Banks' Images: Evidence from Financial Advertising*

Xugan Chen† Allen Hu‡ Song Ma§
Yale *UBC* *Yale and NBER*

Abstract

This paper examines how banks strategically develop their brand image, and how these image-building efforts influence both franchise value and the transmission of monetary policy. Analyzing over a decade of TV commercial videos via an unsupervised video embedding method, we find that banks consistently build their images around one of three dimensions: pricing advantages, superior service quality, and a trustworthy, life-aspirational focus. Banks with strong local market shares emphasize service and life aspirations. Banks generally truthfully advertise pricing and service advantages but rely on emotional appeals when lacking these advantages. They also tailor their images to local demographics, increasing minority representation in targeted areas. Using a border discontinuity design, we show that advertising intensity and style significantly affect deposit quantities and spreads, a factor that becomes especially important during monetary policy transmission. These findings suggest that banks build images to strengthen their market positions and boost franchise value.

JEL Classification: G2, M3, G5

Keywords: Financial Advertising, Banking, Artificial Intelligence, Franchise Value

*We thank Paul Goldsmith-Pinkham, Phil Strahan, and workshop participants at Texas A&M, Tsinghua PBCSF, UBC, and Yale (Marketing). All errors are our own. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

†Yale School of Management, xugan.chen@yale.edu.

‡University of British Columbia, Saunder School of Business, allen.hu@sauder.ubc.ca.

§Yale School of Management and NBER, song.ma@yale.edu.

1. Introduction

Although banks have traditionally been perceived as offering largely homogeneous products, recent studies highlight significant heterogeneity across these institutions in areas such as market share, asset composition, branch services, pricing, and productivity. These differences are central to banks' operations and competitive dynamics, with important implications for the broader economy (Egan, Hortaçsu and Matvos, 2017; Drechsler, Savov and Schnabl, 2017; Egan, Lewellen and Sunderam, 2022; Benmelech, Yang and Zator, 2023; d'Avernas et al., 2023).

For these variations to persist in equilibrium—while attracting a stable customer base and enhancing franchise value—banks must effectively convey their advantages to consumers and cultivate loyalty. Consequently, they often engage in intensive strategic communication to shape and reinforce their brand images. How do banks communicate with their customers to build these images, and how do such image-building activities affect their operations? In this paper, we address these questions by conducting the first systematic study of financial advertising, drawing on more than a decade of data on TV advertising coverage and content.

This analysis is important for two key reasons. First, advertising is a critical operational decision for financial intermediaries, serving as a tool to persuade potential customers and shape the bank's image (Mullainathan, Schwartzstein and Shleifer, 2008; Bertrand et al., 2010; Gurun, Matvos and Seru, 2016). For instance, surveys of Chief Marketing Officers (CMOs) indicate that, on average, banks allocate 9.5% of their annual budget to advertising efforts. Second, financial advertising content provides a unique lens through which to observe how banks actively differentiate themselves from competitors. By leveraging advancements in AI and Large Language Models (LLMs), we analyze the richness of these advertising materials to systematically map them to the heterogeneities observed across banks, offering new insights into how banks strategically communicate their image to consumers.

Our analysis uses a unique dataset of financial advertisements from Nielsen Ad Intel, which contains information on advertisements aired on national and local TV from 2003 to 2020. We use two parts of the data: the advertising creatives (video clips) and the airtime schedules. The creatives data contain 51,349 video clips of advertisements, which we use to

extract the content of the advertisements. This dataset also identifies the advertising institution. The schedule data contain the airtime schedules of each advertisement creative, which we use to capture the specific advertising strategies of financial institutions, particularly the geographic targeting of advertisements across different designated marketing areas (DMAs).

We merge this advertising data with a comprehensive set of financial intermediaries data, including bank balance sheet data from U.S. Call Reports, branch-level deposit data from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) data, mortgage data from the Home Mortgage Disclosure Act (HMDA) data, and small business lending data from the Community Reinvestment Act (CRA) dataset and the Small Business Administration (SBA) dataset. These data are used to construct a broad set of characteristics of financial intermediaries and their business activities.

The banks' images are extracted from advertisements, first using verbal textual data, and then visual and vocal data. On average, each advertisement clip is 27 seconds and 53 words long. Our quantification uses an unsupervised high-dimensional video embedding clustering method, which provides a robust and efficient approach to extract information that represents the most variance in the video. Intuitively, this method analyzes videos by grouping similar narratives, scenes, and events without human input. By clustering, the method efficiently identifies key patterns and variations in the video, making it easier to detect meaningful moments and summarize content.

The method, though unsupervised, delivers a meaningful categorization of banks' primary images in their advertisements. Each advertisement video can be classified into three broad categories. The first category is pricing-related information, including favorable interest rates, loan options, affordability, and special offers and financial benefits. The second category is service quality, including the application and approval process, quality customer service, and availability of mobile and online applications. The third category relates to establishing trust with potential customers and the use of emotional appeals, including the discussion of financial responsibility, expert advice, and financial literacy, or lifestyle and aspirations such as homeownership advantages and successful small business stories. This clustering also aligns well with the marketing literature on coding advertising information and styles (Liaukonyte, Teixeira and Wilbur, 2015; Guitart and Stremersch, 2021; Tsai and

Honka, 2021; Jiang and Kim, 2024) and the finance literature on financial intermediaries (d'Avernas et al., 2023; Jiang, Yu and Zhang, 2022; Zhang, Muir and Kundu, 2024).

In addition, we incorporate information derived from the visual and vocal elements of advertisements, following recent research on non-verbal features in communication (Hu and Ma, 2025; Gorodnichenko, Pham and Talavera, 2023). Specifically, we identify the facial attributes of actors—such as race, gender, and emotional expressions—to assess whether a bank portrays itself as friendly to minority groups or specific genders.

Banks' advertisements exhibit significant diversity in how banks portray their images. 11% of banks focus on their pricing advantages and financial benefits, 17% on customer service and support, 71% focus on building trust and associating their image with aspirational lifestyles. In a variation decomposition exercise, we show that banks' images are mostly explained by bank-fixed effects, bank-year fixed effects, and bank-county fixed effects.

Our first set of analyses focuses on cross-sectional differences in advertising content across financial institutions. These analyses are organized around a central curiosity: is strategic advertising a concrete mechanism through which banks maintain their franchise value, attract customers, and compete with other financial institutions while maintaining their heterogeneous features? Our analysis thus is organized as revisiting the recent literature on bank heterogeneity, but from the perspective of financial advertisement.

Our findings reveal substantial heterogeneity in financial advertising strategies across banks with various important characteristics. First, banks with higher market shares prioritize service quality and life inspiration themes over pricing information, leveraging their established presence to attract broadly. This aligns with d'Avernas et al. (2023), who highlight the superior liquidity services but low deposit rates in the deposit business of large banks.

High-rate banks target rate-sensitive depositors by emphasizing competitive pricing information, while low-rate banks prioritize trust building and emotionally appealing themes to retain loyal and sticky customers, reflecting the distinct behaviors of high- and low-rate banks documented in Zhang, Muir and Kundu (2024). Additionally, banks with high service quality, measured by service charges, branch networks, and consumer complaints, highlight their value-added services and trust-building themes in their advertising, distinguishing

themselves by targeting customers who value enhanced services and personalized banking experience (Jiang, Yu and Zhang, 2022; Zhang, Muir and Kundu, 2024).

We also find that banks strategically adapt their advertising to reflect local demographic compositions, increasing minority representation in advertising targeted at communities with larger minority populations. These findings collectively underscore the strategic use of financial advertising by banks. By aligning their advertising messages with operation strengths, market positions, and customer demographics, banks effectively use advertising as a tool to build and sustain their franchise value and competitive edge in the financial market.

Our second part of the empirical analysis examines the causal relationship between bank advertising and consumer demand for financial products. We demonstrate that both advertising spending and styles significantly influence consumer demand for deposits, mortgages, and small business loans. To ensure robust and credible results, we employ two complementary empirical approaches: a within-county estimation strategy and a border discontinuity design. First, the within-county estimation strategy focuses on variations in advertising spending among banks operating within the same county. This strategy controls for county-year fixed effects to account for local economic opportunities and bank-county fixed effects to absorb differences in banks' baseline market presence. This setup allows us to isolate the impact of advertising on financial product demand within a controlled local environment.

