Banking in the Shadow of Media Slant

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Abstract

We study the effect of a change in media slant on banking decisions made by households. We use the staggered expansion of a conservative local TV news station operator with a well documented bias in broadcasting slant that provides an alarmist view of national events. We find that households shift their deposits from national banks to local banks in areas that are exposed to the news media shock. Households also shift their borrowing activity such that the share of mortgage lending increases at local banks and falls at national banks. These effects are stronger among low-income and male-headed households. We do not find evidence that banks play a role in driving these changes. Banks do not engage in credit rationing – loan approval rates are constant. Banks are not making preferential changes in loan and deposit rates – in fact, deposit rates fall and mortgage rates rise at local banks. Finally, we do not find evidence that banks change their presence in banking markets either on the intensive or extensive margins. Taken together, our results show that media bias alters household financial decision making. We build a theoretical model that incorporates these changes and highlights the negative welfare consequences of media slant on household financial decisions.

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1 Introduction

Information plays a central role in financial markets. It is essential for price formation and building trust in the markets themselves. Media is an important source of information for market participants, through the creation and dissemination of information (Ahern and Peress, 2023). However, media also has the power to impose slant through the information it creates and through the way it presents that information. When facts are presented with biased interpretations, investors, firms, and households may change their behavior due to a change in beliefs about future distribution of outcomes. Empirical evidence shows that media slant changes how households and businesses make decisions (Kaviani et al., 2023; Li et al., 2024; Pan et al., 2024). Media slant often overlaps with political and ideological partisanship, which has been shown to drive financial decisions which include corporate policies, portfolio selection, investment recommendations, and household financial choices (Kempf and Tsoutsoura, 2021; Cookson et al., 2020). However, media slant has a broader influence and perhaps could have more pernicious effects on financial decisions. Households are susceptible to media slant, regardless of whether they vote or have a political party affiliation. Media slant tilts the distribution of beliefs about the future such that they do not reflect the underlying facts that will determine true future outcomes. Unlike beliefs that are formed from explicit political affiliation and partisan sorting choices, media bias is not explicit, and in fact, individuals may not be aware of its presence even as it shapes their beliefs and decisions. In other sectors, regulatory bodies, such as the Consumer and Financial Protection Bureau (CFPB), consider implicit tactics to manipulate consumers to be predatory and require transparency, education, and disclosures to counteract attempts to manipulate consumers. Given that the majority of US households use media, especially broadcast news media, as their primary source of information, media slant may be another source of predatory manipulation. Specifically, trust is a central determinant of household financial inclusion (Brown et al., 2019) and media slant may erode trust in the financial system. To the extent that media slant erodes trust, it may have broad economic implications such as interfering with the transmission of fiscal and monetary policy. An empirical challenge and an open question is to assess whether media slant drives household financial decisions and the extent to which they lead to inefficiencies.

In this paper, we evaluate whether media slant affects household banking decisions and measure the welfare effects of these decisions. We hypothesize that media slant changes the beliefs of households about the nation, the economy, and the safety of financial markets, which, leads households to alter the way they use the financial system. We build a model that illustrates how media slant generates distortion in beliefs and affects how households make banking decisions. Finally, we use institutional features of the US banking system and exogenous variation in media slant to estimate empirically how media slant alters household banking decisions and the welfare effects of these changes on households.

There are several challenges to identifying the role that media slant plays in household banking. We need to identify a setting in which the slant of media coverage changes but not the underlying local and national economic and financial conditions. Second, we need to find a financial instrument that is ubiquitous and unequivocally beneficial. This allows us to study a broad base of households, where we know that access to the financial instrument is optimal, but where individual households also have discretion in how they use it such that we can see them alter their strategies as beliefs change. In the setting, we should be able to see both the household demand for the financial instrument and the supply of the financial instrument so that we can determine whether the supply of finance also changes. Finally, we need variation in media slant that is unrelated to economic conditions, which could also drive changes in how households use finance. This allows us to disentangle whether the effects are driven by general economic sentiment or specific government policies.

We study how a shock to media slant affects how households use the US banking market. The results show that households respond to exogenous shifts in media slant by changing the type of bank that they use for storing deposits and obtaining mortgage loans. They shift their business to banks that operate in narrower geographic markets. The results show that these changes are driven by households rather than by banks. The supply of banks and bank financing does not change; banks do not reduce loan approval rates or the number of branches. Taken together, media slant changes the type of banks that consumers choose to work with thereby changing how households engage with the banking system. We estimate that these changes reduce household welfare.

We focus on the US banking system for several reasons. First, nearly all US households use the banking system. Banks are the primary facilities where households safely store and earn interest on savings. Households use these institutions to obtain home mortgages, thereby building the primary source of wealth for the majority of US households. The banking system is also highly regulated, deposits are FDIC insured, such that deposits and savings are safe from economic uncertainty. Beliefs may change but the financial instrument is risk free. Finally, there is variation in the cross-section of bank types based on size, scope, and geographic footprint and variation in banking markets throughout the US. The data collected on banks are extensive and include loan applications and approvals, deposit balances, and pricing for financial instruments at granular geographic and institution levels.

Our natural experiment is driven by a change in media ownership of local TV stations across the US by Sinclair Broadcast Group (SBG), a media company with well-documented bias in broadcasting behavior. We use the pan-American expansion of stations that Sinclair acquired between 2012 and 2017 as a shock to media slant in a local geography. SBG shifts broadcasting slant to an alarmist view of national events. Our sample is constructed by hand-collecting acquisition data over this period and includes information on the acquired stations and their designated media areas (DMAs). Our approach involves comparing banking outcomes before and after the acquisition of a TV station by SBG with outcomes in areas where SBG did not operate. Our main empirical specification covers news stations operating in 44 states across the US and includes a rich set of controls.

We construct counterfactual geographies in which SBG did not enter to address two complications of a standard difference-in-differences analysis: (i) that SBG's choice of media markets is not random with respect to economic factors and (ii) that, even if random, the expansion was staggered over time, which complicates causal identification due to potential heterogeneous treatment effects. To address the first concern, our identification strategy compares places where SBG successfully entered to those where SBG wanted to enter but was blocked from entering due to a failed acquisition. Specifically, SBG attempted to acquire Chicago-based Tribune Media Corporation, but the acquisition was blocked due to antitrust concerns. To address the second concern, we use empirical strategies developed in recent years with respect to staggered difference-in-differences designs, which account for heterogeneous treatment effects over time and across units. Specifically, we employ the Dube et al. (2023) LP-DiD approach that captures cohort-specific average treatment effects which corrects for heterogeneity in treatment effects across adoption cohorts, and which subsumes many recent estimators such as those developed by Callaway and Sant'Anna (2021) and Cengiz et al. (2019). In addition, we follow Rambachan and Roth (2023) to rigorously test for parallel trends violations.

In our model, bank customers desire an optimal mix of deposit rates and banking services when choosing a bank. We use a bank's geographic footprint to define "local" and "national" banks, where local banks are those that operate in only one state and national banks operate in more than one state. Building off of the model in d'Avernas et al. (2023) that compares large and small banks, we assign their large bank characteristics to our national banks and their small bank characteristics to our local banks. Hence, national banks offer better banking services but poorer deposit rates, whereas local banks offer better deposit rates but poor banking services. This generates endogenous sorting of customers based on their relative demand for deposit rates versus banking services. A critical component that affects their choice is their 'trust' in the bank. This trust is a simple proxy for uncertainty about the economy and the stability of institutions. In our model, households receive a private signal about their local bank and a public signal through the media about the national bank. The bias introduced by SBG distorts this media signal and makes national banks seem less trustworthy. People who were indifferent between local and national banks now strictly prefer the local bank. This distortion increases the propensity for people to switch from their preferred national bank to their local bank, but this choice is suboptimal since the media signal used is incorrect thereby generating a welfare cost.

We find that households moved their deposits from national to local banks in areas that experienced SBG's arrival. The county-level aggregate share of deposits at local banks increased by 1% per year in the first two years such that local banks became the primary holders of deposits in counties where Sinclair entered the media market. Additionally, households increased their reliance on local banks for home mortgages. We observe a rise in HMDA loan applications at local banks in years three through five following Sinclair entry, and this shift is reflected in a statistically significant and comparable decline in the loan application share at national banks. This trend is particularly pronounced among lower-income and male households, demographics that are more susceptible to the type of media bias promoted by SBG.

We find that banks do not modify their operations in these local banking markets. Loan approval rates do not change, but the shift in loan applications means that the total number of approved loans increases at local banks and decreases at national banks. One interpretation of this result is that the shift in deposits provides necessary funding for local banks to increase the number of loans approved. Banks do not alter their local footprint. We find no evidence that the propensity of bank entry and exits or branch expansions and contractions changes within the treated counties. Most importantly, we do not find evidence that deposit rates or mortgage rates at local banks and national banks change so as to attract depositors. In fact, we find evidence that local banks reduce deposit rates and increase mortgage rates in treated counties compared to control counties. At the same time, there is no change in interest rates at national banks. Hence, banks are not driving the change in a household's bank choice through interest rates or access to banks or their branches.

Our results have important welfare implications. Our setting allows us to measure bank supply-side dynamics and household demand side dynamics such that we can identify the impact of information distortion on household financial decision-making and welfare. Prior to SBG entry, households choose local versus national banks based on their preferences and beliefs, and banks' deposit rates and technologies. When households shift their deposits due to media slant, which changes their beliefs, they are making sub-optimal decisions.

We show that our results are robust to different matching, subsample, and estimation choices. Our results using a propensity score matched sample of treatment and control counties are consistent with the main results. We limit the sample of treatment and control counties to those located in states with both Tribune and SBG media and show that our results become stronger and more persistent. We use four alternative estimators of the treatment effects. 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 estimates are robust to the presence of linear and non-linear deviations from the parallel trends assumption in the standard difference-in-differences models.

This paper investigates whether media slant affects household banking decisions, and, if so, the welfare implications of those decisions. The effect of media slant has been studied in other contexts, such as voting outcomes (DellaVigna and Kaplan, 2007; Miho, 2023; Mateen and Romero, 2024), local government budgets (Ash and Galletta, 2023), and police behavior (Mastrorocco and Ornaghi, 2020). Recent studies on the role of media slant in financial decision-making focus on corporate investment and decision making, equity prices, and household equity portfolios (Gurun and Butler, 2012; Kaviani et al., 2023; Pan et al., 2024). By focusing on the banking system, our results demonstrate how media slant can affect a fundamental determinant of household financial inclusion: trust in US banking system (Brown et al., 2019). We find that media bias shifts deposit demand toward local banks, indicating a decline in consumer trust in national banks. Moreover, because media slant affects the banking system, our results show how media and partisan bias can influence the transmission of fiscal and monetary policy. The supply of deposits is essential for credit availability and we observe a subsequent shift in credit supply and demand away from national banks as household switch deposits to local banks (Aguirregabiria et al., 2024).

Investors respond to public information differently, depending on their personal world views, such that financial decisions may not reflect economic or financial fundamentals (Meeuwis et al., 2022). For instance, depositors reduce deposits when banks face negative, but non-financial controversies (Homanen, 2018). In India, political affiliation impacts whether households participate in loan programs (D'Acunto et al., 2021). Following the collapse of Silicon Valley Bank, political leaders' reassurances primarily soothed only their own political supporters (Sandri et al., 2023). Our results show that intentional slant from broadcast media affects households' trust and participation in the financial system. In our setting, media slant casts a negative outlook about the state of affairs in the country and local residents choose to work with local banks over national ones, where they have more private information and less information distortion, but where they face higher prices and lower returns.

The literature has studied the effect of *loss* of information in the context of local newspaper closures in the U.S. This phenomenon, called "news deserts" has received attention in both academia and the popular press, see Abernathy (2018). Gao et al. (2020) find that local governments experiencing local newspaper closures face higher municipal bond yields. Ma et al. (2022) find that local newspaper closures are related to higher interest spreads for borrowers. Finally, Kim et al. (2021) find that local newspaper closures lead to firms increasing their dividend payouts because of poorer monitoring. These studies focus on the loss of information rather than the slant of information, and examine newspaper media, which reaches a more limited population compared to local TV news. Our focus on local news is important because local news channels are an important source of information in the United States. Our sample includes local TV networks, not just cable channels, that are also re-transmitted on cable and satellite.

In terms of banking market dynamics, while related work has explored bank decision-making, such as branching dynamics (Cespedes et al., 2024), our study provides insight into the effects of consumer banking decisions on a local banking market. The impact of media bias on household deposits significantly affects the way that households utilize the local banking market. We demonstrate that diversity in the banking market is vital for promoting financial inclusion; local banks, not just branches of national banks, allow households to maintain bank accounts even when their trust in the financial system changes (Brown et al., 2019). Furthermore, the shift in household demand for local banks shows that consumers can influence the equilibrium allocation of credit between national and local institutions.

With respect to our econometric specification, compared to other papers that use media entry or exit as an identification strategy, our design covers a large population, many states, and counties in a panel set-up (multiple counties across time) in a difference in difference type of approach. We include recent advancements in event study designs that improve estimation, taking into account the staggered entry of SBG in multiple periods.

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

2 Setting and Hypotheses

2.1 Background

2.1.1 Information and Banking

Information is a central component of a well-functioning banking market. Households use information about banks, such as products and pricing, to select whether and where to deposit funds and seek loans. The physical presence of bank branches is central to whether households use the banking system. Beliefs about the stability of banks and the banking system also affect how and where households bank.[1]

2.1.2 Local TV News Media

Our focus on local television news is important because local television channels are an important source of information in the United States. According to Pew Research, television is the most popular source for gathering news for Americans. American television can be seen through broadcast, cable, satellite, or the internet. Broadcast TV is particularly interesting. Within this set, local broadcast television has a larger audience than either Cable or Network TV.[2] Nielsen's National

[1]Of course, although not relevant to our paper, banks need information to make new loans and to monitor existing loans, a subject of a very rich and old literature.

[2]It may be noted that the number of Americans consuming TV news is declining, but about 50% of US adults still consume news this way, http://www.pewresearch.org/fact-tank/2018/01/05/fewer-americans-rely-on-tv-news-what-

Television Household Universe Estimates counts 119.6 million television households in the US.[3] In particular, the number of persons aged two and older in this set is estimated to be 304.5 million. Therefore, the television industry clearly reaches the vast majority of U.S. citizens and ostensibly has an important role in terms of media exposure.

Television stations are responsible for transmitting content over the air (OTA). These stations require a license from the Federal Communications Commission (FCC), which regulates broadcast, cable, and satellite transmissions, and therefore determines the menu of options that each household can access according to their county location. The U.S. is divided into 210 Designated Media Areas (DMA) that cover several counties and often cut across state lines.[4] These areas identify the geographic reach of stations and the characteristics of potential viewers in these areas.

