model therefore predicts exactly the pattern found. Within the class of geographically local banks, the flight to trust favors those with the lowest divergence.

II.7 Welfare

We evaluate welfare at the true divergence δ_{N} rather than at households' beliefs about it. The choice is conservative. Evaluating at households' post-shock beliefs would leave the switchers' loss unchanged, since their realized outcome does not depend on what they believe about the bank they left, and would add a loss of λh_i for every household who stays at the national bank expecting to be exploited. The criterion used here yields the smaller loss.

Let $\mathscr{W}$ denote aggregate household surplus before the shock and $\mathscr{W}'$ after. Let $\mathscr{S}$ be the set of households who switch from N to L, and let $\mathscr{E}$ be the set of households who expect to lose the national bank's accommodation but remain with it because their amenity attachment outweighs the expected loss. The sets $\mathscr{S}$ and $\mathscr{E}$ partition the displaced set $\mathscr{D}$ of Proposition II.3.

Proposition II.7 (Welfare decomposition). *To first order,*

$$\mathscr{W}' - \mathscr{W} \;=\; -\underbrace{\int_{\mathscr{S}} \left(\ell_i - \bar{\ell}_i\right) di}_{\textit{(I) mismatch}} \;-\; \underbrace{\Delta\sigma_{\mathrm{L}} \int_{\mathscr{C}'_{\mathrm{L}}} b_i \, di}_{\textit{(II) transfer}},$$

where both terms are non-negative. Both are losses to households. Term (I) is the horizontal mismatch borne by switchers. Term (II) is the wider spread paid by everyone at the local bank.

Three observations follow.

First, the households who move incorrectly assume that the national bank will not accommodate them. A household who leaves gives up the amenity differential $\ell_i - \bar{\ell}_i$ to obtain at the local bank an accommodation the national bank would have provided. Term (I) is zero for the marginal switcher and rises to λh_i at the top of the band, so the average switcher loses a substantial fraction of the value of accommodation.

Second, term (II) is first-order in the rate movement and falls on the whole local clientele, not only on the movers. The spread is posted, so households already at the local bank pay the wider spread for the same accommodation they were receiving before. By Proposition II.5 the spread widens because of the arrival of high-ψ households. The movers pay it on top of term (I). It is likely the larger of the two terms.

Third, the decomposition takes the pre-shock allocation as the benchmark, which is correct only if the pre-shock belief was not itself distorted. The signal is uninformative about δ_N, so the pre-shock belief is the undistorted one and the shock moves beliefs away from the truth.

II.8 Trust across institutions

Under the model the Gallup evidence is a structural test, because Lemma II.1 sorts institutions into two classes with different exposure to a signal about alignment.

Proposition II.8 (Cross-institution exposure). *Let institution k be characterised by (δ_k, ω_k). The response of measured confidence to a public signal m about institutional alignment is*

$$\frac{d\,\mathrm{Trust}_k}{dm} \;=\; -\,\omega_k \cdot \mathbf{1}\{\delta_k > \underline{\delta}\} \cdot \left|\frac{\partial\,\mathrm{Trust}_k}{\partial \hat{\delta}_k}\right|.$$

Institutions whose divergence lies below the structural threshold have zero *exposure, regardless of ω_k. Their trustworthiness does not depend on enforcement and therefore does not depend on any belief that enforcement can affect.*

Institution	Enforcement	Exposure	Figure 9
Banks (national)	relational, $\delta > \underline{\delta}$, ω high	high	falls
Big business	relational, $\delta > \underline{\delta}$, ω high	high	falls
Small business	structural, $\delta < \underline{\delta}$, ω low	zero	flat
Churches	structural, $\delta < \underline{\delta}$, ω low	zero	flat
Police	structural and local, ω low	zero	flat

One limitation should be acknowledged. The Gallup survey asks about "banks" without distinguishing local from national, so the decline in Panel A of Figure 9 is an average across both types and the model predicts the decline is concentrated in the national component. A survey instrument that separated the two would be the cleanest available test of the mechanism.

II.9 Proofs

II.9.1 Proof of Proposition II.1

Construction. Consider the following strategy profile. The banker accommodates in every discretionary state so long as she has never exploited, and the household maintains the relationship so long as she has never been exploited and terminates permanently otherwise. By Remark II.2, with an arbitrarily small prior on a behavioral type that always exploits, permanent termination is strictly sequentially rational following any observation of $a = X$, so the household's strategy is optimal off path. On path the household strictly prefers to continue, since accommodation yields $h_i > 0$ per discretionary state at no additional cost.