To further address potential endogeneity concerns and identify the causal effects of advertising, we implement a border discontinuity design. This method leverages the natural geographic discontinuities at the borders of DMAs, where consumers on either side of a border share similar observable characteristics and product choices but are exposed to different levels of advertising due to DMA-specific targeting (Shapiro, 2018, 2020). By comparing the performance of the same bank across counties separated by DMA borders, we are able to identify the causal effects of advertising on consumer demand.

Both approaches yield qualitatively and quantitatively consistent results, demonstrating that advertising significantly impacts financial product demand. For example, a one percent increase in deposit advertising spending corresponds to a 0.09-0.12 basis point increase in deposit growth rates. Similar positive effects are observed in mortgage and small business loan origination, with a one percent increase in advertising leading to a 0.02-0.03 percent

increase in the volume of mortgage origination and a 0.005-0.02 percent increase in the volume of small business loan origination.

Importantly, the style of advertising plays a crucial role. Service quality messages prove most effective for deposits, allowing banks to retain depositors and charge higher spreads, while pricing-focused advertising is associated with contemporaneous decreases in deposit growth and deposit spread. Additionally, banks with higher advertising expenditures maintain higher deposit growth and deposit spreads on average. On the other hand, life inspirations and trustbuilding emphasis drives loan origination, including mortgage and small business loan.

Having established the importance of bank images in sustaining market power and franchise value, we now turn to how financial advertising intertwines with monetary policy transmission. We show that when rates rise, advertisements lean more toward emotional and trust-based appeals, while during extended low-rate conditions, banks emphasize practical financial information. This evolution in content underscores how institutions continually adjust their public image to align with both macroeconomic realities and consumers' changing expectations. To examine whether these dynamic adjustments have impact, we incorporate both advertising expenditures and deposit market concentration into panel regressions. In higher-rate periods, banks investing heavily in advertising can command larger deposit spreads. Banks projecting a service-focused image experience even greater swings in deposit spreads and balance sheet adjustments, consistent with heightened market power—albeit at the cost of amplifying their exposure to rate hikes.

Collectively, our empirical findings support the notion that financial institutions build their brand images not only to attract customers but also to build their deposit franchise and strengthen market power. On top of this, by actively tailoring advertising styles to specific products and customer preferences, banks maximize the effectiveness of financial advertising, thereby reinforcing their competitive position and franchise value.

Our paper relates to several strands of literature. First, it contributes to the growing literature on understanding banks' evolving business models and the divergence of heterogeneous banks. A central focus in this literature is the distinction between large and small banks, which differ significantly in their funding structure (Brady and Bassett, 2002; Park

and Pennacchi, 2008; Egan, Hortaçsu and Matvos, 2017) and business strategies (Berger et al., 2005; Cole, Goldberg and White, 2004; Haynes et al., 1999; d'Avernas et al., 2023). Other dimensions of heterogeneity include differences in deposit rates (Iyer, Kundu and Paltalidis, 2023; Zhang, Muir and Kundu, 2024), the likelihood of bank-run due to uninsured deposits (Egan, Hortaçsu and Matvos, 2017; Benmelech, Yang and Zator, 2023), capital structure distinctions between traditional banks and shadow banks (Jiang et al., 2020), and variations in deposit and asset productivity (Egan, Lewellen and Sunderam, 2022). As highlighted in recent literature (Jiang, Yu and Zhang, 2022; Haendler, 2022; Koont, 2023; Zhang, Muir and Kundu, 2024), one key driver of the divergence in banking sector is technological advancement in banking, where high-rate banks compete on prices and hold shorter-term assets with higher credit risk by operating primarily online and attracting less sticky depositors, and in contrast, low-rate banks maintain physical branches and charge higher prices through the retention of relatively more sticky depositors. A key contribution of our paper to this literature is offering a novel perspective on understanding the heterogeneity of banks' characteristics through their advertising strategies. We provide evidence that banks actively communicate their distinct features to consumers and, importantly, we demonstrate that these strategic communications align with the heterogeneity observed in ex-post differences across various dimensions of banking.

Our paper also connects to the literature on how banks generate and sustain value over time. A key driver of bank value identified in the literature is the franchise value of deposit businesses (Chen et al., 2022; Egan, Lewellen and Sunderam, 2022; Drechsler et al., 2024), closely tied to banks' ability to attract and retain customers, maintain pricing power, and differentiate their services. The financial stability of the banking system depends on the relative value of bank assets and liabilities (Egan, Hortaçsu and Matvos, 2017; Minton, Stulz and Taboada, 2019; Ma and Scheinkman, 2020; Gelman, Goldstein and MacKinlay, 2023), making franchise value critical not only for individual institutions but also for systemic stability (Drechsler et al., 2024; Haddad, Hartman-Glaser and Muir, 2023; Jiang et al., 2024; Koont, Santos and Zingales, 2024). Additionally, franchise value plays a central role in the transmission of monetary policy and banks' exposure to interest rate risk (Drechsler, Savov and Schnabl, 2017, 2021) who emphasize the deposit market power channel as measured by

deposit market concentration (HHI). Our paper contributes to this literature by providing a new dimension on the micro-foundations of bank franchise value, where advertising is an important tool through which banks can build and sustain their franchise value. We show how banks actively use advertising to communicate their unique characteristics—such as competitive pricing, superior service quality, and customer focus—to mitigate risks, strengthen customer relationships, and reinforce market power, thereby contributing to their overall valuation and financial stability.

This paper relates to a growing literature studying advertising in financial markets, including studies on advertising mortgages (Gurun, Matvos and Seru, 2016; Grundl and Kim, 2019; Kim, Jiang and Thomadsen, 2023; Jiang and Kim, 2024), insurance (Shapiro, 2020), credit card (Bertrand et al., 2010), mutual funds (Roussanov, Ruan and Wei, 2021; Hastings, Hortaçsu and Syverson, 2017), and banking (Honka, Hortaçsu and Vitorino, 2017; Célérier and Tak, 2023; Mendes, 2024). This paper extends this body of work by offering the first deep look into advertising styles and themes in financial advertising, and by documenting how banks use advertising to actively and strategically highlight their unique characteristics. We also document how these advertising strategies shape consumer demand across various financial products offered by banks, including deposits, mortgages, and business loans.

2. Data and Sample Description

2.1. Data on Financial Advertising

We obtain advertising data from Nielsen's Ad Intel dataset. Nielsen Ad Intel covers individual advertising occurrences across the United States in 210 designated marketing areas (DMAs) for a variety of media types. We focus on advertisements occurring on national TV and local TV from 2003 to 2020. These data include two parts: (i) data on advertising creatives, sometimes also referred to as "impressions", in the form of video clips (the "*Creatives*" data); and (ii) advertisement airtime schedules that track the appearance of each creative on different channels, different geographic regions, and specific times (the "*Schedule*" data). While the schedule data have been recently used in the marketing literature (Shapiro, 2020, 2018; Argente et al., 2021), our paper is the first to use the creatives data in

academic research.

Our creatives data contain 51,349 video clips of advertisements, downloaded through Nielsen's Ad Intel platform after limiting the scope to financial products (i.e., with a product code of B120 or B150). Each video clip is associated with a unique video ID, which allows us to track it in the schedules data. These creatives are also tagged by Nielsen, confirmed by our manual checking, with their advertising financial institution, which we use to connect to information on financial institutions described below. We discuss how we process the advertisement video in Section 3.

The schedule data contain the airtime schedules of each advertisement creative. Most important to us are the air date and time, the duration and the spending of the advertisement, the channel/program on which the advertisement was aired, and the DMAs in which the advertisement was aired. These data are used to capture the specific advertising strategies of financial institutions, including the geographic targeting of advertisements.

[Insert Table 2 Here.]