Typically, local content from these TV stations is restricted to local news shows, while most other content comes from network programming. Local broadcast stations air their news shows but buy syndicated content to air for their remaining slots. Cable news and satellite are also fast-growing sources. However, cable companies routinely buy local news show content from TV stations for the set of channels offered to consumers with cable TV. Therefore, local news shows are typically available to all who have a TV in the area catered by them.

Traditionally, the FCC has looked at broadcast television as a decentralized market. Therefore federal law prohibits monopolies in local areas. Through shell companies and regional marketing agreements, these rules are violated in spirit, and need to be tracked, as we do in this paper.

2.1.3 Sinclair Broadcasting (acquisition history and slant)

Sinclair Broadcast Group (SBG) is the largest television station operator in the US by number of stations, owning 173 stations countrywide and operating roughly 20 more stations through the

type-they-watch-varies-by-who-they-are/.

[3]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: http://www.nielsen.com/us/en/insights/news/2017/nielsen-estimates-119-6-million-us-tv-homes-2017-2018-tv-season.print.html.

[4]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.

use of Local Market Agreements. It has been a publicly-traded firm since 1995, but its majority stake is owned by the family of founder Julian Sinclair Smith. The firm has been noted to offer a conservative slant in its programming.[5] In particular, Sinclair orders its stations to air "must-runs" which are typically conservative takes on conservative issues. For example, in the run-up to the 2016 Presidential Elections the firm required its stations to run a segment asking voters to not vote for Democratic Presidential Nominee Hillary Clinton because of the Democratic party's support for slavery in the 19th century. SBG has grown on the back of organic expansion as well as multiple acquisitions over the last two decades.

Recent literature evaluates the effect of SBG expansion on other outcomes of interest. 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). The channels made a rightward shift in slant while experiencing a very small decrease in viewership. Even more recently, the literature has found a negative effect of these channel acquisitions on the response of local police toward crime and the levels of popularity of the Obama administration and Democratic performance in general elections (Mastrorocco and Ornaghi, 2020; Levendusky, 2022). These changes are consistent with the documented effects of press coverage on citizen knowledge, politicians' actions, and policy (Snyder Jr and Strömberg, 2010).

In particular, after 2012 SBG started a rapid expansion campaign that enabled them to gain access to new 57 DMAs. Figure 1 shows the expansion of SBG from 2012 to 2018. After 2012 SBG more than doubled its presence across the entire U.S. The company started with operations in 5 states (AL, ME, MN, MS, and NH) before 2012 and expanded to have operations in 41 states after 2018 (all continental states except for AZ, CO, CT, DE, LA, ND, and NJ). The company now has operations in most of the big 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. This, of course, translates to an increase in number of potential counties in which its conservative slant

[5] About the conservative bias of the TV stations owned by this group and its attempt to by-pass regulation, see: https://www.nytimes.com/2017/08/14/us/politics/how-a-conservative-tv-giant-is-ridding-itself-of-regulation.html.

might have an effect. To be precise, in terms of political affiliation, the company increased its presence from 134 electoral districts to 236.

[FIGURE 1 ABOUT HERE]

2.1.4 The Failed Acquisition of Tribune Media

In 2017, SBG announced its intention to acquire Chicago-based Tribune Media Corporation, which owns 43 media stations, for approximately $3.9 billion. However, the acquisition was not completed due to concerns about creating an oligopoly in the television broadcasting market. After more than one year of speculation and growing concerns about the pertinence of the merger by interests 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. 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 the areas covered by Tribune Media serve as plausibly valid counterfactuals for areas that SBG successfully entered. We use these areas as a control group in our analysis and compare their banking market outcomes with those areas in which SBG started operations. We think that given the company's interest, these markets are similar and therefore comparable with the places in which the acquisition was successful.

2.2 Model

We introduce a simple model that incorporates local and national banks in a given region. We construct regional banking markets that have both local and national banks. Local banks offer higher deposit rates and national banks offer a broader range of products and services. Customers trade-off the benefits coming from deposit rates and banking services. Motivated by the empirical set-up, we incorporate 'trust' in a local or national bank in the minds of customers. While banks understand the state of their businesses, customers may build biased perceptions about the larger economy and the stability of financial institutions because of the news media shock. Given the nature of the media bias, consumers may become skeptical of national banks and prefer local banks. Our model captures this bias in a simple manner, as a reduction of trust that they have for national banks. The model allows us to consider the welfare effects of this media shock, which we aim to estimate.

We consider a county where there are two banks, $j = 1, 2$, where $j = 1$ is a local bank, and $j = 2$ is a national bank. The two banks differ in the mix of deposit rate r_j and services l_j they offer. We assume that, according to the findings in d'Avernas et al. (2023), the local bank offers a better deposit rate than the national bank, $r_1 > r_2$, while the national bank offers better services, $l_1 < l_2$. For simplicity, we will assume $l_1 = 0$.

The county has a continuum of consumers of measure 1. The customers, denoted by i, differ from each other in their ideal point for bank services, $\bar{l}_i \in [0, 1]$. Their utility from choosing any bank j is given by:

$$U_{ij} = m_j r_j - (l_j - \bar{l}_i)^2$$

where utility depends on two sources. First, the rate offered by the bank r_j multiplied by the 'trust' in the bank m_j. Second, customers prefer to lie closer to their ideal bank service point $\bar{l}_i$. Naturally, there is a trade-off between choosing a better interest rate versus choosing a bank offering better bank services.

Under this set-up of consumer preferences, and bank availability, there will exist a cut-off customer, above which all customers will prefer to bank with the national bank.

Proposition 1. *Customers strictly prefer the national bank over the local bank if*

$$\bar{l}_i > \frac{m_1 r_1 - m_2 r_2 + l_2^2}{2 l_2}$$

The following comparative static is immediately obvious then that,

Corollary 1. *The cutoff consumer increases as the difference between $m_1 r_1 - m_2 r_2$ increases.*

Naturally, there will be a share of customers with the local bank s_1 with the remaining customers being with the national bank, under equilibrium.

The role of m_j is to capture the notion of trust that customers have in the local or national bank. We could further micro-found this role based on signals that customers receive, a local private signal m_1, and a media signal m_2. Under an unbiased media, m_2 would be an important way for customers to assess if they can trust the national bank with their deposits. Under such a scenario, the choice by customers and the choice by the social planner will be aligned, and the decentralized solution will be socially optimal.

In the case of the shock we study, slant coming from SBG media lowers m_2 to $\tilde{m_2} < m_2$, while not affecting the local private signal, the latter being related to what customers see and perceive in their own county. It is easy to see that in that case, the share of depositors in the local bank will increase to $\tilde{s_1} > s_1$. However, since this change in shares is driven by biased beliefs, this allocation is socially less desirable. Depositors who shift their deposits to local banks because of $\tilde{m_2}$ are suffering a welfare loss.

2.3 Data

We combine three 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.

One of the important pieces of data we collect is the history of acquisitions of SBG 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). We hand collect this data from SBG company filings, archives of the acquired companies' websites, and confirmations from independent media reports. Our data are unique and detailed – in addition to acquisitions of the large companies, we also track the acquisition of 13 individual independent stations acquired in 13 different DMAs by SBG between 2012-16. Apart from direct ownership, SBG is known to be closely associated with other companies such as Cunningham Broadcasting

Corporation and Deerfield Broadcasting corporation (among several others) with which it has Local Market Agreements (LMAs). These LMAs allow SBG to bypass FCC's local duopoly rule. We track these LMAs as well, allowing us to remove contamination in our empirical analysis that could come from stations indirectly owned by SBG. Our final data set gives us the station name, the corresponding channel (if any), the DMA in which it is located, and the date SBG entered each DMA. We matched the DMAs with the respective counties using publicly available data. With this combined information, we can identify in which year the entry of SBG started to influence 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. The HMDA mortgage loan data provides 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 data from RateWatch, a division of Standard and Poor's, for branch-level deposit rates and mortgage rates. The data are gathered through surveys of bank branches that cover different types of deposits and loans, including savings accounts, time deposits, and mortgages. The data cover the 2007-2019 period and responding branches account for roughly 80% of total domestic deposits (MORELLI et al., 2024). We compute average deposit rates across five deposit products, which include money market, savings account, and 12, 24, and 60 month certificate of deposits (CDs). We compute mortgage rates using the average of 10, 15, 20, and 30 year fixed rate mortgages. We construct bank-county-year averages of the deposit and mortgage data.

When there is 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 not information for these, we choose the average within the state to estimate the closest points with information r^1_{cst} and r^0_{cst}.

We complement these data with a large dataset on demographic characteristics recovered from the 2000 and 2010 census at the census tract level. With these data, we can construct both district and county characteristics such as total population share, the female share of the population, the black share of the population, the Hispanic share of the population, the Asian share of the population, the native American share of population, the share of the population 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, the rural share of the population, the share of high school graduates, the share of college graduates, the share of labor aged population employed in agriculture and manufacturing, the share of employment, crime rates, the average household income, the share of the population below poverty line, the share of the population on Medicare, the uninsured share of the population, the number of housing units, the share of veterans, the share of the population with social security, infant mortality deaths, and the water use per capita. We use these data to show the observable characteristics according to market structure and as well to account for potential differences between places in which SGB operates and those in which it does not using a matching correction on these observables.

2.3.1 Descriptive Statistics

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. Columns 2 - 4 summarize the subsample of these counties that are in our quasi-experimental analysis. 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.

[TABLE 1 ABOUT HERE]

In Figure 2 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.[6]

3 Methods

3.1 General Strategy

In our empirical analysis, we estimate the effect of the conservative-biased news outlet on the local banking market in each place. Our general strategy is to compare the change in the banking market 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. Our approach involves comparing consumer deposits, and bank branching, rate-setting, and lending outcomes before and after the acquisition of a TV station by SBG (the news outlet) with those in areas where SBG did not operate. We hypothesize that the "trust" signal, which may be distorted by media slant, will motivate households to keep deposits closer to home. Hence, we segment the banking market into two types of banks: local banks are banks that operate within one county or one state; national banks are banks that operate in multiple states.[7]

In our framework, the concept of a "local" bank should capture a geographical component and a psychological component. Because our interventions occur at the local geographic level, we must distinguish banks with operations that are more focused within a single market and therefore more influenced by changes in the local economy from those that operate a multimarket banking network (Berger et al., 2014). In terms of psychology, the nature of the information shock is a shift to news coverage from local to national news, and a shift in tone that is more alarmist about the state of affairs at the national level. Ultimately these changes give information with slant to customers and change coverage to information that is non-local to where households live. Mateen

[6] We present summary statistics for the counties in Table 2. These level differences, as usual will be absorbed in the DiD design. What's important is the absence of parallel trends.

[7] All our results are robust to comparing unicounty and unistate banks separately.

and Romero (2024) show that this shift polarizes local elections and Kuang et al. (2024) shows that consumers believe that the Federal Reserve has political bias. Therefore, the media slant should bias consumers against trusting national banking institutions. Our split between national and local banks should reflect the boundaries of trust where a local bank is the opposite of a multimarket national bank.

Our final definition of local bank (banks that operate in only one state) and national bank (banks that operate in more than one state) is broad enough so that most geographic areas have at least one local institution but narrow enough that the banks defined as local do indeed cater to local clientele. Defining local banks using state-level geography is also consistent with the historic bank regulation and subsequent deregulation, such as the Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994 (IBBEA), which created national bank branching networks from state-by-state banking systems.

3.2 Choice of Control Group

There is heterogeneity in the places where SBG does not operate, and it might be the case those places are not fully comparable to the areas where there is an SBG TV station. To rule out the possibility of a non-observable shock affecting those places that could contaminate our empirical results, we limit our comparison. For each cohort, the comparison groups are those places where SBG did not operate but could not because of the failed acquisition of Tribune Media. This strategy ensures we are comparing to each cohort places in which SBG was interested in expanding and therefore takes care of the selection problem.

3.3 The Problem with Naive Two-Way Fixed Effects

SBG gradually increased its presence in different areas; that is, it was a staggered entry. A recent body of literature has shown that 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 heterogenous treatment effects. When analyzing these models, results are uninformative about the presence of pretends or anticipatory behavior, and coefficients would not capture the outcome dynamics produced by the entry of SBG (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 time and across units. In this case, the estimator uses forbidden comparisons (i.e., using early treated units as controls for units treated later).

Table 3 assesses the extent of this problem, showing the decomposition proposed by Goodman-Bacon (2021). We show in Table 3 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 for both the county level of analysis and the electoral district, showing that some ATT would enter with negative weights. This implies that using TWFE in our context would most likely lead to biased estimates.

[TABLE 3 ABOUT HERE]

3.4 Main Model

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

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

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_{ct}^l is a dummy variable that takes the value one if SBG operates in county c after l years. With staggered treatment, if treatment effects are dynamic and heterogeneous, the coefficient θ_l is biased and does not capture the true effect of SBG.

To take into account the dynamic and heterogeneous nature of the treatment effect across adoption cohorts, we use 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 extremely transparent. Importantly, our results are robust to using these estimators as well, which we show in Section 5. Since the Dube et al. (2023) approach is recent, 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 et al. (2024) and residualize the outcomes from the state-time fixed effects, using only the control observations. We denote these outcomes with a tilde, $\tilde{Y}$. Not all states where SBG entered had Tribune operations, however. To avoid dropping these states, we modify the state definition by using 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 4. Results become even stronger to restricting the analysis to states with Tribune presence, as discussed in Section 5.

We estimate the following equation for each time interval period period l between 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.[8] 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. A reason why we choose this method is its simplicity in its ability to directly control 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).

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

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. However, 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).

3.5 Alternative Methods

We use alternative estimators, truncated samples, and violations of the parallel trends assumption to explore the robustness of our findings. The results of these methods are presented in Section 5.

In addition to our baseline specifications, we employ alternative procedures to estimate causal effects in difference-in-difference settings with staggered adoption. We also present results using three alternative estimators. The first is the Callaway and Sant'Anna (2021) (CS) procedure,

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

which estimates group-time specific ATT, avoiding forbidden comparisons and aggregating them as averages for each period.[9] The second is the Sun and Abraham (2021) (2018) 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). Finally, we include the de Chaisemartin and d'Haultfoeuille (2021) (CDH) estimator, where the ATT measures the instantaneous treatment effect of transitioning from being untreated to treated.