The banker's constraint. Payoffs are bounded and discounted, so the one-shot deviation principle applies and it suffices to check a single deviation in a single discretionary state. On path, the banker's continuation value satisfies

$$W_j(h_i) = \pi_i + \lambda(1-\delta_j)h_i + \beta W_j(h_i) \implies W_j(h_i) = \frac{\pi_i + \lambda(1-\delta_j)h_i}{1-\beta},$$

which is (IA6). In a discretionary state, accommodation yields $(1-\delta_j)h_i + \beta W_j(h_i)$ and exploitation yields γh_i followed by termination, worth zero. Accommodation is optimal iff $\beta W_j(h_i) \geq \big(\gamma - 1 + \delta_j\big)h_i = \Delta_j h_i$. Substituting W_j and using $\Theta = \beta/(1-\beta)$,

$$\Theta\big[\pi_i + \lambda(1-\delta_j)h_i\big] \;\geq\; \Delta_j h_i \iff \Theta\pi_i \;\geq\; h_i\big[\Delta_j - \lambda\Theta(1-\delta_j)\big] = h_i\mu_j,$$

which is (IA8). If $\mu_j \leq 0$ the inequality holds for every $h_i \geq 0$ and $\mathscr{H}_j = +\infty$. If $\mu_j > 0$, dividing by $\pi_i\mu_j > 0$ gives $\chi_i = h_i/\pi_i \leq \Theta/\mu_j = \mathscr{H}_j$, as claimed. Conversely, if $\chi_i > \mathscr{H}_j$ then no grim-trigger equilibrium sustains accommodation, since the constraint fails and the deviation is profitable, and because grim trigger delivers the harshest available punishment, no other equilibrium sustains it either.

Comparative statics. Write $\mu_j = \Delta_j - \lambda\Theta(1-\delta_j)$.

(i) Since $\partial\mu_j/\partial\Theta = -\lambda(1-\delta_j)$,

$$\frac{\partial\mathscr{H}_j}{\partial\Theta} = \frac{\mu_j + \Theta\lambda(1-\delta_j)}{\mu_j^2} = \frac{\Delta_j}{\mu_j^2} \;>\; 0$$

whenever $\Delta_j > 0$, which is the relational-trust case of Lemma II.1. When $\Delta_j \leq 0$ trust is structural and $\mathscr{H}_j = +\infty$ independent of Θ. Since $\partial\Theta/\partial\beta = 1/(1-\beta)^2 > 0$, the claim follows by the chain rule.

(ii) Since $\partial\mu_j/\partial\delta_j = 1+\lambda\Theta > 0$ and the numerator Θ does not depend on δ_j,

$$\frac{\partial\mathscr{H}_j}{\partial\delta_j} = -\frac{\Theta\,(1+\lambda\Theta)}{\mu_j^2} \;<\; 0.$$

(iii) Neither b_i nor σ_j appears in Θ or μ_j. $\square$

II.9.2 Proof of Lemma II.2

Fix household i and bank j with $\mu_j > 0$. By (IA8) and (IA5), the smallest spread at which accommodation is credible for i is $\underline{\sigma} = \psi_i/\mathscr{H}_j$. Compare two arrangements. Under the first the household is served with trust at $\underline{\sigma}$ and obtains, per period,

$$-\underline{\sigma}\,b_i + \lambda h_i = -\frac{\psi_i b_i}{\mathscr{H}_j} + \lambda h_i = -\frac{h_i}{\mathscr{H}_j} + \lambda h_i = h_i\left(\lambda - \frac{1}{\mathscr{H}_j}\right),$$

using $\psi_i b_i = h_i$. Under the second she is served without trust at a zero spread and obtains zero. The first is weakly preferred iff $\lambda \geq 1/\mathscr{H}_j$, that is iff $\mathscr{H}_j \geq 1/\lambda$, and since $h_i > 0$ scales both terms identically the comparison does not depend on i.