In Table 2 Panel (a), we present the summary statistics of the advertising data. The data contain 51,349 unique advertisements from 2,739 unique financial institutions. The advertisements are aired in 210 unique DMAs. The average duration of the advertisements is 27 seconds, with a median of 30 seconds. The average air months of an advertisement creative is 13 months, the median of 4 months. Most of the advertisements are aired on local TV, with 96% of the advertisements aired on local TV and 20% on national TV. The average number of airings of an advertisement is 1,560 on local TV and 1,340 on national TV. And the average spending of an advertisement is 0.20 million on local TV and 3.98 million on national TV.

Life Cycle and Geographic Coverage of Bank Advertising. With the sample described above, we now use summary statistics to document the fact that bank commercials have relatively short life cycles, and banks use different commercials in different DMAs in Figure 1.

[Insert Figure 1 Here.]

Panel (a) of Figure 1 shows the distribution of tenure for each creative video. 48% of creative videos were only shown on TV for less than three months. The median and average tenure of financial commercials is four and fourteen months, respectively. Such a pattern is robust for the sample of standard thirty-second commercials, both banks and non-banks, and different types of banks (such as banks with different sizes, deposit rates, and HHIs).

Panel (b) of Figure 1 illustrates the geographic coverage of bank advertising. The dark blue line indicates the annual average number of DMAs where banks run advertising. The light blue line shows the average number of DMAs each commercial covers. The dark blue line is persistently higher than the light blue line. Such a pattern highlights the fact that banks run different commercials in different regions.

Taken together, Figure 1 documents the stylized facts that banks constantly update the content of their TV commercials, with the median life cycle of a creative being four months; banks actively use different commercials in different markets.

2.2. Data on Financial Intermediaries

We link the advertising data to a broad set of financial intermediaries data widely used in the literature. These data include the Federal Reserve's bank balance sheet data, the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) data, the Home Mortgage Disclosure Act (HMDA) data, and small business lending data from the Community Reinvestment Act (CRA) dataset and the Small Business Administration (SBA) dataset.

We obtain bank balance sheet data from U.S. Call Reports provided by Wharton Research Data Services (WRDS). The data contain quarterly information extracted from the income statements and balance sheets of all U.S. commercial banks and their bank holding companies. This bank-level information is then linked to branch-level deposit information from FDIC's SoD. The data cover the universe of U.S. bank branches at an annual frequency from 1993 to 2023. We augment these deposit data with retail deposit rates extracted from Ratewatch, which collects weekly branch-level deposit rates by product. The data cover 54% of all U.S. branches as of 2013. We also supplement the bank balance sheet data with the advertising expenses from Compustat for publicly listed U.S. bank holding companies, using

the linkage file provided by the Federal Reserve Bank of New York.[1]

On the lending side, we obtain US mortgage market data using the Home Mortgage Disclosure Act (HMDA) data. The HMDA covers the near universe of U.S. mortgage applications, including both originated and rejected applications. The HMDA data are available from 1990 to 2021. The HMDA data contains detailed loan-level information on the borrower, the loan, the property, and the lender. We use the HMDA data to construct the mortgage outcomes, including the number of applications, the number of originations, the amount of originations, and the origination rate for each financial institution. It is worth noting that these financial institutions may be beyond the banking sector, including non-bank lenders and credit unions.

We also obtain small business lending data from the CRA dataset and the SBA dataset. Though these data are known to be imperfect, they have been widely used by finance research to study lending activities by banks. The CRA data contain information on business loans originated by banks, but are only available for loans with commitment amounts below $1 million originated by banks with more than $1 billion in assets. The SBA data contains information on small business loans guaranteed by the SBA. These data are used to construct the small business lending outcomes, including the number of applications, the number of originations, the amount of originations, and the origination rate for each financial institution.

These banking data are linked together through a combination of unique identifiers, including the Federal Reserve's RSSD ID, the FDIC's certificate number, and the HMDA's respondent ID. The data are then merged with the advertising data using the financial institution's name through a fuzzy-matching algorithm.

Table 2 Panel (b) presents the summary statistics of the financial intermediaries data. The data contain 13,751 unique financial institution with available data on Call Reports from 1986 to 2021. The data represent a bank holding company-year panel combining multiple datasets. Any unavailable data for any bank-year observation is recorded as missing. The average total assets of a bank, sourced from the U.S. Call Report, is 9,207 million dollars,

[1]We access the data as of March 2024 at https://www.newyorkfed.org/research/banking_research/crsp-frb, which contains PERMCO-RSSD links from June 30, 1986 to September 30, 2023.

with a median value of 498 million dollars. For the sample of publicly listed bank holding companies from Compustat, the average amount of advertising expenses is 18 million dollars, with a median value of 0.69 million. In comparison, the average amount of non-interest expense from the U.S. Call Report is 707 million dollars. Using the data from FDIC Summary of Deposits, banks have deposits of 1,276 million dollars, operate 15 branches, and exhibits an average deposit Herfindahl-Hirschman Index (HHI) of 0.23 on average. Additionally, the average amount of mortgage originations from HMDA and small business loans from CRA is 310 million dollars and 361 million dollars, respectively.

3. Method: Quantifying Banks' Images

In this section, we describe our method to empirically quantify banks' images using advertising videos. As outlined in Hu and Ma (2025), video content has three informational dimensions: visual, verbal, and vocal. In most of our analysis, we first focus on the verbal dimension—namely what is said in each advertisement clip. This choice is motivated by practical considerations, as video clips in earlier years often suffer from lower visual resolution, making textual analysis more consistently reliable. After establishing insights from the verbal content, we extend our analysis to the visual and vocal dimensions as additional measures to capture the broader messaging strategies used in bank advertisements.

3.1. An Unsupervised Video Embedding Method

3.1.1. Step 1: Learning Information Through High-Dimensional Embedding. We first extract the text from the advertising videos' sound tracks using speech-to-text model `Whisper` provided by OpenAI. On average, each video contains 53 words. We then represent each text v as a high-dimensional embedding vector d_v using the `gte-Qwen2` model, a leading open-sourced pre-trained language model developed by Alibaba's NLP group. This process maps each video transcript into a 1536-dimensional vector, preserving rich semantic information.

3.1.2. Step 2: Product Category Clustering. Next, as a preparation step, we identify the product categories using an unsupervised clustering approach. This is not directly related

to quantifying banks' images delivered to customers, but this categorization is useful in our analysis and within-product comparisons. The underlying intuition behind our product categorization is that the most significant variance in the embedding space likely reflects the core product features—that is, a mortgage advertisement should be very different from a general banking service advertisement.

The process is as follows. First, to make sure that we capture the most significant variance, we apply `PaCMAP`, a state-of-the-art approach in the dimension reduction literature, to project the original 1536-dimensional embedding vectors d_v into a 2-dimensional space $\tilde{d}_v$. `PaCMAP` preserves both global and local structure of the data in the original data, ensuring that the reduced representation retains meaningful distinctions. Second, we use hierarchical agglomerative clustering (HAC) to group the videos based on their projected embeddings. This clustering method constructs a hierarchy of clusters, which allows us to interpret the clusters at multiple levels of granularity. Third, we extract the most important and frequent keywords from each group to label the resulting clusters. To do so, we use the widely-used approach in the text analysis literature called "term frequency-inverse document frequency" (TFIDF, Loughran and McDonald, 2011). It assigns each term a weight inversely proportional to the frequency of the term across all documents, ensuring that labels reflect distinguishing features rather than generic banking terms.

[Insert Figure 2 Here.]

Our clustering method identifies six primary product categories: personal deposits, business banking, personal credit, mortgages, investment and retirement services, and general banking services. These categories are well separated in the embedding space, as shown in Figure 2. A more granular level of clusters, shown in Figure A.2, reveals thirteen subcategories. For example, the personal credit category includes three sub-products, including credit card, auto loan, and credit rewards. We rely on the most important keywords to interprete the clusters. For example, the cluster labeled "personal deposit" is characterized by keywords such as "bank", "checking account", and "card", while the "mortgage" cluster includes top keywords like "mortgage", "home", and "loan".