A fundamental assumption of our estimation relies on including a set of never-treated counties that could have been treated. To achieve this, we utilize the counties where Tribune operated, as these represent locations where SBG showed intentions to enter. However, these areas might differ from those where SBG entered, particularly since the planned acquisition of Tribune would have occurred later, potentially leading to discrepancies in county characteristics. To evaluate this possibility, we conducted a test to ensure the overlap in observable characteristics between the two types of counties. First, we estimated a LASSO model following Belloni et al. (2014), where the dependent variable indicates whether the county was affected by SBG's entry. After identifying the variables that best predict treatment, we estimat the propensity score and follow Crump et al. (2009) to truncate the sample, thereby increasing overlap, and subsequently re-estimate our baseline model on the common support.

Finally, to assess the validity of our main identifying assumption (that potential outcomes after treatment are the same for treated and never-treated cohorts), we test the robustness of our findings against moderate linear and non-linear violations of the parallel trends assumption, following Rambachan and Roth (2023). Although graphically, there do not appear to be parallel trend violations, because the coefficients for banking market outcomes before the entry are around zero and not significant, we follow the partial identification method proposed by Rambachan and Roth (2023) and test the robustness of our conclusions to the presence of linear and non-linear deviations from the parallel trend.

[9] 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.

4 Results

This section presents our main findings of the effects of media slant on the consumer preferences for local and national banks (section 4.1), the response of local and national banks to the changes in consumer preferences (section 4.2), and a discussion of the results (section 4.4).

4.1 Main results: Consumer preferences

4.1.1 Consumer Deposits

We use the entry of SBG media to test for a causal relationship between media slant and consumer preferences for banks. In Figure 3 we report the results of our examination of whether local residents change how they allocate deposits between local and national banks. We use the local deposit share, which is the fraction of total county deposits in local banks, to measure whether deposits increased at local banks. The results indicate that local residents shift their deposit activity to local banks and away from national banks. In Panel A, the deposit share at local banks increased by 1% per year in the first two years in counties where Sinclair entered the media market. In contrast, Panel B shows that the deposit share fell at national banks by 1% per year over this same time period.

[FIGURE 3 ABOUT HERE]

Our results are robust to different matching, subsample, and estimation choices, which we discuss in detail in the robustness section.

4.1.2 Consumer Loan Applications

Next we examine whether changes in consumer preferences affect whether consumers submit their housing loan applications to local or national banks. Figure 4 shows results of an analysis of the share of total HMDA loan applications at local banks (panel A) and national banks (panel B). The figure demonstrates an increasing share of loan applications at local banks, which increases to about 1% per year in years 4 and 5 following SBG media entry. The loan application share at national banks exhibits the opposite pattern. Although the patterns are clear, the results are not statistically significant. In subsequent analyses we explore heterogeneity in these results by consumer demographics which include: income, gender, and race.

[FIGURE 4 ABOUT HERE]

First, we examine whether the share of loan applications varies for high income individuals and low income individuals (Figure 5). Figure 5 shows that high income individuals do not appear to change their loan applications following SBG entry. However, the results reveal that there is a statistically significant increase in the share of loan applications of low income individuals at local banks. The share of loan applications at local banks increases in years three through five and peaks at 2% per year in the fifth year following SBG entry. This shift is reflected in a statistically significant and comparable decline in the loan application share at national banks.

[FIGURE 5 ABOUT HERE]

In robustness analysis, we repeat this analysis on gender and race. The male residents exhibit similar patterns at local and national banks although they are statistically weaker and the female, white, and non-white populations do not exhibit these shifts in loan applications. These results are reported and discussed in the robustness section.

4.2 Supply Side: Bank response

We examine whether banks respond to these shifts in consumer demand by changing their loan approvals. We also examine whether the shifts in consumer demand lead banks to alter their local presence in the banking market through entry and exit decisions.

Figures (6) – (7) show trends in loan approval rates at local and national banks across all applicants. There is no change in a bank's approval rate for local or national banks (Figure (6). When we disaggregate the results by borrower demographics, there are no discernible differences in loan approval rates at local and national banks by income (Figure 7). The robustness section presents results by gender and race.

[FIGURE 6 ABOUT HERE]

[FIGURE 7 ABOUT HERE]

We examine whether the share of loan approvals across bank types. Figures (8) – (9) show trends in loan approval shares at local and national banks across all applicants. Local banks command a higher share of loan approvals. This is especially pronounced four years after SBG entry. There is a corresponding decline in the share of loan approvals that occur at national banks, which becomes statistically significant in the fourth year following SBG entry (Figure (8). When we disaggregate the results by borrower demographics, the trends are consistent between high and low income populations. However, the results are statistically and economically significant for 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 (Figure 9). The robustness section presents results by gender and race.

[FIGURE 8 ABOUT HERE]

[FIGURE 9 ABOUT HERE]

Finally, we examine whether these shifts affect how banks manage their presence in the local banking market on the extensive and intensive margins. On the extensive margin, we estimate the probability that a bank enters or exits a local banking market for banks located in counties where SBG media entered the market compared to control counties. Figure (10) shows whether banks are more likely to enter or exit these markets, respectively. Neither national or local banks exhibit a higher propensity to begin operations in a county following SBG media entry. Likewise, neither national nor local banks exhibit a higher propensity to cease operations in counties affected by SBG media entry.

[FIGURE 10 ABOUT HERE]

On the intensive margin, we estimate the probability that a bank expands or reduces its branching network within affected counties compared to control counties. Figure 11 shows that there is no increase in the probability that local banks open a new branch (Panel A). However, in Panel B, there is some evidence that national banks are more likely to open a new branch in the first year following SBG media entry, but that they are also less likely to open a branch four years after SBG media entry. However, it appears that the magnitudes of these effects are 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.

[FIGURE 11 ABOUT HERE]

4.3 Pricing Effects

We examine loan and deposit rates to determine whether local and national banks are providing incentives for consumers to switch deposit and lending preference by adjusting prices.

To measure changes in lending rates, we focus on the rates that banks charge for 10, 15, 20, and 30 year fixed rate mortgages. Mortgage rates are salient for consumers. Moreover, banks and customers negotiate mortgage rates such that they reflect competitive forces in the local banking market. The results show that mortgage rates are increasing at local banks and do not change at national banks. To the extent that banks are adjusting prices, local banks appear to be taking advantage of the surge in loan demand by increasing the mortgage rates they charge to consumers. At the same time, we do not see a surge in mortgage rates at national banks which suggests that rates are not increasing in the area overall.

[FIGURE 12 ABOUT HERE]

Next we examine the deposit interest rates that banks pay depositors. Local banks tend to compete on deposit rates and offer higher rates than large and national banks (d'Avernas et al., 2023).

Hence deposit rates provide another way to detect whether banks are using higher deposit rates to attract depositors. Figure 13 shows that local banks reduce deposit rates by up to 2 percentage points per year in the three years following SBG entry. Panels B and D show that national banks do not change their deposit rates. When we replace missing observations with zeros (Panel C), the reduction in deposit interest rates are more muted, but the decline is still visible albeit less significant economically and statistically. These results suggest that local banks, at the very least, are not using deposit interest rates to attract deposits, and may in fact use the surge in market power as an opportunity to reduce deposit interest.

[FIGURE 13 ABOUT HERE]

4.4 Discussion

In Section 4.1 we tested our first hypothesis that media slant influences how consumers use the local banking system by examining two banking decisions: deposits and mortgage applications. Our primary analysis shows that local banks increase the share of county-level deposits, which suggests that media slant leads consumers to shift their banking needs to local banks away from national banks. We also show that mortgage loan applications reflect this shift towards local banks. In terms of timing, statistically significant changes in the loan application share occur three years following treatment. Hence, these shifts lag the changes in deposits that occur immediately following the entry of SBG media. In Section 4.1.2 we show that there is a strong demographic component of these results. The magnitude and statistical significance of these results is concentrated in low income and male applicants. We do not find responses along racial lines.

In Section 4.2 we tested our second hypothesis that banks are affected either directly or indirectly by media slant. The results show that local banks approve more loans when their share of loan applications increases. Likewise, national banks approve fewer loans when their share of loan applications falls. We posit that these shifts are possible due to the changes in deposit shares that give local banks a larger deposit base to use for lending. In sum, the change in consumer behavior leads banks to change how they allocate resources.

Banks may change their branching networks due to uncertainty created by media slant or due to changing customer demand for local and national banking. We examine how banks manage their local presence by examining new entry and expansion into local banking markets. Local and national banks do not expand into new markets or increase their current banking presence in local markets. Our analysis also shows that banks do not reduce their banking footprint. Shifts in consumer demand do not drive national banks out of local markets. Hence, banks do not change irreversible investment in reponse to media slant.

Finally, we examine whether banks are actively promoting these changes in consumer behavior by altering their deposit and loan rates following SBG entry. If banks were trying to attract depositors and borrowers they would offer higher deposit rates and lower lending rates. Our results show that national banks do not alter pricing of either product. For local banks, we find evidence that if local banks do change rates, they are increasing loan rates and reducing deposit rates. These pricing decisions work against the hypothesis that local banks use pricing to attract business. In fact, the results suggest that local banks are exercising their market power by charging consumers higher prices and offering them lower returns.

In sum, our results suggest that the bank responses are driven by consumer responses rather than direct effects of media slant on bank decision making. Overall, the results show that consumers influenced by media slant are willing to change their banking choice away from equilibrium allocations when they are hit with a shift in media coverage that is not linked to true information events.

5 Robustness

Our results are robust to different matching, subsample, and estimation choices.

The analyses reported in Figures (14) – (15) explore the robustness of this result to alternative modeling choices. Figure 14 Panels (a) and (b) repeat our main analysis on a propensity score matched sample of treatment and control counties. On this sample, the magnitude of the treatment effect, about 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. Next, we limit the sample of treatment and control counties to those located in states with both Tribune and SBG media. In Figure 14, Panels (c) and (d) 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. In Panel B, the national deposit share declines by almost 2% per year over the five year treatment window. The results in both panels are statistically significant in the five years following SBG entry.

Figure 15 reports the deposit share results using four alternative estimators of the treatment effects. We repeat our main analysis 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.

[FIGURE 14 ABOUT HERE]

[FIGURE 15 ABOUT HERE]

We explore the extent to which non-linear deviations from the standard DiD model may affect our estimates. To assess the validity of our main identifying assumption (that potential outcomes after treatment are the same for treated and never-treated cohorts), we tested the robustness of our findings against moderate linear and non-linear violations of the parallel trends assumption, following Rambachan and Roth (2023). Finally, we test the robustness of our results to violations of the parallel trend assumption. Although graphically, there do not appear to be parallel trend violations, since the coefficients for elections before the entry are around zero and not significant, we follow the partial identification method proposed by Rambachan and Roth (2023) and test the robustness of our conclusions to the presence of linear and non-linear deviations from the parallel trend. Figure 16 reports the results.

[FIGURE 16 ABOUT HERE]

In Figure 17, Panels (a) and (b) we show that the magnitude and direction of loan applications of male residents exhibit similar patterns at local and national banks although they are statistically weaker. The results in Figures (17), Panels (c) and (d) through (18), Panels (c) and (d) report that female, white, and non-white populations do not exhibit these shifts in loan applications.

[FIGURE 17 ABOUT HERE]

[FIGURE 18 ABOUT HERE]

When we disaggregate the results by borrower demographics, there are no discernible differences in loan approval rates at local and national banks by gender (Figure 19) or race (Figure 20).

[FIGURE 19 ABOUT HERE]

[FIGURE 20 ABOUT HERE]

6 Conclusion

Media slant alters individual perceptions about the risk of financial institutions. We show that this causes individuals to prefer local over national banks. As consumers shift deposits to local banks, their borrowing activity follows such that local financial institutions increase market share.

Consumer demand for the services of financial institutions is an essential part of the banking market. However, the role that consumers play in shaping the market is difficult to quantify because the use of financial institutions by consumers is near ubiquitous. We utilize the staggered expansion of a television operator with a conservative bias, SBG, as a shock to individual beliefs to determine whether and how consumers shape the local banking landscape. The setting provides a unique shock to households that does not have a material effect on the information and beliefs of financial institutions.

We find that the deposit share at local banks increases and at the same time the share falls at national institutions. Loan applications follow. Application activity increases at local banks and falls at national banks. We investigate how banks respond to these shifts. Bank loan approval activity keeps pace with these changes such that loan approvals do not decline overall. Hence, individuals in the local banking market do not experience a constriction in the availability of loans. We also find that new bank entrants or existing bank exits do not increase. Moreover, incumbent banks are not more likely to open or close local branches.

These results demonstrate that media bias has a first-order effect on consumer behavior that extends beyond civics and into the household pocketbook. Moreover, we are able to identify that these effects have a strictly negative impact on household economic welfare. Regulators need to take this into account. While our findings primarily pertain to the nuances of the American political system, they offer valuable insights into the effects of media bias on the functioning of democracy.

References

Abernathy, P. M. (2018). *The expanding news desert*. Center for Innovation and Sustainability in Local Media, School of Media and ....

Aguirregabiria, V., R. Clark, and H. Wang (2024). The geographic flow of bank funding and access to credit: Branch networks, local synergies and competition. *arXiv preprint arXiv:2407.03517*.

Ahern, K. R. and J. Peress (2023). *The role of media in financial decision-making*. Edward Elgar Publishing.

Ash, E. and S. Galletta (2023). How cable news reshaped local government. *American Economic Journal: Applied Economics 15*(4), 292–320.

Belloni, A., V. Chernozhukov, and C. Hansen (2014, May). High-dimensional methods and inference on structural and treatment effects. *Journal of Economic Perspectives 28*(2), 29–50.

Berger, A. N., W. Goulding, and T. Rice (2014). Do small businesses still prefer community banks? *Journal of Banking & Finance 44*, 264–278.

Borusyak, K., X. Jaravel, and J. Spiess (2024). Revisiting event-study designs: robust and efficient estimation. *Review of Economic Studies*, rdae007.

Brown, J. R., J. A. Cookson, and R. Z. Heimer (2019). Growing up without finance. *Journal of Financial Economics 134*(3), 591–616.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230. Themed Issue: Treatment Effect 1.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer (2019). The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics 134*(3), 1405–1454.

Cespedes, J., E. X. Jiang, C. Parra, and J. Zhang (2024). Branching out inequality: The impact of credit equality policies. *Available at SSRN 4702125*.

Cookson, J. A., J. E. Engelberg, and W. Mullins (2020). Does partisanship shape investor beliefs? evidence from the covid-19 pandemic. *The Review of Asset Pricing Studies 10*(4), 863–893.

Crump, R. K., V. J. Hotz, G. W. Imbens, and O. A. Mitnik (2009). Dealing with limited overlap in estimation of average treatment effects. *Biometrika 96*(1), 187–199.