For the equivalent form, $\mathscr{H}_j \geq 1/\lambda \iff \Theta/\mu_j \geq 1/\lambda \iff \lambda\Theta \geq \mu_j$. Substituting $\mu_j = \Delta_j - \lambda\Theta(1-\delta_j)$,

$$\lambda\Theta \;\geq\; \Delta_j - \lambda\Theta(1-\delta_j) \iff \lambda\Theta\big[1+(1-\delta_j)\big] \;\geq\; \Delta_j \iff \lambda\Theta\big(2-\delta_j\big) \;\geq\; \Delta_j. \qquad \square$$

II.9.3 Proof of Proposition II.2

By (IA12), household i chooses L iff $\ell_i \leq \bar{\ell}(i)$, so its probability of choosing L is $F_\ell(\bar{\ell}(i))$, which is strictly increasing in $\bar{\ell}(i)$ because F_ℓ is strictly increasing on its support. The trust term in $\bar{\ell}(i)$ is

$$\lambda h_i\Big[\mathbf{1}\{\chi_i \leq \mathscr{H}_{\mathrm{L}}\} - \mathbf{1}\{\chi_i \leq \mathscr{H}_{\mathrm{N}}\}\Big] = \begin{cases} 0, & \chi_i \leq \mathscr{H}_{\mathrm{N}}, \\ \lambda h_i > 0, & \mathscr{H}_{\mathrm{N}} < \chi_i \leq \mathscr{H}_{\mathrm{L}}, \\ 0, & \chi_i > \mathscr{H}_{\mathrm{L}}, \end{cases}$$

where the middle case uses $\mathscr{H}_{\mathrm{L}} > \mathscr{H}_{\mathrm{N}}$. Holding the price term fixed, $\bar{\ell}(i)$ is therefore higher by exactly λh_i on the contested band and identical outside it, which delivers the three cases and the two jumps. $\square$

II.9.4 Proof of Proposition II.3

(i) By Proposition II.1(ii), $d\hat{\delta}_{\mathrm{N}} > 0$ implies $d\mathscr{H}_{\mathrm{N}} < 0$. Write $\mathscr{H}'_{\mathrm{N}} < \mathscr{H}_{\mathrm{N}}$ for the post-shock capacity. Households with $\chi_i \leq \mathscr{H}'_{\mathrm{N}}$ and households with $\chi_i > \mathscr{H}_{\mathrm{N}}$ have unchanged trust status at both banks and hence unchanged $\bar{\ell}(i)$. Households in $\mathscr{D} = \{i : \chi_i \in (\mathscr{H}'_{\mathrm{N}}, \mathscr{H}_{\mathrm{N}}]\}$ move from case (a) to case (b) of Proposition II.2, so their cutoff rises from $\bar{\ell}_i$ to $\bar{\ell}_i + \lambda h_i$. Integrating the change in choice probabilities over $\mathscr{D}$ gives the stated expression, which is strictly positive because F_ℓ is strictly increasing and $\lambda h_i > 0$. Since each household banks with exactly one bank, $s_{\mathrm{L}} + s_{\mathrm{N}} = 1$ identically, so $ds_{\mathrm{N}} = -ds_{\mathrm{L}}$.

(ii) Immediate from the assumption that the extensive margin of banking participation is fixed. No household enters or exits the banking system, and balances b_i are unaffected by which bank holds them.

(iii) The set $\mathscr{D}$ is an interval at the top of the support of χ among households previously trusted at N, by construction. □

II.9.5 Proof of Corollary II.1

A household revises its deposit relationship in the period the belief changes, so the deposit response is complete at $t = 0$. A household expresses its revised preference in the mortgage application data only in the first period in which it has occasion to apply. If occasions arrive independently with per-period hazard η, the probability that a given displaced household has had at least one occasion by the end of period t is $1 - (1-\eta)^{t+1}$, and by the law of large numbers across the continuum this is also the fraction of the long-run application-share effect realized by t. Setting this equal to $\frac{1}{2}$ and solving, $(1-\eta)^{t^*+1} = \frac{1}{2}$, so $t^* = \ln(1/2)/\ln(1-\eta) - 1$. At $\eta = 0.15$ this is 3.27. □