In Panel (a) of Table 2, we presents the distribution of the product categories in the

advertising videos. Personal banking and business banking accounts for 15% and 27% of the advertisement, while the mortgage product and credit card product accounts for 18% and 7% of the advertisement. We also find that one financial institution may offer different products in different advertisements. For example, a bank may advertise both mortgage and business loan products.

Cross-Validating Product Categories Using LLM We also use a large language model (LLM) to identify the product categories by submitting the extracted text to ChatGPT. Specifically, we ask ChatGPT to classify the text into one of the following categories: banking services, business loan, personal credit, mortgage and real estate, investment and brokerage, retirement financial services, and insurance. To make sure the response of GPT is reliable, we fixed the random seed and set the temperature to 0 to make GPT's outputs more deterministic. We also ask GPT to provide the confidence level of its answer on a scale between 0 and 1 and an explanation for each answer, which allows for manual verification of the reasoning behind the scores. In Panel (a) of Table A.1, we show that product categories extracted independently from the clustering method and LLM align very well. For example, among the videos categorized as personal deposit by our clustering method, 83.3% are also categorized as personal deposit by LLM. Intuitively, the two methods should be very similar, as both are based on the same extracted text. This further validates the robustness of our results to extract advertising categories.

3.1.3. Step 3: Quantifying Banks' Images Using Advertising Persuasive Information and Features. Next, we quantify banks' images, focusing on the persuasive elements of advertisement text. Our goal is to uncover recurring persuasive themes that banks use to shape their brand image and influence consumer perception.

To do so, we extend our embedding-based approach—intuitively, we hold the product category constant (i.e., compare a mortgage advertisement with another mortgage advertisement), and focus on how the image is crafted. Technically, since product categories drive the most variance in the embedding space, we isolate the second most significant source of variation, which are persuasive themes.

To remove product-related variance, we construct a residual embedding space. We first obtain the probability distribution p_v of each video over product categories by measuring the distance between its own embedding $\tilde{d}_v$ and the cluster centroids. We then project the original embeddings into a residual space using a residual-marker matrix $I - P(P^TP)^{-1}P^T$ with the original embedding space, where P is the probability distribution matrix of all the videos.

Applying the same `PaCMAP` + HAC clustering procedure to the residual embeddings, we uncover three broad persuasive themes: financial information, service quality, emotional appeal and trust-building. Panel (b) of Figure 2 shows that the second most variance in the embedding space is driven by the persuasive themes. Each broad category contains more specific subcategories, as shown in Panel (b) of Figure A.2. Table 1 summarizes the broad persuasive themes and their detailed subcategories, with the most important keywords for each sub-theme. For example, the cluster labeled "financial information" contains two sub-subcategories, interest rate and payment plan, characterized by most important keywords "rate" and "payment", respectively. The "service quality" cluster includes terms such as "service", "online", "local", and "community", further dividing into three sub-categories—"online service", "local service", and "community support".

It is worth noting that these image clusters emerge organically from the unsupervised method. It not only aligns with the marketing literature, where frameworks for coding advertising information and styles are emerging (Liaukonyte, Teixeira and Wilbur, 2015; Guitart and Stremersch, 2021; Tsai and Honka, 2021; Jiang and Kim, 2024), but also is consistent with the insights from the finance literature, which has identified key dimensions along which financial intermediaries differ, potentially influencing consumer behavior (d'Avernas et al., 2023; Jiang, Yu and Zhang, 2022; Zhang, Muir and Kundu, 2024). This classification balances the need for a comprehensive understanding of the advertising content with the need for a parsimonious set of categories that can be reliably coded.

Cross-Validating Image Quantification Using LLM Similarly, we also use the ChatGPT model to classify the text into the categories we obtained from the clustering method. In our prompt submitted to the model, we query the GPT with the name of the financial institution

Table 1. Categories of Banks' Images

Broad Persuasive Information	Detailed Persuasive Information	Related Keywords
Financial Information	Interest Rates	rate, month, low, APR, fixed, APY
	Payment Plans	free, payment, debt, foreclosure, cash
Service Quality	Online Service	mobile, online, mobile banking, easy, App
	Local Service	state, location, local, community, service
	Community Support	community, local, business, help, support
Emotional Appeal and Trust Building	Future Goals	financial, life, help, business, plan, goal
	Financial Management	money, credit, save, retirement, debt
	Life Fulfillment	life, dream, love, feel, happy, moment
	Family Focus	dad, kid, like, house, family, mom
	Sports & Entertainment	game, got, win, official, fan, team
	Holiday Greetings	holiday, happy, Christmas, merry, wish
	Professional Expertise	financial, client, advisor, wealth, business, management
	News Updates	news, day, brought, week, morning, fox
	Market Information	trade, stock, gold, market, trading, investor

and the transcript of the advertisement video, and in response, GPT generates a string of text containing the probability distribution of the list of categories in Table 1. Figure **??** shows the prompts format used to query GPT. We provide the list of persuasive elements of advertisements and require the probabilities of all categories should sum up to one. In Panel (b) of Table A.1, we show that persuasive information extracted from the LLM is highly consistent with the clustering method.

3.1.4. Step 4: Aggregate Banks' Overall Images. Up to this point, we have quantified the persuasive elements of each advertisement. In this step, we aggregate the persuasive elements from the advertising videos to create a comprehensive image for each bank at the different levels.

We begin with the bank's image for each year. Initially, we calculate the embedding representation of the bank's image annually by determining the occurrence-weighted average of the videos' embeddings for each bank within that year. We then apply the previous two steps to obtain the average persuasive information and features for each bank in a given year.

This process is flexible and can be applied to any level of aggregation. For example, we can quantify the bank's image for the liability side and asset side separately by averaging the persuasive elements of the advertisements of the product categories from liability and

asset side, respectively. Alternatively, we can also aggregate the bank's image represented in different counties, which is useful for understanding how banks strategically tailor their images to different local demographics.

3.2. Examples of Banks' Images

The combination of our unsupervised learning and LLM-based classification provides a robust and cross-validated framework for understanding how financial institutions craft their public image. In this subsection, we offer some examples of outcomes of these methods.

Example of Financial Information The financial information category intends to capture the financial benefits of the product, including interest rates and payment plans.

> *"While others just talk about their lending, we're taking action. Right now, our fixed-rate commercial loans have rates as low as 3.5%. It's time to get back to business."*
>
> *"You've got more options than you think. And our HARP loan lets you refinance at a much lower rate, even if you owe more than your home is worth. Lower your monthly payment and free up some cash flow. You can qualify right over the phone. Today's refinance rate is 3.5% APR."*
>
> *"Open a premium checking account and get $300 when you set up direct deposit."*

Example of Service Quality The service quality category includes information on mobile and online applications, local service, and community support.

> *"We'll make your construction loan process quick and easy. And when you're ready to move in, your final home loan can be ready, too."*
>
> *"A local bank that's committed to our community and invested in its future. You'll get access to banking experts, a partner in the mortgage process, convenient locations, an advisor for your business, and so much more. It all starts when you open your account."*

"You're going to love our new mobile app. Bank from your computer, tablet, or phone with the same look and feel and only one user ID and password. Pay quickly by taking a picture of a paper bill or pay anyone anywhere. It's all so easy with a mobile app."

Example of Emotional Appeal and Trust Building Our last broad persuasive theme is the emotional appeal and trust building. For emotional appeal, we focus on the financial goals and financial management, life fulfillment, family focus, sports and entertainment, and holiday greetings.

"There is nothing like a home in Maine and a bank that makes you feel at home. We have money to lend for dreams like yours with real people you can talk to and smart solutions right here. We're strong and sound with the mortgage you need for the home of your dreams. Catch a great rate at VAT Savings when you're here, your home. Equal Housing Lender, member FDIC. There's a confidence in there."

"We share our world with billions of people, each going through unique expe-riences, hopefully accomplishing just what they set out to do. But we can't do it alone. We have a better chance of achieving our dreams with a great part-ner. For those times, trust us. Now in your corner and proud to be part of this community."