D'Acunto, F., P. Ghosh, and A. G. Rossi (2021). Political partisanship and the transmission of fiscal policy. *Available at SSRN 3837682*.

d'Avernas, A., A. L. Eisfeldt, C. Huang, R. Stanton, and N. Wallace (2023). The deposit business at large vs. small banks. Technical report, National Bureau of Economic Research.

de Chaisemartin, C. and X. d'Haultfoeuille (2021). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *SSRN Electronic Journal*.

DellaVigna, S. and E. Kaplan (2007). The fox news effect: Media bias and voting. *The Quarterly Journal of Economics 122*(3), 1187–1234.

Dube, A., D. Girard, Òscar Jordà, and A. M. Taylor (2023). A local projections approach to difference-in-differences event studies. Working papers, NBER Working Paper 31184.

Dube, A., D. Girardi, O. Jorda, and A. M. Taylor (2023). A local projections approach to difference-in-differences event studies. Technical report, National Bureau of Economic Research.

Gao, P., C. Lee, and D. Murphy (2020). Financing dies in darkness? the impact of newspaper closures on public finance. *Journal of Financial Economics 135*(2), 445–467.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of econometrics 225*(2), 254–277.

Gurun, U. G. and A. W. Butler (2012). Don't believe the hype: Local media slant, local advertising, and firm value. *The Journal of Finance 67*(2), 561–598.

Homanen, M. (2018). Depositors disciplining banks: The impact of scandals. *Chicago Booth Research Paper* (28).

Kaviani, M., L. Y. Li, H. Maleki, and P. G. Savor (2023). Media, partisan ideology, and corporate social responsibility. *Partisan Ideology, and Corporate Social Responsibility (March 1, 2023).*

Kempf, E. and M. Tsoutsoura (2021). Partisan professionals: Evidence from credit rating analysts. *The journal of finance 76*(6), 2805–2856.

Kim, M., D. Stice, H. Stice, and R. M. White (2021). Stop the presses! or wait, we might need them: Firm responses to local newspaper closures and layoffs. *Journal of Corporate Finance 69*, 102035.

Kuang, P., M. Weber, and S. Xie (2024). Perceived political bias of the federal reserve. Technical report, National Bureau of Economic Research.

Levendusky, M. S. (2022). How does local tv news change viewers' attitudes? the case of sinclair broadcasting. *Political Communication 39*(1), 23–38.

Li, Y., M. Kaviani, H. Maleki, and C. X. Mao (2024). Media, inventors, and corporate innovation. *Media, Inventors, and Corporate Innovation (October 31, 2024).*

Ma, Z., D. Stice, H. Stice, and Y. Zhang (2022). Local newspaper closures and bank loan contracts. *Available at SSRN 4014321.*

Martin, G. J. and J. McCrain (2019). Local news and national politics. *American Political Science Review 113*(2), 372–384.

Mastrorocco, N. and A. Ornaghi (2020). Who watches the watchmen? local news and police behavior in the united states.

Mateen, H. and D. A. Romero (2024). Something biased this way comes: The effect of media on house elections in the us. *Available at SSRN 4983580*.

Meeuwis, M., J. A. Parker, A. Schoar, and D. Simester (2022). Belief disagreement and portfolio choice. *The Journal of Finance 77*(6), 3191–3247.

Miho, A. (2023, 11). Small screen, big echo? political persuasion of local tv news: evidence from sinclair. *Working paper*.

MORELLI, J. M., M. MORETTI, and V. VENKATESWARAN (2024). Geographical diversification in banking: Astructural evaluation.

Pan, Y., E. Pikulina, S. Siegel, and T. Y. Wang (2024). Political divide and the composition of households' equity portfolios. *Available at SSRN 4381330*.

Rambachan, A. and J. Roth (2023). A More Credible Approach to Parallel Trends. *The Review of Economic Studies 90*(5), 2555–2591.

Roth, J. (2022, September). Pretest with caution: Event-study estimates after testing for parallel trends. *American Economic Review: Insights 4*(3), 305–22.

Sandri, D., F. Grigoli, Y. Gorodnichenko, and O. Coibion (2023). Keep calm and bank on: panic-driven bank runs and the role of public communication. Technical report, National Bureau of Economic Research.

Snyder Jr, J. M. and D. Strömberg (2010). Press coverage and political accountability. *Journal of political Economy 118*(2), 355–408.

Sun, L. and S. Abraham (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics 225*(2), 175–199. Themed Issue: Treatment Effect 1.

Table 1: Market structure before 2011

	Complete sample	Tribune sample		
		Treated	Control	Total
National and local	2584	714	356	1070
No National and local	418	148	29	177
National and no local	93	43	7	50
No national and no local	19	7	0	7
Total	3114	912	392	1304

Notes: Table 1 summarizes the banking market of counties in our sample. Local banks are those operating in only one state and national banks are those operation in more than one state. The "Tribune Sample" consists of counties where SBG entered the media market or attempted to enter between 2012 and 2018. Treated counties are those where SBG entered and control counties are those where entry was blocked by regulators.

Table 2: Descriptive Statistics by Market Structure

Variable	Local			National		
	Without	With	Diff	Without	With	Diff
	(1)	(2)	(3)	(4)	(5)	(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)	

Notes: Table 2 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 3: Two-way Fixed Effects Decomposition and Weights

	All Sample	Tribune
	(1)	(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

Notes: Table 3 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 4: State assignment comparison states without tribune

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

Notes: 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.

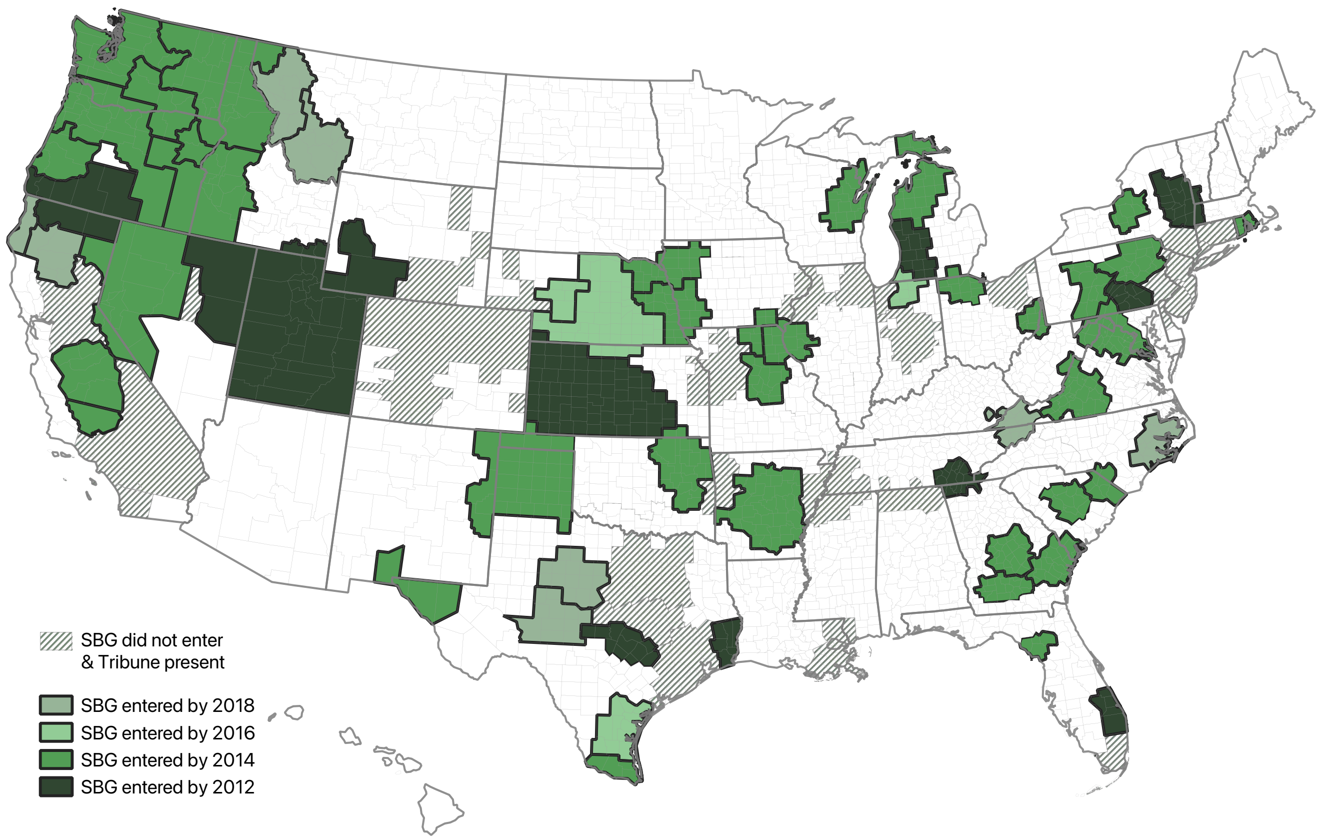
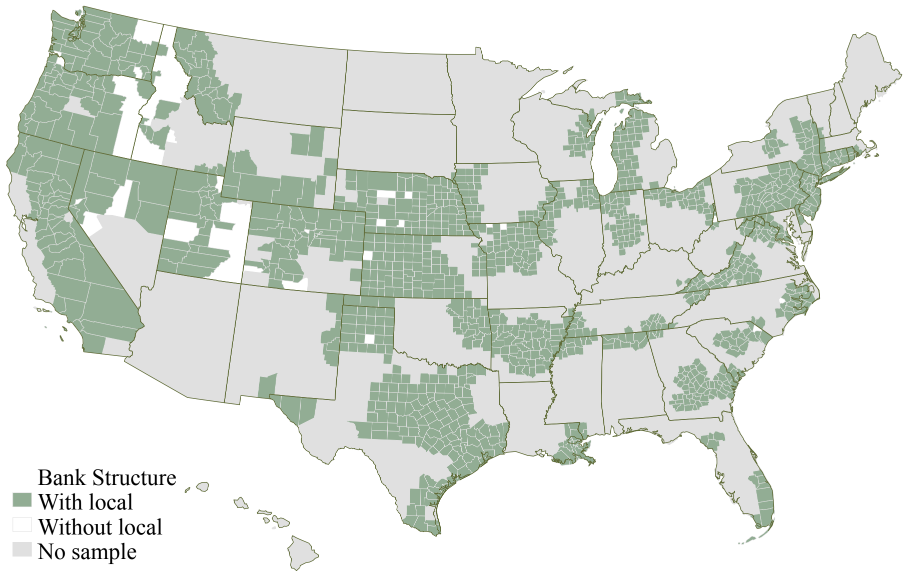


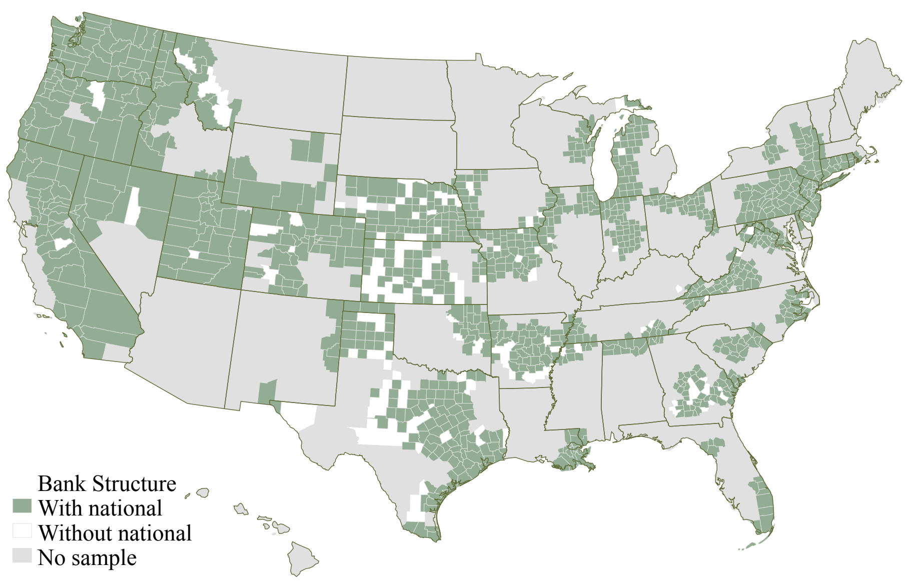
Figure 1: Geographical distribution of SBG acquisition history

Notes: Figure 1 presents the spatial distribution of SBG operations and its acquisitions over time. It also shows the area of operations for Tribune Media that Sinclair was unable to acquire.

Figure 2: Geographical distribution of local and national banks



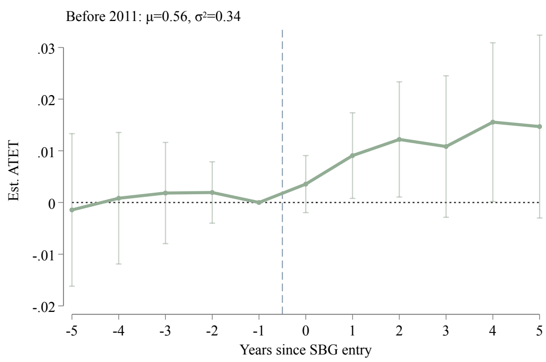
(a) Local Banks



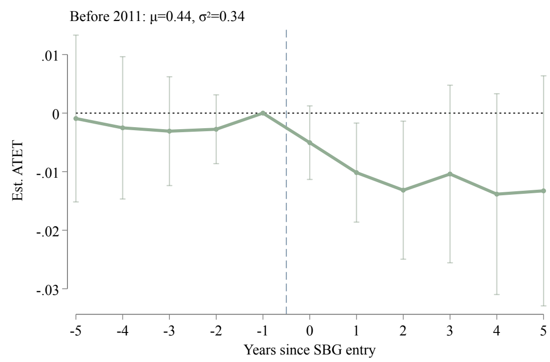
(b) National Banks

Notes: Figure 2 presents the spatial distribution of local (Panel A) and national (Panel B) banks in U.S. counties as of 2010. Local banks are those operating in only one state and national banks are those operation in more than one state.