II.9.6 Proof of Proposition II.4

Consider the deviation identified in Section C.5.1, in which the bank exploits every customer currently in a discretionary state. In the period of the switch a fraction λ of $\mathscr{C}_j$ is in a discretionary state. On path the franchise value is

$$W_j = \frac{\int_{\mathscr{C}_j} \pi_i \, di + \lambda(1-\delta_j) \int_{\mathscr{C}_j} h_i \, di}{1-\beta},$$

so that continuing to accommodate yields $(1-\delta_j)\lambda \int_{\mathscr{C}_j} h_i \, di + \beta W_j$, while switching yields $\gamma\lambda \int_{\mathscr{C}_j} h_i \, di$ and no continuation, since the switch is observed and the clientele leaves. Accommodation is sustained iff

$$\Theta\Big[\int_{\mathscr{C}_j} \pi_i \, di + \lambda(1-\delta_j)\int_{\mathscr{C}_j} h_i \, di\Big] \;\geq\; \lambda\Delta_j \int_{\mathscr{C}_j} h_i \, di \iff \Theta\int_{\mathscr{C}_j} \pi_i \, di \;\geq\; \lambda\big[\Delta_j - \Theta(1-\delta_j)\big]\int_{\mathscr{C}_j} h_i \, di,$$

which is (IA14). Substituting $\pi_i = \sigma_j b_i$ and dividing by $\Theta \int_{\mathscr{C}_j} b_i \, di > 0$,

$$\sigma_j \;\geq\; \frac{\mu_j^P}{\Theta} \cdot \frac{\int_{\mathscr{C}_j} h_i \, di}{\int_{\mathscr{C}_j} b_i \, di} = \frac{\bar{\psi}_j}{\mathscr{H}_j^P}.$$

A deviation on a single customer, which under public observation also forfeits the franchise for a gain of at most γh_i, is dominated by that deviation and is never the binding one.

For the equality, suppose $\sigma_j > \bar{\psi}_j/\mathscr{H}_j^P$. Every member of $\mathscr{C}_j$ strictly prefers the spread $\bar{\psi}_j/\mathscr{H}_j^P$, at which accommodation is still sustained and each pays strictly less. A rival posting $\bar{\psi}_j/\mathscr{H}_j^P + \varepsilon$ for $\varepsilon > 0$ small enough sustains the agreement with the same clientele, attracts all of $\mathscr{C}_j$, and earns strictly positive rents. Hence no spread strictly above the bound survives competition.
□

II.9.7 Proof of Proposition II.5

(i) Write $H_{\mathrm{L}} = \int_{\mathscr{C}_{\mathrm{L}}} h_i\, di$ and $B_{\mathrm{L}} = \int_{\mathscr{C}_{\mathrm{L}}} b_i\, di$, so $\bar{\psi}_{\mathrm{L}} = H_{\mathrm{L}}/B_{\mathrm{L}}$, and let $H_{\mathscr{D}}, B_{\mathscr{D}}$ be the corresponding aggregates over the arriving set $\mathscr{D}$, with $\psi_{\mathscr{D}} = H_{\mathscr{D}}/B_{\mathscr{D}}$. Post-shock,

$$\bar{\psi}'_{\mathrm{L}} = \frac{H_{\mathrm{L}} + H_{\mathscr{D}}}{B_{\mathrm{L}} + B_{\mathscr{D}}}.$$

The mediant inequality gives $\bar{\psi}'_{\mathrm{L}} > \bar{\psi}_{\mathrm{L}}$ iff $H_{\mathscr{D}}/B_{\mathscr{D}} > H_{\mathrm{L}}/B_{\mathrm{L}}$, that is iff $\psi_{\mathscr{D}} > \bar{\psi}_{\mathrm{L}}$. Given Proposition II.4, $\sigma^*_{\mathrm{L}} = \bar{\psi}_{\mathrm{L}}/\mathscr{H}^P_{\mathrm{L}}$ and $d\sigma^*_{\mathrm{L}}/d\bar{\psi}_{\mathrm{L}} = 1/\mathscr{H}^P_{\mathrm{L}} > 0$, with $\mathscr{H}^P_{\mathrm{L}}$ unaffected by the shock because $\hat{\delta}_{\mathrm{L}}$ is, to first order, unchanged by (IA10). On the deposit side $\sigma_{\mathrm{L}} = \bar{r} - r_{\mathrm{L}}$, so r_{L} falls. On the lending side $\sigma_{\mathrm{L}} = \rho_{\mathrm{L}} - \bar{\rho}$, so ρ_{L} rises.