"Most ideas don't begin in a bank. But we'll join you wherever you break ground on your dreams. We exist where ideas exist. You have the dream. We have the team."

For trust building, we focus on the professional building, news updates, and market information.

"We here to talk about the recent changes in the government insured reverse mortgage program. Making it safer for homeowners. The benefits of reverse mortgage are tremendous. Giving seniors the financial freedom and security while allowing seniors to stay in their home. While turning their home equity into tax

free monthly income. So are you 62 or older, on your own home, need a steady income flow each month? Then call my friend"

"At Edmonton Bank, we know the key role that small and medium-sized businesses play in the community. After all, we've been helping them grow for over a century. Our lenders have the expertise to help you make the right decision for you and your business. From financing a single store to multiple locations, you'll always get competitive rates and friendly professional service that sets us apart from the competition."

"Are you in good hands? At any minute, you could be a victim of fraud. Fraud could mean lower credit scores and higher interest rates when you apply for a credit card. It's a problem waiting to happen. Check your credit score. "

3.3. Additional Measures: Visual and Vocal Features

We also extract some major visual and vocal features from advertising videos. We identify the facial attributes of the actors in the advertising video, including race, gender, age, and emotion. To do so, each video was first extracted into image frames using a fixed frame rate of one frame per second. These frames were then processed using the `DeepFace` Framework: Faces were detected using the `Retinaface` model, and the `VGG-Face` model was employed to extract facial embeddings. The DeepFace attribute model was used to classify facial attributes such as age, gender, and race. The race classification categories included Asian, White, Middle Eastern, Indian, Latino/Hispanic, and Black. For the purposes of empirical analysis, we consolidated Asian, Middle Eastern, and Indian into a single "Asian" category, though we maintained these distinctions when evaluating the model's performance. Next, faces from the same video were grouped as individual actors using Hierarchical Agglomerative Clustering. This step allows us to consistently identify and label the same actor in the video. We aggregated the facial attributes for each actor using only high-quality frames and model predictions with high confidence. Finally, we aggregated these attributes at the video level, providing a comprehensive demographic profile of the actors within each video.

In the Internet Appendix, we provide extensive analysis to assess the performance of this empirical framework. We compare the racial share of advertisement extracted from our

framework with other sources of data (Table A.3). Then we manually labeled 400 videos with true labels of race and gender. In the step of aggregating into video-person level information, we apply two filters, including (1) keeping high-quality frame and (2) high confidence model prediction. For these 400 video, after these two filters, there are 270 videos with high-quality race and gender information. The performance of our model are reported in Table A.4 and Table A.5.

3.4. Banks' Images: Distribution and Variance Decomposition

Figure 3 shows the distribution of the financial advertising persuasive content by creatives.[2] The most common advertising theme is through emotional appeals and trust-building (72%), followed by highlighting the service quality (17%) and information on pricing and financial benefit (11%). We also provide more detailed categorizations in Figure A.4. Within financial information, the percentage of creative focusing on interest rate (5%) and payment plans (6%) are equally similar. Within service, the most common subcategory is local service (13%). Within emotional appeals and trust-building, professional building accounts for largest share (19%), and financial management (12%), life fullfillment (8%), sports and entertainment (9%), news updates (9%), and market information (9%) are equally important. It is worth noting that additional emotional appeals and trust-building from the visual content of the advertisement may not be captured in the text data.

[Insert Figure 3 Here.]

We now decompose the variances in the images banks deliver in their advertisements. We do so by using a bank-county-video-year panel and regressing log advertising spending and shares of advertising themes on several sets of fixed effects. Figure 4 presents the contributions of different sets of fixed effects to advertising variations.

As a baseline, we begin with product $\times$ year fixed effects. We find that around 4–7% of the advertising variations can be explained by banks using different themes for different financial products. Intuitively, banks may use different themes for different products because they have different target customers and different marketing strategies. Consistent with

[2]We also present the distribution weighted by airtime, and the pattern remains similar.

this pattern, we find that different financial products put different weight on persuasive themes in their advertisements, as shown in Figure A.5. The banking service, including personal deposit, business banking, and general banking services, is more likely to highlight service quality, while asset-releted products, such as mortgage and credit card, are more likely to highlight pricing and financial benefits. We then add county $\times$ year fixed effects, increasing R^2 by about 7.3% for advertising spending and 2.1% for advertising themes. Such a pattern suggests that differences across local markets, such as local market concentration and economic conditions, are not the main drivers of banks' advertising decisions.

We now focus on time-invariant and time-varying bank heterogeneity (i.e., bank and bank $\times$ year fixed effects). R^2 significantly raises by around 11% for spending when we augment bank fixed effects to the regression. For advertising themes, the increase is more pronounced, with a 15% increase. We further observe even more salient increases in R^2 when time-varying bank heterogeneity is added to explain advertising choices—a 25.2% increase for spending and a 42.7% increase for themes. These results strongly indicate that bank heterogeneity is the main driver of banks' advertising decisions. In other words, differences in banks' advertising choices reveal important information about bank heterogeneity—how they differ from each other in size, business model, product market strategy, and so on. Finally, we consider bank $\times$ county fixed effects, which capture the matching between banks and counties. Such a factor explains considerable variations in spending (a 29.4% increase) and in themes (a 20.3% increase).

[Insert Figure 4 Here.]

4. Heterogeneous Banks, Heterogeneous Images

In this section, we analyze the images banks choose to convey in their advertising. A key motivation behind our analysis is the development in theories and empirics of heterogeneities in banks' business strategies and operations. Our analysis thus is organized as a revisiting of the literature on bank heterogeneity, by describing heterogeneities in financial advertising strategies by various important characteristics of banks. These analyses are motivated by a central theme: examining bank's image-building using advertising allows us to provide a

concrete mechanism on how banks actively and strategically maintain their franchise value, attract customers, and compete with other financial institutions while maintaining their heterogeneous features.

We consider a bank-county-year panel, in which each observation represents a bank b in county c in year t. The dependent variable is a dummy variable indicating the specific images conveyed in the creative creative, i.e., price advantage, superior service, or trust building and emotional appeals. The key independent variables are indicators of bank characteristics, which we denote as D. We estimate the following model:

$$Bank\ Image_{b,c,t} = \beta \cdot D_{b,c,t-1} + \eta_{c,t} + \epsilon_{b,c,t}, \tag{1}$$

We consider a broad set of bank characteristics D, including bank local market power as captured using local county-level market shares, deposit rate setting behaviors, service quality, and local customer demographic characteristics. The model includes county-year fixed effects $\eta_{c,t}$, which absorb time-varying changes in market opportunities, regional demographics, local preferences, and other variations at the county-time level. In other words, the model effectively compares advertising strategies of banks with different characteristics in the same county around the same time. The standard errors are clustered at the county level to be conservative. When applicable, we separately consider advertising strategies for the deposit business (liability side) and lending business (asset side, such has mortgage and business loans).

4.1. Local Market Share and Bank Images

Our first set of analysis examines how the financial advertising strategies of banks vary with their local market power, and we compare banks with above-median or below-median market shares in the county in the respective business, i.e., deposits or loans. This literature has documented that banks' local market power allows them to enjoy preferred rates (lower deposit rates and high loan rates). In equilibrium, for these market powers to be sustained, there must be some notion of the perceived cost associated with switching, or equivalently, the perceived benefit associated with staying with certain bank.

[Insert Table 3 Here.]

Table 3 presents the results on how banks with market powers advertise. Across all product categories, banks with higher local market shares more heavily stress their service quality and/or incorporate life inspirations and trust-building components in their image. In deposit services, while banks generally highlight their service quality in the advertisement with an unconditional mean of 13.12%, we find that high-market-share banks emphasize more on service quality advertising, with 1.05 percentage point higher weights. This is 8% increase from the unconditional mean. In the business loan category, high-market-share banks have 2.27 percentage points higher weights on service quality in their image building, which is 85% of the unconditional mean of 2.62%.