Figure 3: **Main result - Deposit Shares**



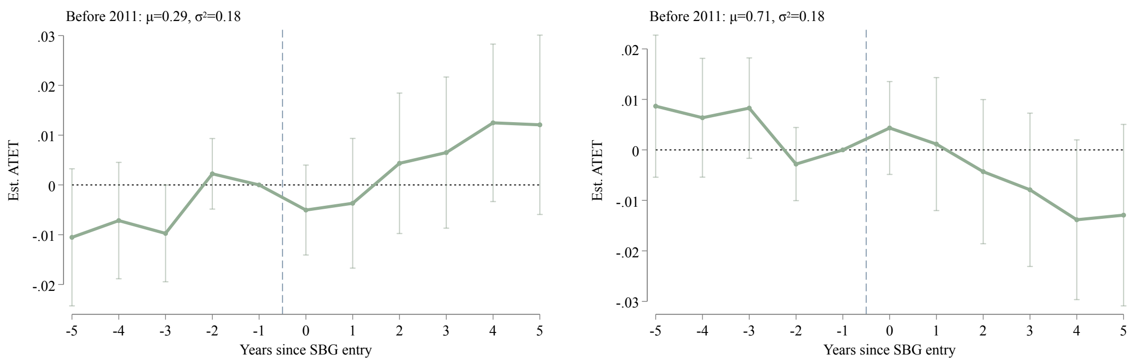
(a) Uni-county and Uni-state Banks



(b) National Banks

Figure 3 depicts 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. We report estimates using variance-weighted 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 operation 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 year of SBG entry in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

Figure 4: **Main Result - Loan application shares**

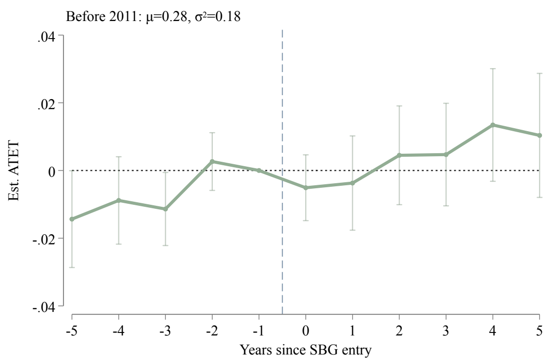


(a) Uni-county and Uni-state Banks

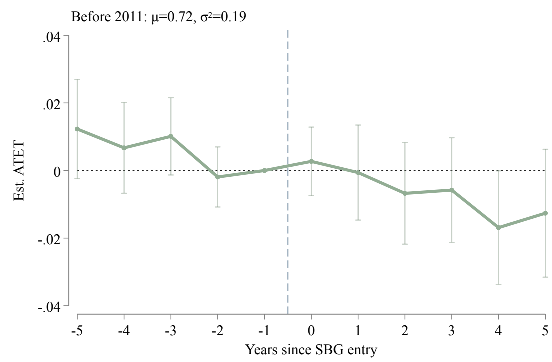
(b) National Banks

Figure 4 depicts 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. We report estimates using variance-weighted 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 operation 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

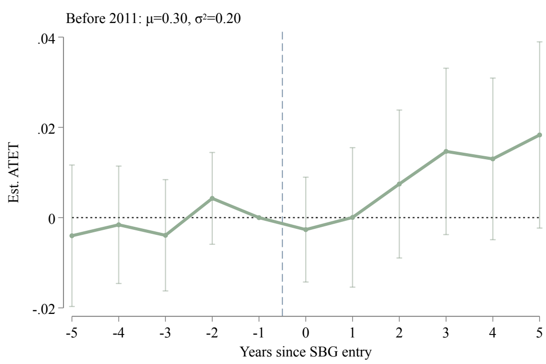
Figure 5: Loan application shares (by applicant income)



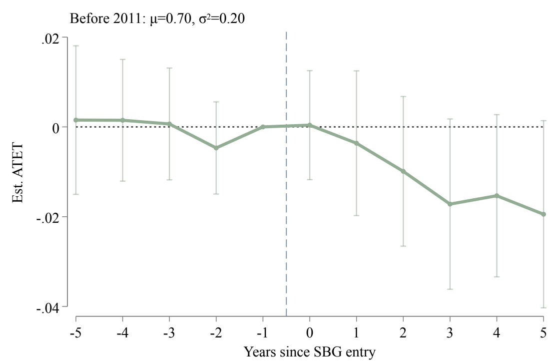
(a) Uni-county and Uni-state Banks – High Income



(b) National Banks – High Income



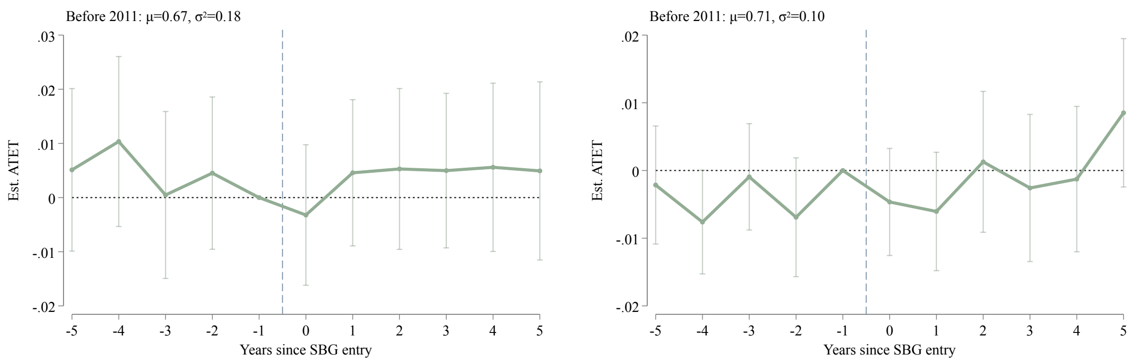
(c) Uni-county and Uni-state Banks – Low Income



(d) National Banks – Low Income

Figure 5 depicts coefficient estimates from an event study analysis of the effects of SBG entry on the distribution of loan applications received by local and national banks depending on an applicant's income. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects. We report estimates using variance-weighted 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 operation 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 in a county that are 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

Figure 6: Loan approval rate

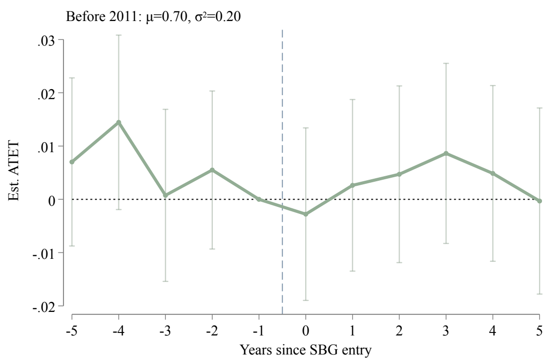


(a) Uni-county and Uni-state Banks

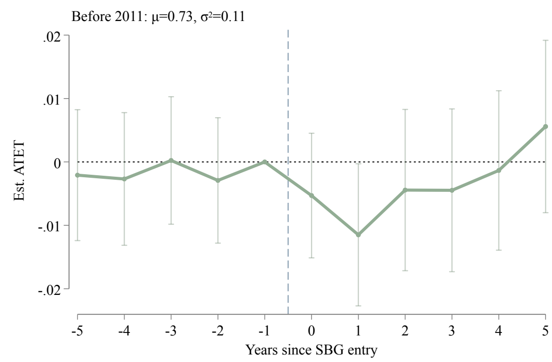
(b) National Banks

Figure 6 depicts 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. We report estimates using variance-weighted 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 operation in more than one state. The loan approval rate is the fraction of loan applications that are approved at local banks (Panel A) and national banks (Panel B). Event time zero denotes the first full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

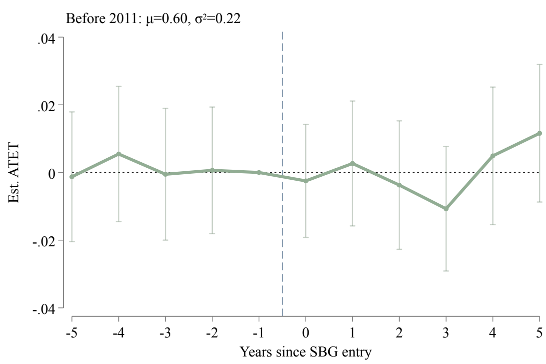
Figure 7: Loan approval rate (by applicant income)



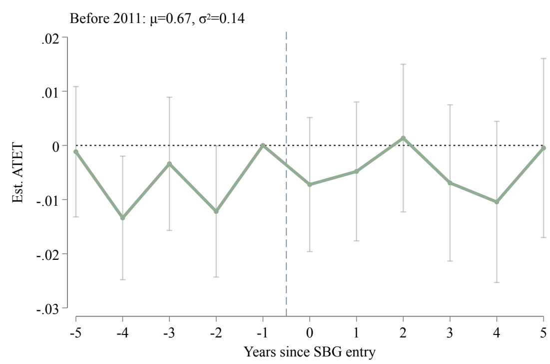
(a) Uni-county and Uni-state Banks – High Income



(b) National Banks – High Income



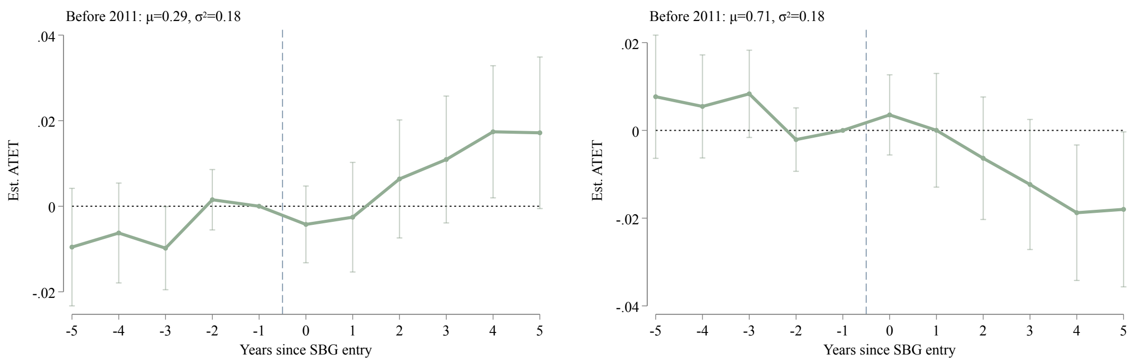
(c) Uni-county and Uni-state Banks – Low Income



(d) National Banks – Low Income

Figure 7 depicts coefficient estimates from an event study analysis of the effects of SBG entry on the loan approval rates of local and national banks depending on an applicant's income. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects. We report estimates using variance-weighted 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 operation 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 at 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

Figure 8: Shares of approved loans

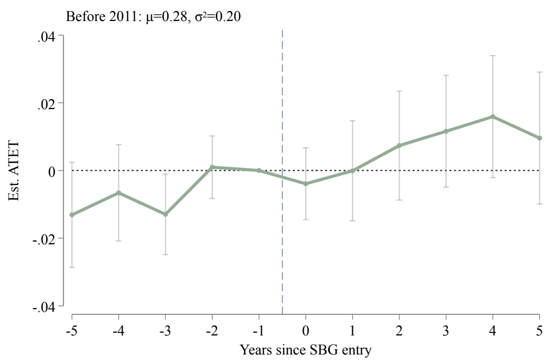


(a) Uni-county and Uni-state Banks

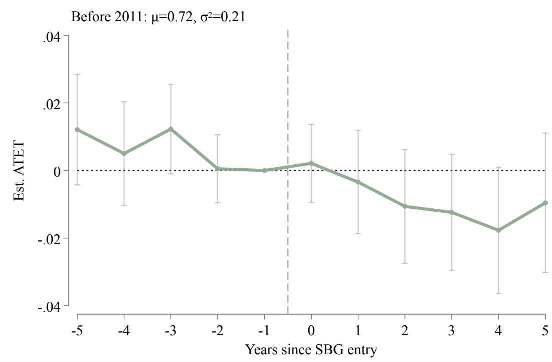
(b) National Banks

Figure 8 depicts coefficient estimates from an event study analysis of the effects of SBG entry on the share of approved loans by local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects. We report estimates using variance-weighted 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 operation in more than one state. The share of approved loans is the fraction of total loan approvals in the county held at local banks (Panel A) and national banks (Panel B). Event time zero denotes the first full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

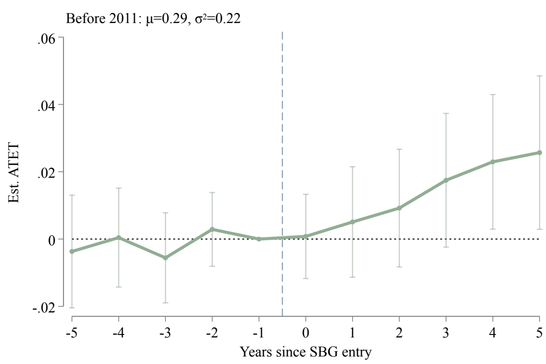
Figure 9: Shares of approved loans (by applicant income)



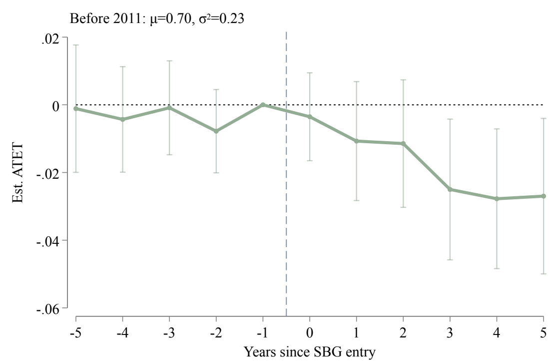
(a) Uni-county and Uni-state Banks – High Income



(b) National Banks – High Income



(c) Uni-county and Uni-state Banks – Low Income

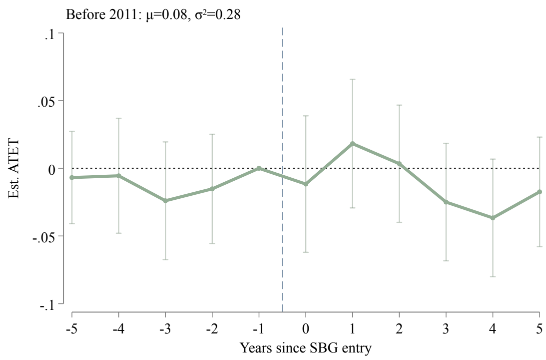


(d) National Banks – Low Income

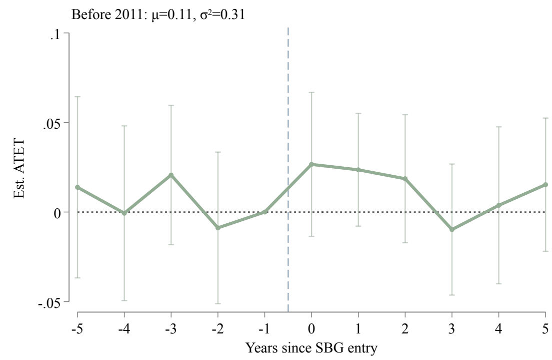
Figure 9 depicts coefficient estimates from an event study analysis of the effects of SBG entry on the shares of approved loans by local and national banks depending on an applicant's income. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects. We report estimates using variance-weighted 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 operation in more than one state. High (low) income applicants are those with above (below) median income at the county level. The share of approved loans is the fraction of total loan approvals in the county held at 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