(ii) By Proposition II.3(iii), $\mathscr{D}$ consists of the highest-χ_i and hence, at a common σ_{N}, the highest-ψ_i members of $\mathscr{C}_{\mathrm{N}}$. Removing a subset with above-average ψ lowers the ratio of aggregates, again by the mediant inequality, so $\bar{\psi}'_{\mathrm{N}} < \bar{\psi}_{\mathrm{N}}$. Hence $\bar{\psi}'_{\mathrm{N}}/\mathscr{H}^{P\prime}_{\mathrm{N}} < \sigma_{\mathrm{N}}$ is possible even though $\mathscr{H}_{\mathrm{N}}$ has fallen, and in any case the constraint is no longer the binding determinant of σ_{N}. The posted spread is then set by the unconstrained pricing problem, which the shock does not perturb. $\square$

II.9.8 Proof of Proposition II.7

Evaluate each household's payoff at the true δ_{N}. The shock changes $\hat{\delta}_{\mathrm{N}}$ and leaves δ_{N}, and hence the national bank's constraint (IA8), unchanged, so every household in $\mathscr{D}$ satisfies $\chi_i \le \mathscr{H}_{\mathrm{N}}$ after the shock as before. Partition $\mathscr{D}$ into switchers $\mathscr{S}$ and stayers $\mathscr{E}$. For $i \in \mathscr{E}$, the household remains at N and is accommodated, so her payoff is unchanged. For $i \in \mathscr{S}$, the household moves to L, where $\chi_i \le \mathscr{H}_{\mathrm{L}}$ and she is accommodated, so she retains λh_i and forgoes the amenity differential. Her per-period loss relative to the pre-shock allocation is $\ell_i - \bar{\ell}_i \ge 0$, which is zero for the marginal switcher and positive for inframarginal ones. For every $i \in \mathscr{C}'_{\mathrm{L}}$, the widened spread transfers $\Delta\sigma_{\mathrm{L}} b_i$ per period from the household to the bank's shareholders. It is a loss to the household and a gain to the bank, and its incidence is described in Remark II.3. Summing and discounting at β gives the stated decomposition up to the common factor $(1-\beta)^{-1}$, which we suppress. $\square$

II.10 Notation

Symbol	Name	Definition and role
β	discount factor	common; folds in time preference and exogenous separation
Θ	enforcement multiplier	$\beta/(1-\beta)$, common to both banks
λ	discretion frequency	probability a discretionary state arises in a period
γ	extraction rate	share of the household's stake captured by exploiting, with $1-\gamma$ destroyed
h_i	discretionary stake	value to i of accommodation in a discretionary state
b_i	balance or loan size	scale of the contractible business
ψ_i	stake intensity	h_i/b_i, a primitive
π_i	rent	$\sigma_j b_i$, the bank's per-period earnings on the relationship
χ_i	trust intensity	$h_i/\pi_i = \psi_i/\sigma_j$, depends on the posted price
δ_j	divergence	$1-\delta_j$ is the weight the banker places on the household's payoff
$\underline{\delta}$	structural threshold	$1-\gamma$, below which trust needs no enforcement
Δ_j	net divergence	$\delta_j - \underline{\delta}$, static temptation per unit of stake
μ_j	net temptation intensity	$\Delta_j - \lambda\Theta(1-\delta_j)$
$\mathscr{H}_j$	trust capacity	Θ/μ_j, the largest χ_i the bank can credibly serve
μ_j^P, $\mathscr{H}_j^P$	aggregate counterparts	$\lambda[\Delta_j - \Theta(1-\delta_j)]$ and Θ/μ_j^P (Section II.5)
σ_j	spread	$\bar{r} - r_j$ on deposits, $\rho_j - \bar{\rho}$ on loans
ℓ_i	amenity taste	horizontal preference for the national bank
m, ω_{ij}	media signal and weight	$\omega_{ij} = \tau_m/(\tau_m + \tau_{ij})$
$\bar{\psi}_j$	aggregate stake intensity	$\int_{\mathscr{C}_j} h_i / \int_{\mathscr{C}_j} b_i$; determines the minimum credible spread
$\mathscr{C}_j$	clientele	households served by bank j under a relational agreement
$\mathscr{D}, \mathscr{S}, \mathscr{E}$	displaced, switchers, stayers	$\mathscr{D} = \mathscr{S} \cup \mathscr{E}$

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