Bank with higher local market shares more heavily incorporate life inspirations and trust-building in their images for loan products. These life inspirations include success stories of a small business obtaining credit, or an inspiring lifestyle such as home ownership. One rationale behind this finding is that banks with higher local market power can better capture increased demand in banking services, thus incentivizing general borrowing or depositing activities can benefit than those banks which can only capture less of the demand. For banks with less local presence, it makes more sense for them to focus on discussing their own products. This difference can be seen clearly in advertising mortgage products: high-market-share banks are 4.86 pp more likely to include life inspiration contents in their advertisement, a 5.4% increase from the sample mean. The impact is even stronger in the business loan category.

On the flip side, banks with higher local market shares are less likely to incorporate pricing-related content in their image. This pattern holds for all product categories. In terms of magnitude, when compared to banks with lower market shares, high-market-share banks' images have roughly 30% lower mention of pricing advantages from the unconditional mean. This focus on service quality is consistent with the findings by d'Avernas et al. (2023) on the heterogeneity of deposit business. They argue that customers of large banks tend to value superior liquidity services more highly and exhibit lower sensitivity to deposit rates.

The pattern of image building across market power also provides a concrete angle to understand how banks sustain such advantages as low deposit rates. Our results suggest

that banks with market power create an image with superior quality, trust, and general affection. This potentially drives consumers' low sensitivity to pricing.

4.2. Images on Deposit Rates and Service Quality

The previous analysis is consistent with an interpretation that banks use the images portrayed in advertising to sustain market power and attract customers. In doing so, do banks truthfully highlight their competitive advantages to provide information to consumers, or do they provide information to deceive consumers? This not only can help us better understand the image-building strategies of banks, but also help us shed light on the role of advertising in the financial sector (Gurun, Matvos and Seru, 2016).

We examine how financial advertising strategies differ between banks that offer different deposit rates and service quality. We first focus on three core retail deposit products using the data from Ratewatch: interest checking accounts with less than $2,500, $10,000 12-month CDs, and $25,000 money market deposit accounts. These products represent the primary types of retail deposits in banks' core offerings, including checking, small time, and savings deposits. Follow the methodology in Zhang, Muir and Kundu (2024), for each of the three deposit rates, we rank all the banks within the same county in the specific year, and define high-rate banks as those with above-median average rankings and low-rate banks as those with below-median average rankings.

[Insert Table 4 Here.]

Panel (a) of Table 4 shows that high-rate banks tend to emphasize pricing information in their advertising for deposit products, with 0.27 pp higher weights than low-rate banks, representing 13.5% of the unconditional mean of 2.03%. This emphasis is intuitive, as high-rate banks seek to attract rate-sensitive depositors by highlighting their competitive pricing. This finding is consistent with Zhang, Muir and Kundu (2024), which suggests that high-rate banks attract depositors who are responsive to rates.

In contrast, low-rate banks are more likely to incorporate trust-building and emotional appealing themes in their advertising. For example, for time deposit rates, low-rate banks are 4.14 pp more likely to include trust-building themes, equivalent to 4.9% of the unconditional

means. This suggests that low-rate banks attract customers by fostering trust and long-term relationships, aligning with the argument in Zhang, Muir and Kundu (2024) which argues that low-rate banks rely on sticky depositors and maintain physical branches to support their local community presence.

Our next set of analysis examines how financial advertising strategies differ between banks with high versus low service quality in their deposit products. We measure a bank's service quality using two indicators: branch network and consumer complaints. Following Egan, Hortaçsu and Matvos (2017) and Zhang, Muir and Kundu (2024), we define the branch network as the number of branches scaled by total deposits, reflecting a bank's physical presence and the extent of services it provides to depositors. Consumer complaints can serve as a more direct measure of service quality. We compute the measure of consumer complaints as the number of complaints received in a given year per dollar of deposits, using the data from the Consumer Financial Protection Bureau's (CFPB) Consumer Complaint Database. Banks with fewer complaints are expected to offer a higher level of service (Egan, Hortaçsu and Matvos, 2017; Egan, Lewellen and Sunderam, 2022).

In Panel (b) of Table 4, we show that high-service-quality banks are significantly more likely to emphasize service quality and trust-building themes across all three measures of service quality. For example, banks with a broader branch network are also more likely to emphasize service quality (5.57 pp, or 40.7% from the unconditional mean). Similar effects can be observed when using low service complaints as the indicator for service quality. Banks with lower complaints place 9.01 pp more weight on service quality in their advertising, representing 65.9% of the unconditional mean. This evidence collectively supports the idea that banks with higher service quality target customers who value enhanced services and personalized banking experience. By emphasizing service quality, these banks likely aim to attract customers who see value in a premium banking experience, even at a higher cost (Jiang, Yu and Zhang, 2022; Zhang, Muir and Kundu, 2024).

Interestingly, across both panels, a general pattern is that high-deposit and high-service quality banks use less trust-building or emotional appeals in their image-building. One interpretation is that when banks have concrete advantages to offer customers, they intensively do so and lower the weight of less concrete components.

4.3. Advertising and Customer Demographics

Our analysis so far shows that banks actively use financial advertising to highlight distinct advantages based on various heterogeneities. These advertising strategies suggest that banks are aware of their unique strengths and strategically make choices about how they communicate these advantages to attract specific customer segments.

One important factor that may further support this argument is the demographic characteristics of their customer base. Banks might adjust their advertising to better connect with the specific customer base, such as the population composition of the communities. In this section, we further explore this idea by exploiting the geographic variations of financial advertisements within the same bank in each year.

We analyze how the racial attributes of the actors in advertising videos vary according to the demographic characteristics of the counties in which banks operate. Now we consider differences between counties with above or below 80 percent quantiles of the share of Black or African American, Hispanic, and Asian population for the same bank in the respective business, i.e., deposits or loans. The choice of 80 percent quantiles is because the top 20 percent of counties roughly account for half of the African American, Hispanic, and Asian population. The key set of controls for identification is the bank-year fixed effects, which absorb all time-varying differences between banks.

[Insert Table 5 Here.]

Table 5 presents the results: across two business categories, in counties with a higher percentage of Black, Hispanic, and Asian residents, banks are more likely to feature more Black, Hispanic, and Asian actors in their advertisements, respectively. Specifically, the representation of Black, Hispanic, and Asian actors in deposit-related advertising is all 0.11 pp higher, equivalent to 0.7%, 10.3%, and 1.9% relative to the unconditional mean, respectively For asset-related advertising, the increase is 0.17 pp (or 0.8%) for Black actors, 0.14 pp (or 15.9%) for Hispanic actors, and 0.21 (or 3.8%) for Asian actors.

These patterns suggest that banks target their advertising to align with the demographic composition of their local markets, potentially as a strategy to enhance relatability and

appeal to specific customer groups. By featuring actors representative of the local population, banks may be seeking to foster a sense of trust within these communities.

5. Banks' Images, Franchise Value, and Monetary Policy

Does banks' image-building have real impacts? In this section, we show that bank advertising spending and advertising styles significantly affect the demand for various financial products, including deposits, mortgages, and small business loans. We use two complementary empirical setups. We first employ a within-county estimation strategy, which exploits within-county variations by comparing different banks operating in the same county. To further establish causal interpretation, we then implement a border discontinuity design, which leverages the discontinuities in local advertising at DMA borders, generated by the local TV market delineation. We then implement two bank-level analyses, linking bank images to bank value, deposit spreads, and market power, and document how our results provide a potential mechanism to understand banks' market power and monetary policy transmission.

5.1. Within-County Estimation

We start from a within-county estimation strategy to a bank (b)-county (c)-year (t) panel. We estimate the following specifications:

$$Y_{b,c,t} = \beta \ln(\text{Ad})_{b,c,t} + \alpha_{b,c} + \eta_{c,t} + \epsilon_{b,c,t}, \tag{2}$$

where $Y_{b,c,t}$ is the outcome variables for various financial products, such as the growth rate of deposits, change in deposit spread, and mortgage and small business loan origination, of bank b in county c at t; $\ln(\text{Ad})_{b,c,t}$ is the log amount of product-specific advertising spending by b in county c at t, which is calculated based on which DMA county c belongs to; $\alpha_{b,c}$ are bank-county fixed effects, which absorb all level differences in demand for bank b's products across counties; $\eta_{c,t}$ are county-year fixed effects, which absorb variations such as changes in local lending opportunities, economic conditions, and demographics. Our results are robust to including bank-year fixed effects. We focus on a sample where banks have positive advertising spending in a county. Therefore, the estimated coefficients capture the

intensive margin effects of advertising on demand for financial products. Standard errors are clustered at the county level. Such a specification exploits the within-county variation by comparing different banks with the differential intensity of advertising, but operating in the same county.