6.1 Banks

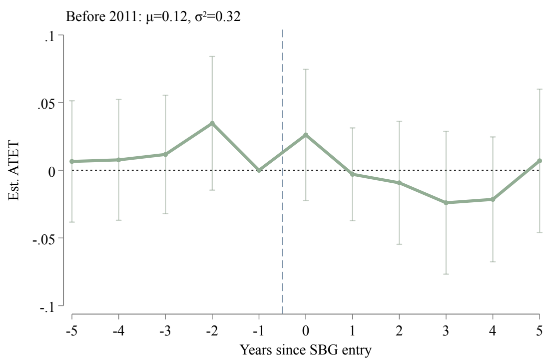
Figure 10: Probability of bank entry and exit



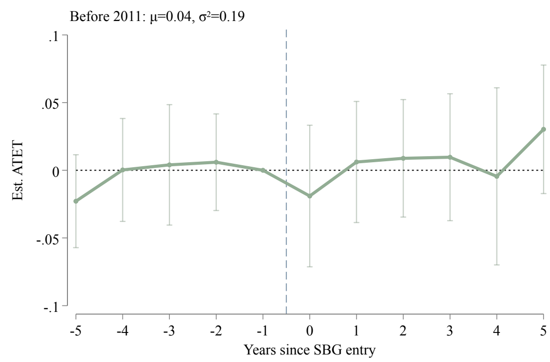
(a) Uni-county and Uni-state Banks – Entry



(b) National Banks – Entry



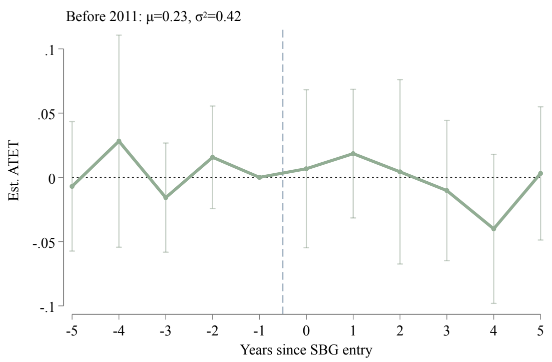
(c) Uni-county and Uni-state Banks – Exit



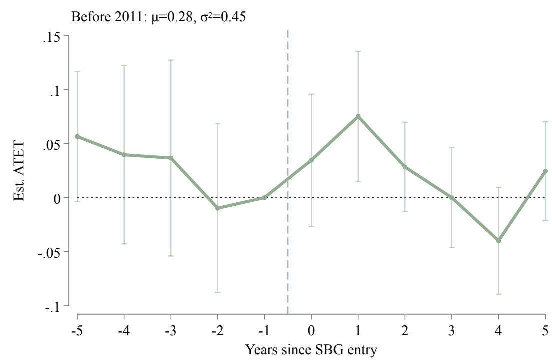
(d) National Banks – Exit

Figure 10 depicts 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. We report estimates using variance-weighted 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 operation in more than one state. Bank entry is defined as opening a branch in a county where the banks did not operate previously (Panel A – local banks and Panel B – national banks). Bank exit is defined as closing all branches 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

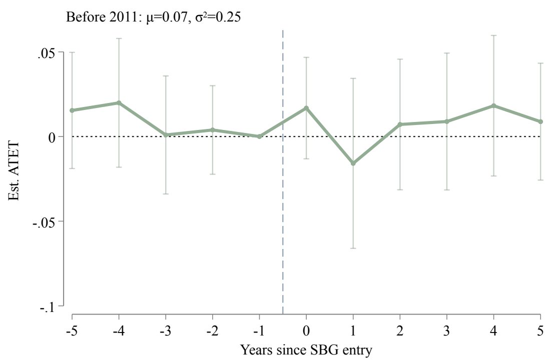
Figure 11: Probability of branch opening and closing



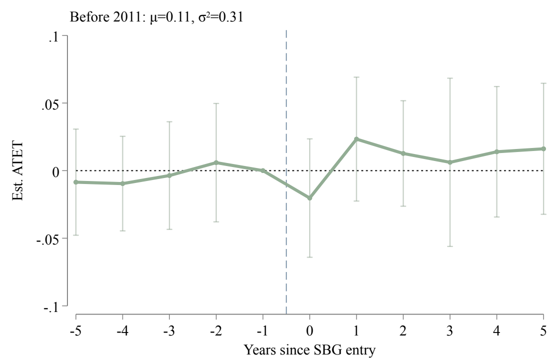
(a) Uni-county and Uni-state Banks – Branch Openings



(b) National Banks – Branch Openings



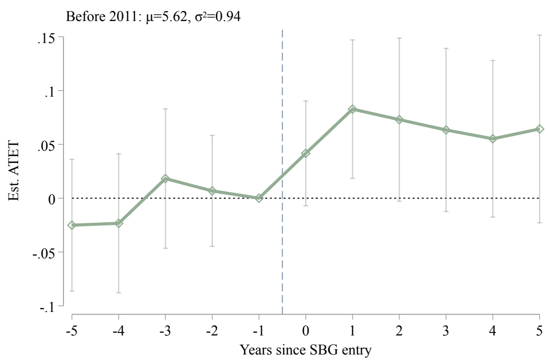
(c) Uni-county and Uni-state Banks – Branch Closures



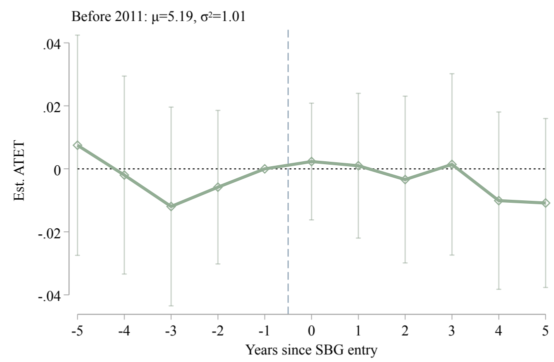
(d) National Banks – Branch Closures

Figure 11 depicts 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. We report estimates using variance-weighted 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 operation in more than one state. Branch openings are defined as a bank opening a branch in a county where it operates other branches (Panel A – local banks and Panel B – national banks). Branch closures are defined as closing 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

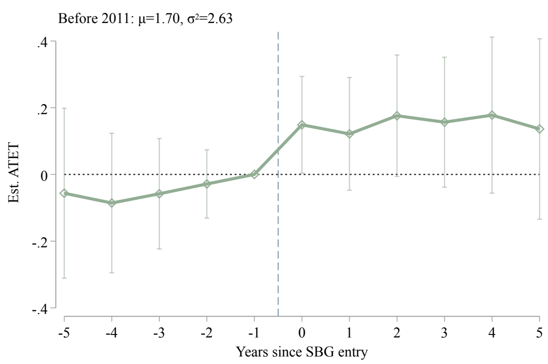
Figure 12: Rate Watch - Mortgage rate



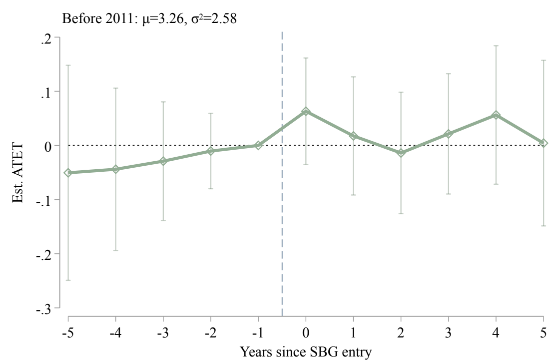
(a) Uni-county and Uni-state Banks - Interpolated



(b) National Banks - Interpolated



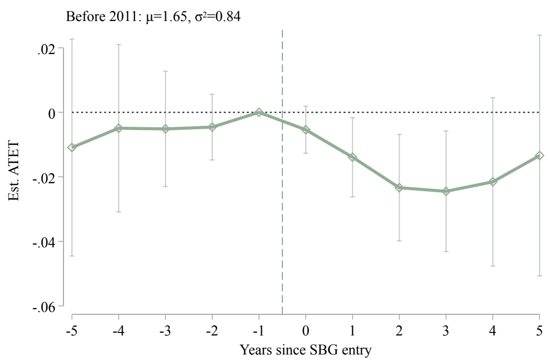
(c) Uni-county and Uni-state Banks - Modified



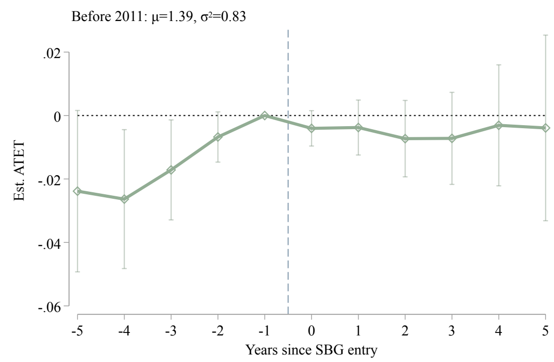
(d) National Banks - Modified

Notes:
Figure 12 depicts 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. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects. We report estimates using variance-weighted 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 operation in more than one state. To account for county-years with missing mortgage data, Panels A and B present results with the mortgage rate interpolated at the county then state-levels and include an indicator variable for missing county-year pairs. Panels C and D modify the mortgage rates by setting missing observations to 0 and include an indicator variable for missing county-year pairs. Event time zero denotes the first full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

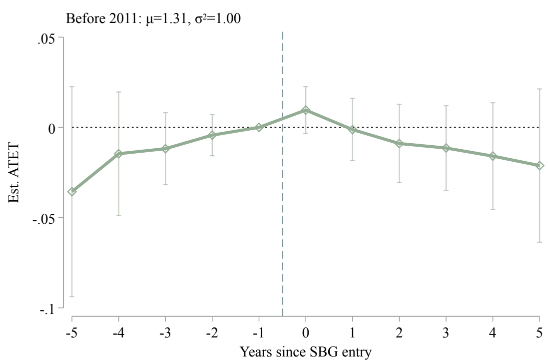
Figure 13: Rate Watch - Deposit rate



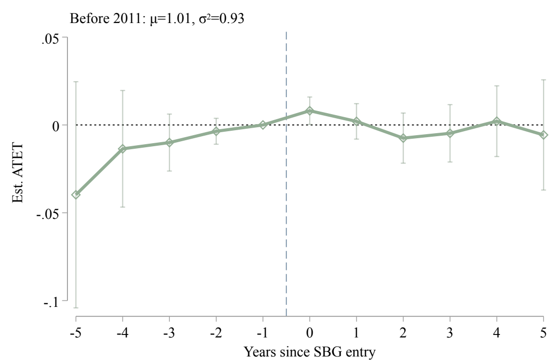
(a) Uni-county and Uni-state Banks - Interpolated



(b) National Banks - Interpolated



(c) Uni-county and Uni-state Banks - Modified

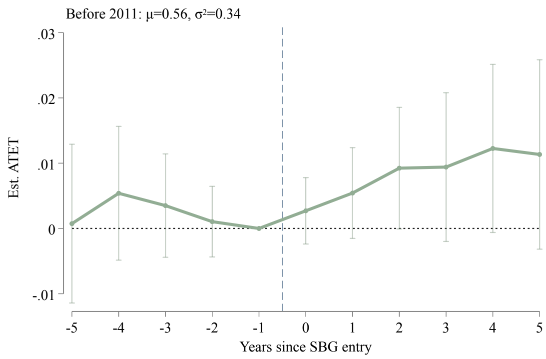


(d) National Banks - Modified

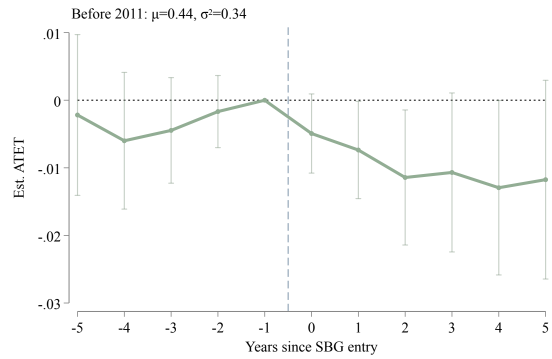
Notes: Figure 13 depicts coefficient estimates from an event study analysis of the effects of SBG entry on the average deposit rates on the combination of money market, savings account, and 12, 24, and 60 month CDs paid by local and national banks. We use the Dube et al. (2023) local projection model to estimate group-time average treatment effects. We report estimates using variance-weighted 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 operation in more than one state. To account for county-years with missing deposit data, Panels A and B present results with the deposit rate interpolated at the county then state-levels and include an indicator variable for missing county-year pairs. Panels C and D modify the deposit rates by setting missing observations to 0 and include an indicator variable for missing county-year pairs. Event time zero denotes the first full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

6.2 Robustness Figures

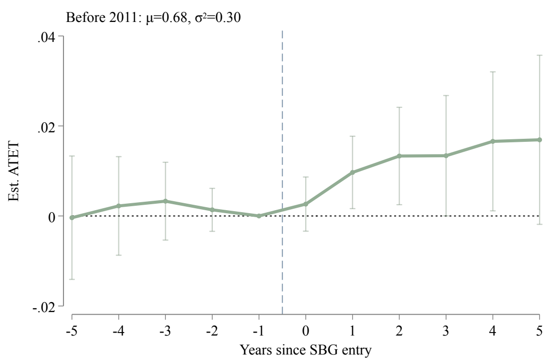
Figure 14: **Main result** – Matched sample and Sample restricted to states with both Tribune and SBG



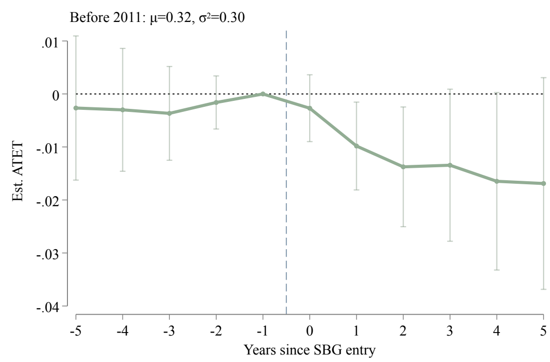
(a) Uni-county and Uni-state Banks – Matched Sample