In some specifications, we also include $\ln(\text{Ad})_{-b,c,t}$, the log amount of product-specific advertising spending for all other banks in county c at t, excluding the focal bank b. This leave-one-out advertising measure captures the potential spillover effect of other banks' advertising on the demand for the focal bank's financial products.

To understand the effects of bank image on the demand for various financial products, we also include two dummy variables of bank images, including pricing information $1(\text{Pricing})_{b,c,t}$ and service quality $1(\text{Service})_{b,c,t}$, and omit emotional appeal and trust building $1(\text{Emotion/Trust})_{b,c,t}$. Table 6 displays the results.

[Insert Table 6 Here.]

Panel (a) of Table 6 presents results on deposits. Columns (1) to (3) show a strong positive relationship between deposit advertising and deposit growth rate. In terms of magnitude, a one percent increase in deposit advertising spending is associated with an additional 0.12 basis points growth rate of deposits with a mean growth rate of 5.3 percentage points. We also find that advertising by other banks in the same county significantly lowers the deposit spread charged by the focal bank. This pattern is consistent with the notion that banks use advertising to strengthen their market power, invest in their franchise value, and gain an edge in local market competition.

Among all the advertising styles, highlighting service quality seems to be the most effective strategy to attract depositors, as indicated in Column (3), with a magnitude of 53 basis points. Conversely, banks with images on pricing information exhibits 1.54 basis points lower growth rate of deposits.

Columns (4) to (6) show that banks that spend more on advertising tend to charge higher deposit spread, on average. The effects of bank images are consistent with the results on deposit growth rate. While banks highlight service quality to attract depositors and charge higher deposit spreads, banks mentioning more pricing information in commercials tend to

be contemporaneous declines in deposit spread.

Panel (b) of Table 6 presents results on loans. Columns (1) to (3) document a significant positive relationship between mortgage advertising and the dollar amount of mortgage origination. A one percent increase in mortgage advertising spending is associated with a 0.02 percent increase in mortgage origination. Columns (4) to (6) show that financial advertising has similar effects on small business loan origination, with a magnitude of 50 basis points. In terms of advertising style, incorporating life inspirations and trustbuilding in their images is the most effective approach to increase loan product origination, including both mortgage and small business loan.

5.2. Identification: Border Discontinuity Design

Identifying the causal effects of advertising can be difficult due to various forms of endogeneity. While advertising is a firm choice, equilibrium forces may cause advertising to be correlated with the demand or performance in a county for reasons other than a treatment effect of advertising. Firms might also use rules of thumb based on targeting past or expected demand of the product market rather than perceived treatment effects, leading to concerns about reverse causality. The within-county estimator allows us to control some of such confounding effects. We now switch to an alternative design, establishing the causal relationship between image-building via financial advertising and demand for financial products using a border discontinuity design.

In specific, we follow the economics and marketing literature (Shapiro, 2018, 2020), and exploit the exogenous variation from the geography discontinuities at the borders of DMA markets by taking advantage of the discrete nature of local television markets. The intuition is, consumers who live on the opposite sides of DMA borders face different levels of advertising, because of market factors elsewhere in their DMA. But they have similar observable characteristics and choice sets of products. Therefore, we adapt the border discontinuity design by controlling for unobservable geographic characteristics with bank-border-year fixed effects. We also control for bank-county fixed effects to further absorb any unobservables related to the banks' specific demand in one county.

[Insert Figure 5 Here.]

To illustrate, Figure 5 shows the Pittsburgh and Johnstown-Altoona DMAs in the state of Pennsylvania. The border region used in the border discontinuity design is highlighted in bold. Therefore, we are comparing how demand for financial products provided by the same bank on the Pittsburgh and Johnstown-Altoona side of the border changes, when the two sides of the border receive a different advertising exposure by the same bank.

Consider a bank (b)-county (c)-border ($d(c)$)-year (t) panel. Let $d(c)$ stand for the border group to which county c belongs. We estimate the causal effect of advertising on the demand for financial products using border regression discontinuity design using the following specifications:

$$Y_{b,c,t} = \beta \ln(\text{Ad})_{b,c,t} + \alpha_{b,c} + \eta_{b,d(c),t} + \epsilon_{b,c,d(c),t}, \tag{3}$$

where $Y_{b,c,t}$ is the outcome variables for various financial products, such as the growth rate of deposits, change in deposit spread, and mortgage and small business loan origination, of bank b in county c at t; $\ln(\text{Ad})_{b,c,t}$ is the log amount of product-specific advertising spending by b in county c at t, which is calculated according to which DMA county c belongs to; $\alpha_{b,c}$ are bank-county fixed effects, which absorb all level differences in demand for bank b's products across counties; $\eta_{b,d(c),t}$ are bank-border-year fixed effects, which account for time-varying bank-specific local demand shocks. By adding these two sets of fixed effects, we are effectively comparing the demand for financial products provided by the same bank across different counties within a border group with differential exposure to advertising. Therefore, the identifying assumption is that, without differential advertising intensity and styles, the same bank would have similar trends in demand for financial products in every county within a border group.

As in the previous analysis, we again focus on a sample where banks have positive advertising spending in a county. Therefore, the estimated coefficients capture the intensive margin effects of advertising on demand for financial products. Note that the same bank (b)-county (c)-year (t) observation could repetitively appear in the sample several times with different borders ($d(c)$) since a county may belong to several borders at the same time. Standard errors are clustered at the bank-county level and border-year level.

Similar to the implementation in within-county estimation, we also include $\ln(\text{Ad})_{-b,c,t}$,

the log amount of product-specific advertising spending for all other banks in county c at t, excluding the focal bank b. This leave-one-out advertising measure captures the potential spillover effect of other banks' advertising on demand for the focal bank's financial products. We also interact advertising spending with the estimated probability of advertising styles.

In order to examine the differential effects of different bank images on demand for financial products, We replace the advertising variable with two dummy variables of bank images, including pricing information $1(\text{Pricing})_{b,c,t}$ and service quality $1(\text{Service})_{b,c,t}$, and omit emotional appeal and trust building $1(\text{Emotion/Trust})_{b,c,t}$. Table 7 displays the results.

[Insert Table 7 Here.]

Panel (a) of Table 7 shows how deposit advertising affects deposit outcomes. Columns (1) to (3) reveal a strong positive effect of deposit advertising on deposit growth rates. Specifically, a 1% increase in deposit advertising spending is associated with an additional 0.09 basis points increase in the deposit growth rate, relative to a sample of 5.3 percentage points. Columns (4) to (6) indicate that banks with higher advertising expenditures tend to charge higher deposit spreads on average, aligning with prior evidence that advertising-intensive banks are able to maintain higher deposit spreads. Similar to what we find in Section 5.1, banks emphasizing service quality in their images attract more depositors (93 basis points) and charge higher spreads (3.3 percentage points). Meanwhile, banks highlighting pricing information in their images are associated with contemporaneous decreases in deposit growth rate and deposit spread. This finding again supports the idea that banks actively use advertising to build their deposit franchise, from which banks obtain market power and charge high deposit spreads.

Panel (b) of Table 7 shows how loan advertising affects mortgage and small business loan origination. Columns (1) to (3) show that mortgage advertising has a significant positive effect on the dollar amount of mortgage origination. Quantitatively, a one percent rise in mortgage advertising spending corresponds to a 0.03% increase in mortgage origination. Columns (4) to (6) demonstrate positive effects on small business loan origination. Banks that build trust with their customers in their images attract higher origination on mortgage and small business loan.