(b) National Banks – Matched Sample



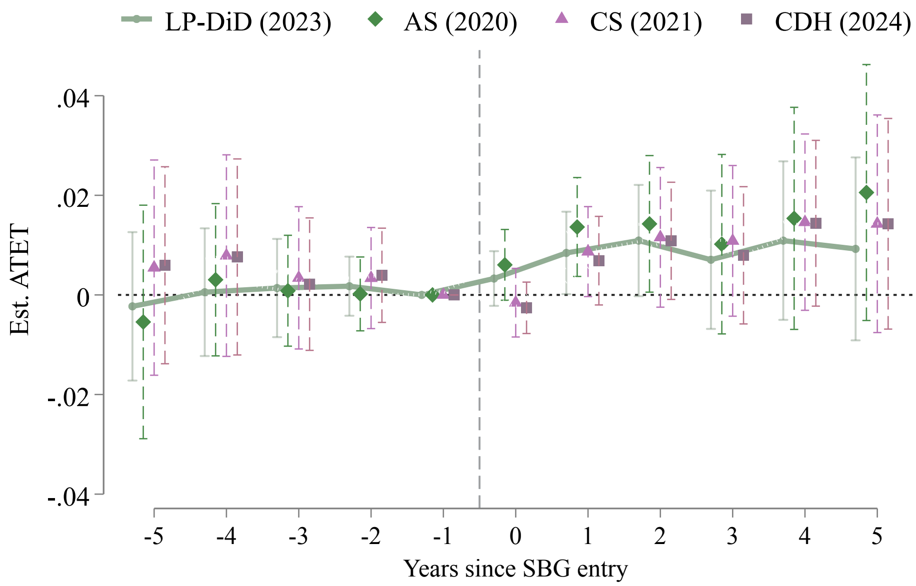
(c) Uni-county and Uni-state Banks – Tribune Sample



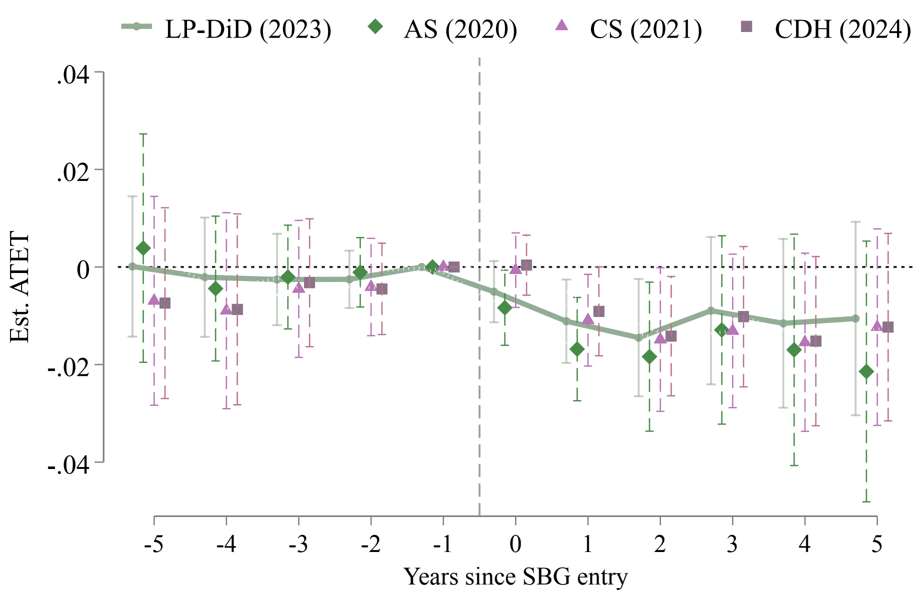
(d) National Banks – Tribune Sample

Notes: Figure 14 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.

Figure 15: **Main result** – Different estimators



(a) Uni-county and Uni-state Banks

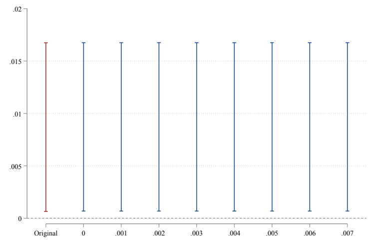


(b) National Banks

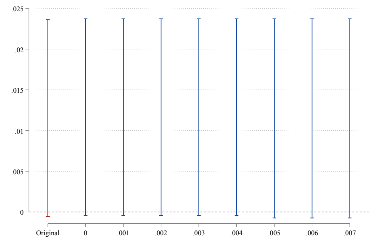
Notes: Figure 15 presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry and three different models for the treatment of the entry of Sinclair. We present the model suggested by Callaway and Sant'Anna (2021) (CS), the regression model suggested by Sun and Abraham (2021) (AS), and the model suggested by de Chaisemartin 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 operation in more than one state. Brackets represents a 95% confidence interval using cluster standard errors at the CZ level.

Figure 16: **Main result** – Parallel trends violations

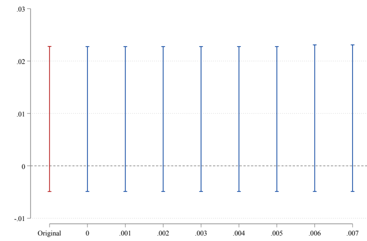
Uni-county and Uni-state Banks



(a) 1 Year

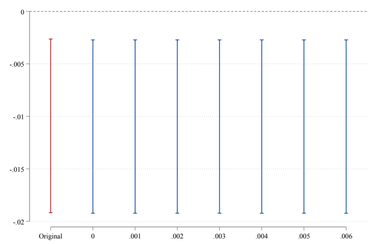


(b) 2 Year

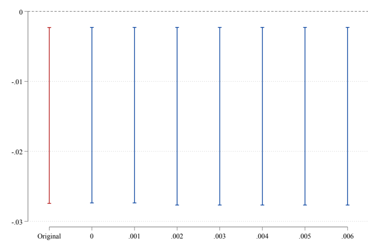


(c) 3 Year

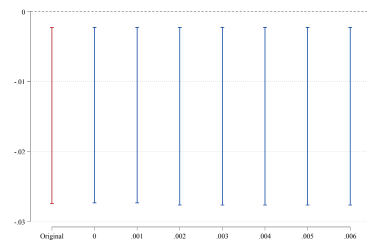
National Banks



(d) 1 Year



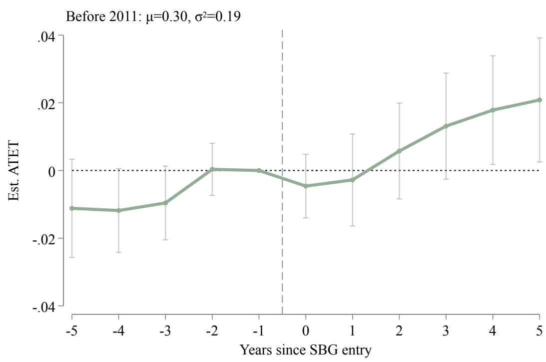
(e) 2 Year



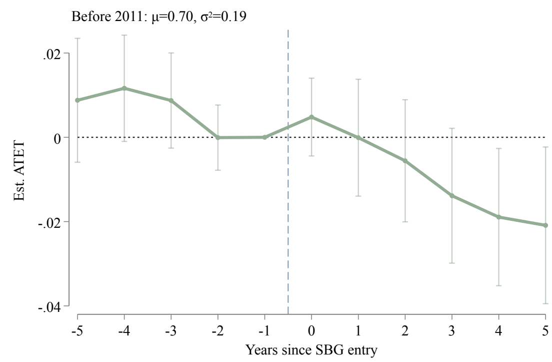
(f) 3 Year

Notes: Figure 16 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 3. 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 operation 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)

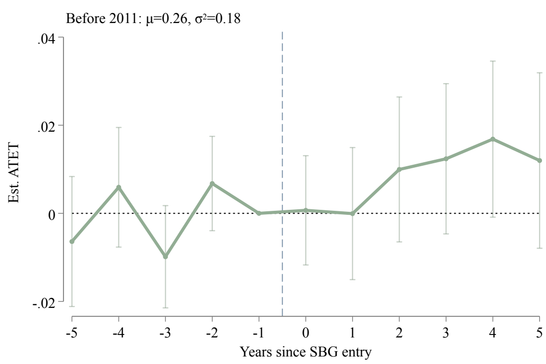
Figure 17: Loans applications shares by gender (Using data from 2007)



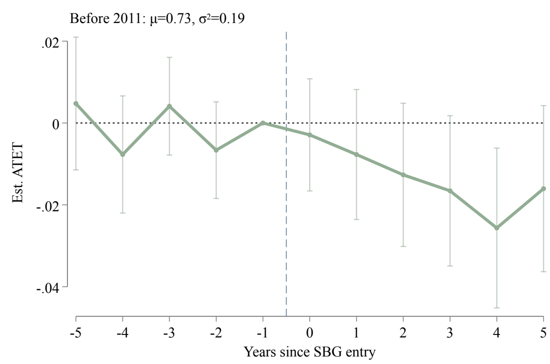
(a) Uni-county and Uni-state Banks – Male



(b) National Banks – Male



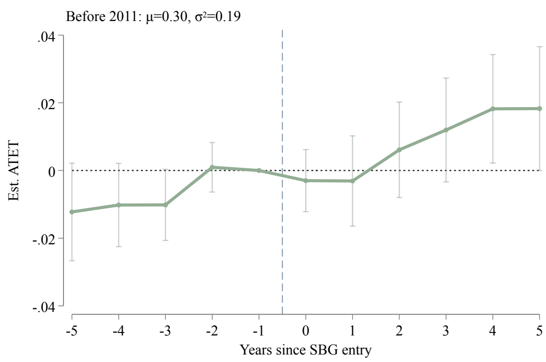
(c) Uni-county and Uni-state Banks – Female



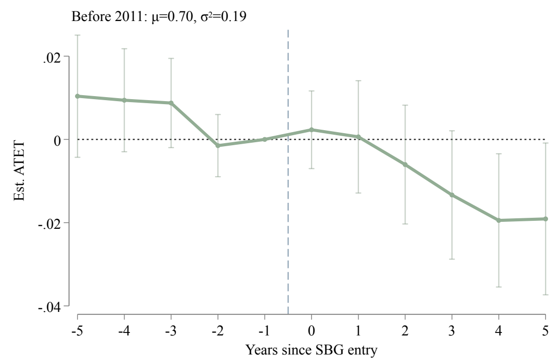
(d) National Banks – Female

Notes: This figure presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry. The shaded region represents a 95% confidence interval using cluster standard errors at the province level.

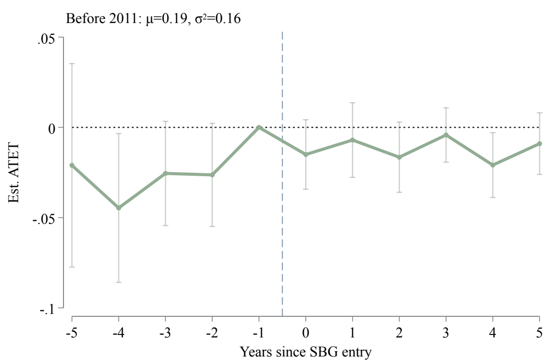
Figure 18: Loans applications shares by Race (Using data from 2007)



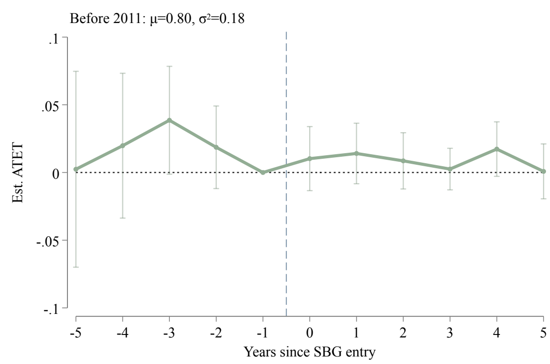
(a) Uni-county and Uni-state Banks – White



(b) National Banks – White



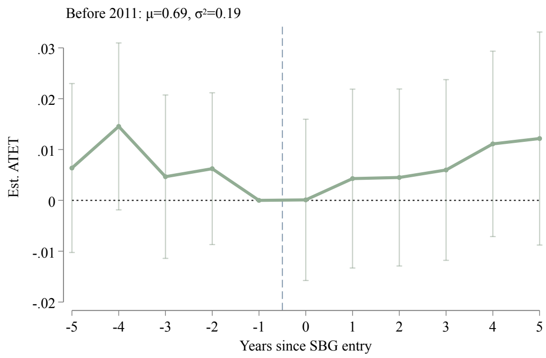
(c) Uni-county and Uni-state Banks – Non-White



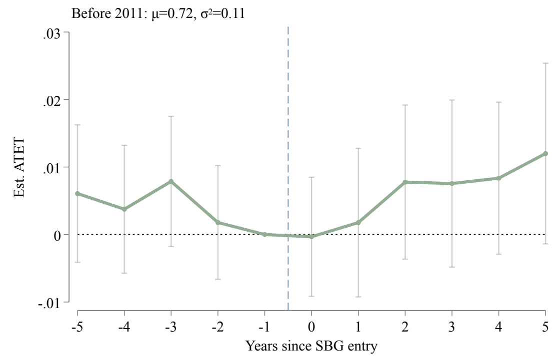
(d) National Banks – Non-White

Notes: This figure presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry. The shaded region represents a 95% confidence interval using cluster standard errors at the province level.

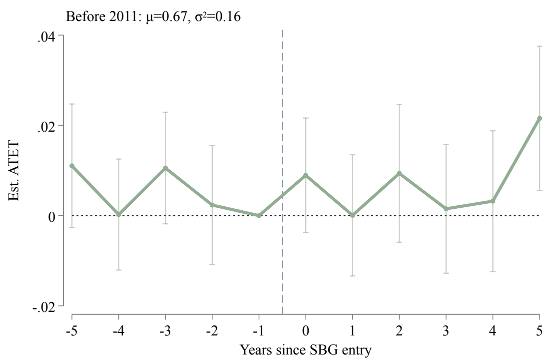
Figure 19: Loans approving rate by Gender (Using data from 2007)



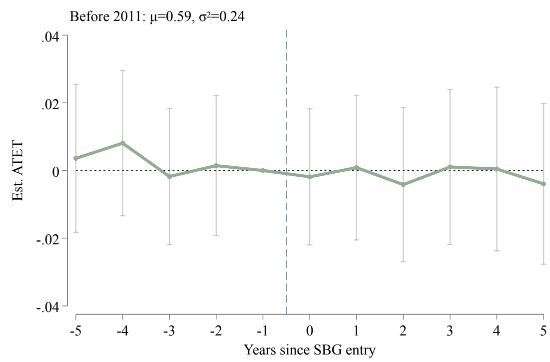
(a) Uni-county and Uni-state Banks – Male



(b) National Banks – Male



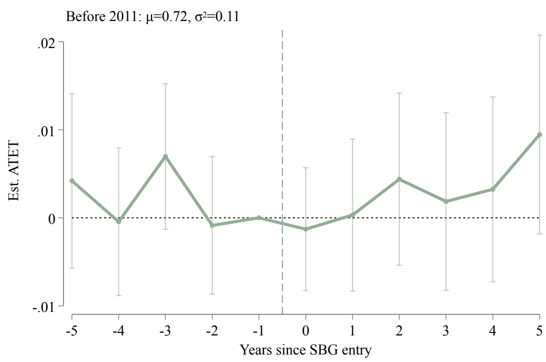
(c) Uni-county and Uni-state Banks – Female



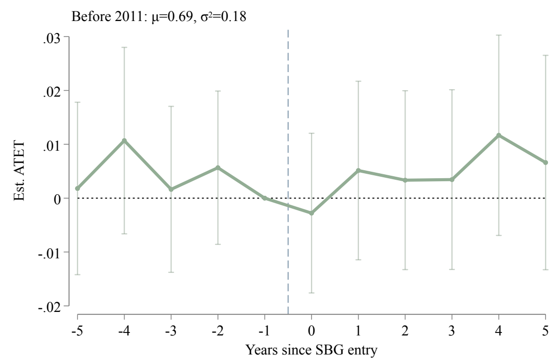
(d) National Banks – Female

Notes: This figure presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry. The shaded region represents a 95% confidence interval using cluster standard errors at the province level.

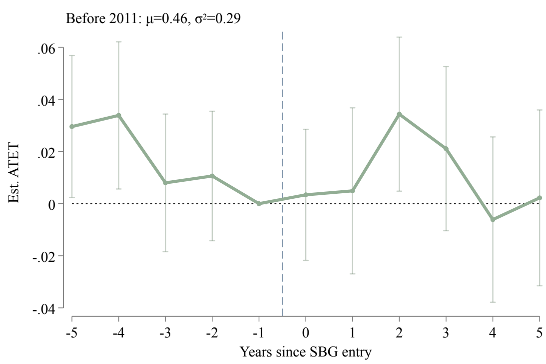
Figure 20: Loans approving rate by race (Using data from 2007)



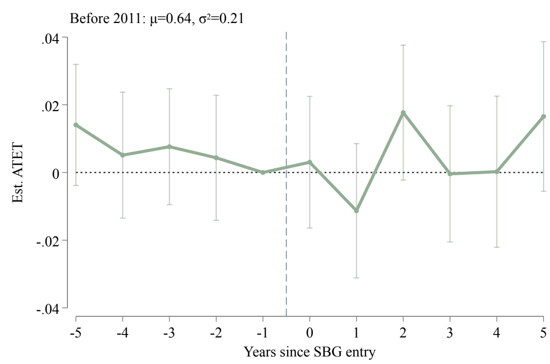
(a) Uni-county and Uni-state Banks – White



(b) National Banks – White



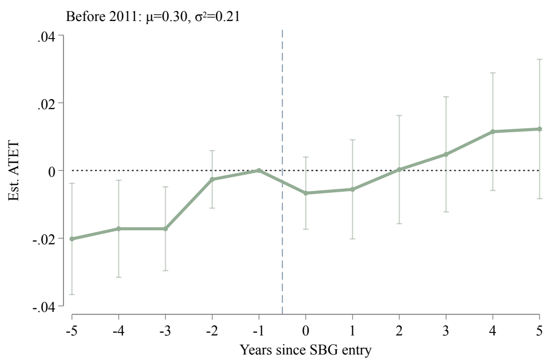
(c) Uni-county and Uni-state Banks – NonWhite



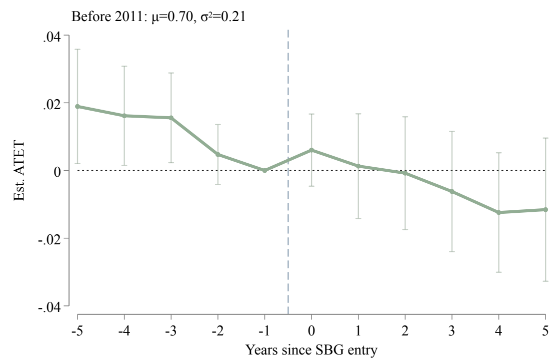
(d) National Banks – NonWhite

Notes: This figure presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry. The shaded region represents a 95% confidence interval using cluster standard errors at the province level.

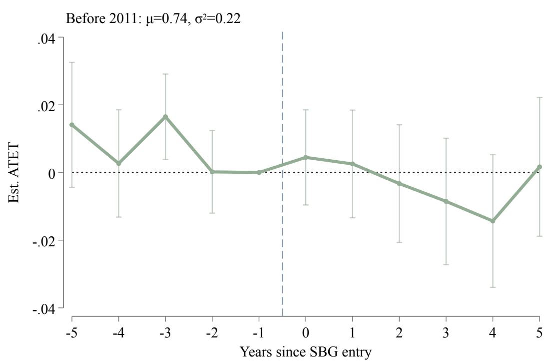
Figure 21: Loans approved shares by gender (Using data from 2007)



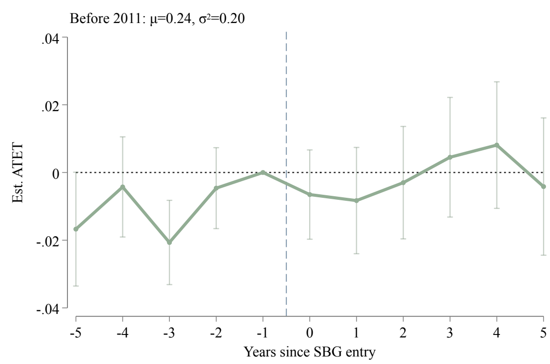
(a) Uni-county and Uni-state Banks – Male



(b) National Banks – Male



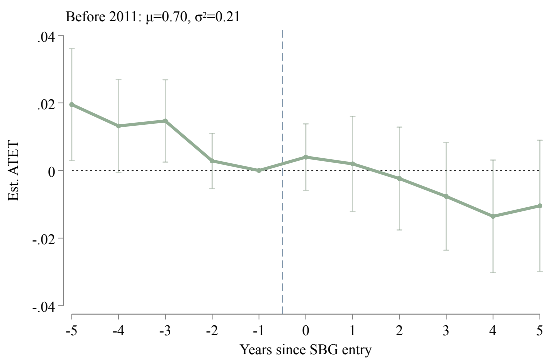
(c) Uni-county and Uni-state Banks – Female



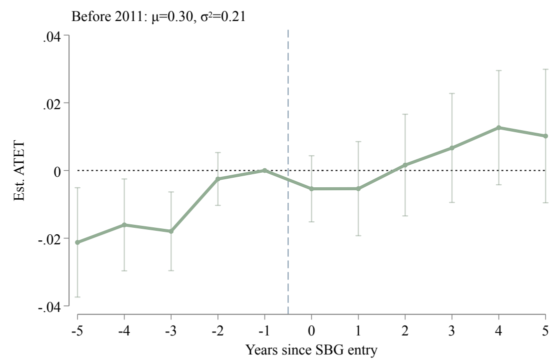
(d) National Banks – Female

Notes: This figure presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry. The shaded region represents a 95% confidence interval using cluster standard errors at the province level.

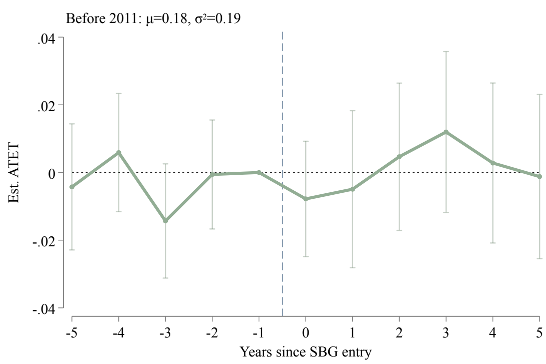
Figure 22: Loans approved shares by race (Using data from 2007)



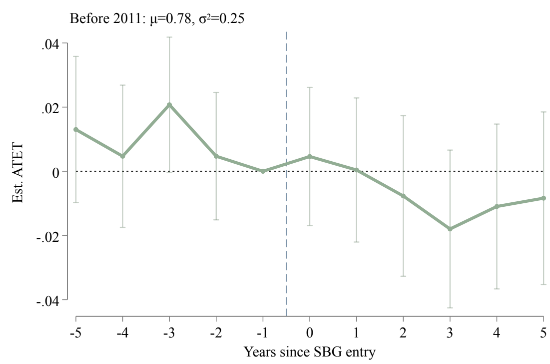
(a) Uni-county and Uni-state Banks – White



(b) National Banks – White



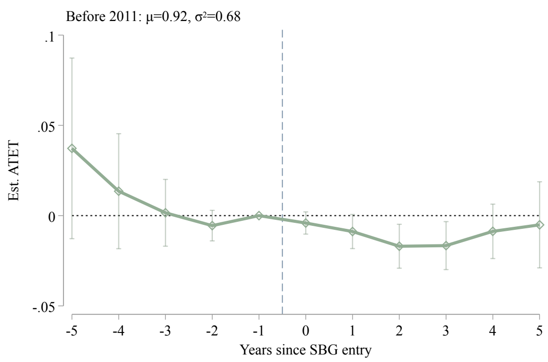
(c) Uni-county and Uni-state Banks – Non-White



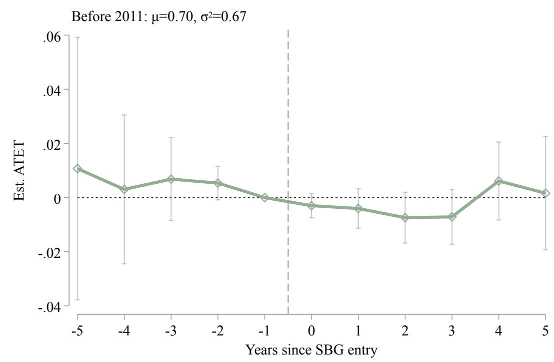
(d) National Banks – Non-White

Notes: This figure presents the event study coefficients following Dube et al. (2023) for the treatment SBG entry. The shaded region represents a 95% confidence interval using cluster standard errors at the province level.

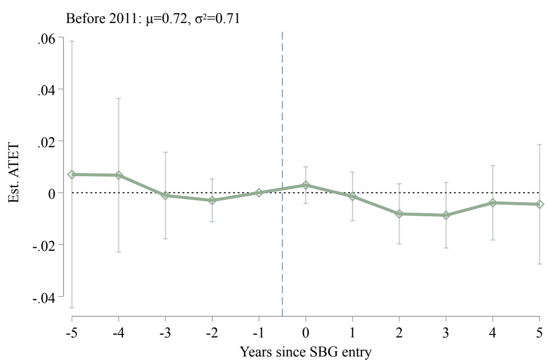
Figure 23: Rate Watch - Deposit rate (Money Market rates)



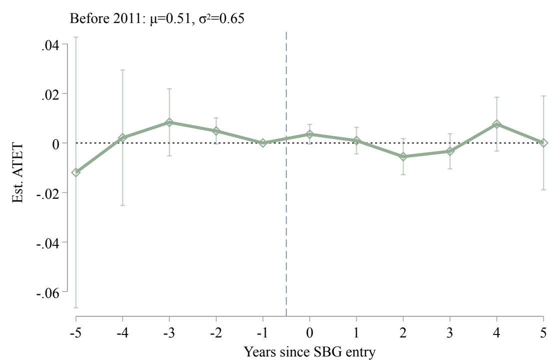
(a) Uni-county and Uni-state Banks - Interpolated



(b) National Banks - Interpolated



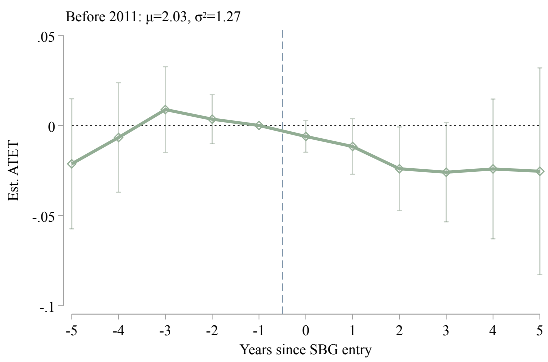
(c) Uni-county and Uni-state Banks - Modified



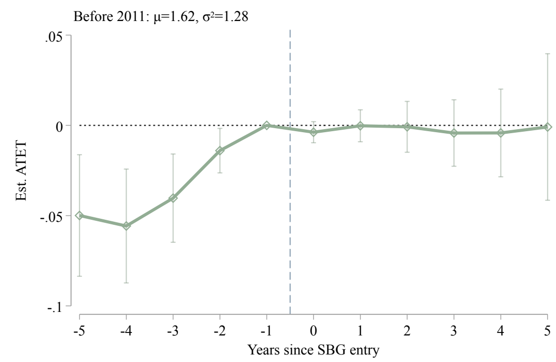
(d) National Banks - Modified

Notes: Figure 23 depicts 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. We report estimates using variance-weighted 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 operation 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.

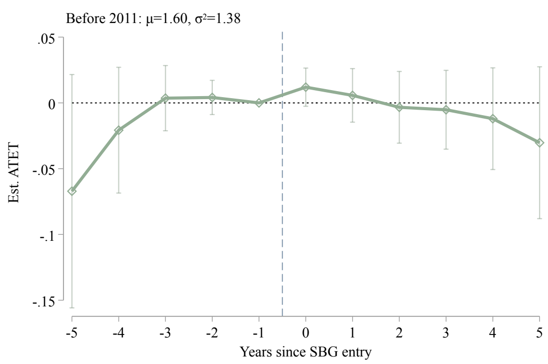
Figure 24: Rate Watch - Deposit rate (12-month CD rates)



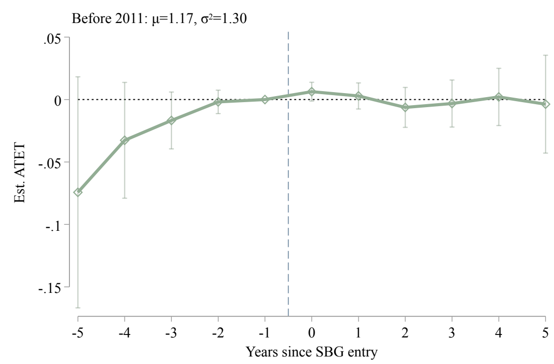
(a) Uni-county and Uni-state Banks - Interpolated



(b) National Banks - Interpolated



(c) Uni-county and Uni-state Banks - Modified



(d) National Banks - Modified

Notes: Figure 24 depicts 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. We report estimates using variance-weighted 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 operation 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 full year of SBG operation in a county. The bars represent 95% confidence intervals. Standard errors are clustered at the CZ level.