5.3. Bank Images and Bank Value

In this section, we build upon our detailed micro-county-level identified results, and extend our analysis on banks' image to bank-level. This provides an opportunity to connect advertising intensity and bank images to several important dimensions of bank characteristics studied in the literature. These include bank deposit and asset productivity (Egan, Lewellen and Sunderam, 2022), bank market power (Drechsler, Savov and Schnabl, 2017, 2021; Drechsler et al., 2024), and franchise value (Demsetz et al., 2007).

We use the bank holding company (b)-quarter (t) panel and estimate the following specifications:

$$Y_{b,t} = \beta \left(\frac{\text{Ad Expense}}{\text{Non-Interest Expense}} \right)_{b,t-1} + \gamma X_{b,t-1} + \eta_t + \epsilon_{b,t}, \tag{4}$$

where $Y_{b,t}$ is bank characteristics such as productivity, funding stability, or market power of bank b at t; $\left(\frac{\text{Ad Expense}}{\text{Non-Interest Expense}} \right)_{b,t-1}$ is the advertising expense scaled by total non-interest expense; $X_{b,t-1}$ is a list of lagged bank controls, including the log of the bank's total assets, the bank's Z-Score (the bank's ROA plus its equity ratio divided by its standard deviation of ROA), the bank's ROA, the bank's equity to assets ratio, the bank's deposits to assets ratio and the bank's deposit and mortgage market concentration HHI, following Gelman, Goldstein and MacKinlay (2023) and Egan, Lewellen and Sunderam (2022); η_t are time fixed effects. We use a sample with non-missing and positive advertising expenses. Standard errors are clustered at the bank level using wild bootstrap. Such a specification exploits the cross-sectional variation of banks because some measures, such as the volatility of deposit growth rate across years, are cross-sectional by nature. Table 8 displays the results.

[Insert Table 8 Here.]

Columns (1) and (2) in Table 8 show that banks with higher advertising expenses have higher deposit and asset productivity, as measured in Egan, Lewellen and Sunderam (2022). Such a finding is consistent with both customer-based and technology-based explanations of dispersion in bank productivity. Banks actively use advertising to strengthen their market power, target customers with different demographics, build trust, and differentiate themselves from competitors.

Columns (3) and (5) indicate that financial advertising is positively correlated with the bank deposit power market and franchise value. Following Drechsler, Savov and Schnabl (2017) and Drechsler, Savov and Schnabl (2021), we use the deposit spread and the deposit beta to measure market power. The deposit spread is the difference between the Fed funds rate and the bank deposit rate, a "markup" that banks charge on deposits. The deposit rate is computed as quarterly total domestic deposit expense divided by quarterly total domestic deposits and then annualized (multiplied by four). Column (3) documents a significant positive relationship between advertising and deposit spread, namely banks with higher advertising expenses tend to have higher deposit spreads and therefore higher deposit market power. In terms of magnitude, a one percentage point increase in advertising expense is associated with an 7 bps increase in deposit spread, whose mean value is 45 bps.

Our second measure of deposit market power is deposit beta, which is the sensitivity of bank's deposit rate to changes in the Fed funds rate. The deposit beta is calculated by regressing the change in its deposit rate on contemporaneous and lagged changes in the Fed funds rate and then summing the coefficients. Intuitively, a bank with high market power has a low deposit beta, while a bank with low market power, such as one funded mostly by wholesale deposits, has a beta close to 1 and charges almost no spread (Drechsler, Savov and Schnabl, 2021). Column (4) documents an insignificant relationship between advertising and deposit beta. Such a pattern suggests that the variation in bank deposit market power can come from many other sources, such as branches, salaries, and technology, and cannot be fully explained by advertising alone. Column (5) documents a significant positive correlation between banks' Tobin Q and advertising spending. Consistent with the findings on banks' deposit power market, effort in crafting images by advertising positively contributes to banks' franchise value.

To summarize, the empirical evidence suggests that financial advertising contributes to banks' franchise value as banks with higher advertising expenses tend to have higher deposit and asset productivity, higher funding stability, and higher deposit market power. Such findings suggest that advertisement is an important way through which banks invest in building a deposit franchise, which gives them market power.

5.4. Bank Images and Transmission of Monetary Policy

After establishing the importance of bank images on market power and franchise value, we now link financial advertising to the transmission of monetary policy. To motivate why this is important, we first present the aggregate time series dynamics of bank images along monetary policy cycles. Figure 6 illustrates how financial advertising themes have evolved over time, revealing a dynamic relationship between banks' advertising strategies and monetary policy changes. Notably, shifts in the Federal Funds rate coincide with adjustments in the themes banks emphasize. During periods of rising interest rates, banks reduce their focus on pricing information and service quality in advertisements, instead placing greater emphasis on emotional appeals and trust-building. Conversely, during the zero-lower bound period from 2008Q4 to 2015Q3, when interest rates were low, banks highlighted financial information more prominently. These patterns suggest that banks strategically adapt their advertising strategies and tailor their public image to align with changing economic conditions and consumer sensitivities.

[Insert Figure 6 Here.]

To more clearly test this hypothesis, following Drechsler, Savov and Schnabl (2017), we estimate the following specifications on the same bank holding company (b)-quarter (t) panel:

$$\begin{aligned} Y_{b,t} =& \beta^{\text{Ad}} \ln(\text{Ad})_{b,t-1} + \gamma^{\text{Ad}} \Delta\text{FF}_t \times \ln(\text{Ad})_{b,t-1} \\ &+ \beta^{\text{HHI}} \text{Deposit-HHI}_{b,t-1} + \gamma^{\text{HHI}} \Delta\text{FF}_t \times \text{Deposit-HHI}_{b,t-1} \\ &+ \alpha_b + \eta_t + \epsilon_{bt}, \end{aligned} \tag{5}$$

where $Y_{b,t}$ is balance sheet components such as deposits and loans of bank b at t; ΔFF_t is the change in the Fed funds target rate at t; $\ln(\text{Ad})_{b,t-1}$ is lagged quarterly advertising expense of bank b at $t-1$; $\text{Deposit-HHI}_{b,t-1}$ is the lagged bank-level deposit concentration of bank b at $t-1$, α_b are bank fixed effects and η_t are time fixed effects. We use a sample with non-missing and positive advertising expenses. We cluster standard errors at the bank level.

The coefficient of interest is γ^{Ad}, which captures how financial advertising may affect the transmission of monetary policy shocks ΔFF_t to the outcome variables Y_{bt}. To isolate the

effect of financial advertising from deposit market concentration studied by Drechsler, Savov and Schnabl (2017), we control for deposit market concentration Deposit-HHI$_{b,t-1}$ and its interaction term with Fed fund rate change $\Delta \text{FF}_t \times$ Deposit-HHI$_{b,t-1}$. Table 9 shows the results.

[Insert Table 9 Here.]

Table 9 presents the results for bank liabilities (such as the growth rate of deposits, change in deposit spread, and the growth rate of total liabilities) and results for bank assets (such as loans and securities).

On the liability side, Column (1) shows that banks with higher advertising expenses are able to charge higher deposit spreads (measured as the Fed funds rate minus deposit interest expense divided by total deposits) when the Fed funds rate rises. At the same time, as Column (2) indicates, banks that advertise more experience greater deposit outflows. However, such an interactive effect cannot offset the large positive baseline effect of advertising, namely banks that advertise more do collect more deposits on average. Column (3) shows that rises in Fed funds rate have a significant contractive effect on bank total liabilities, for banks of high advertising intensity.

On the asset side, Column (4) confirms that total loans decline in line with total liabilities as Fed funds rate rises. Such a pattern holds for total assets, as shown in Column (6). Results on securities in Column (5) are insignificant. This finding can be explained by the fact that advertising is mainly consumer-oriented, which affects consumer-related bank balance sheet items (e.g., deposits and loans) instead of items related to institutions or capital markets (e.g., securities).

Panel (b) in Table 9 documents differential responses to monetary policy by banks with heterogeneous images. For example, banks highlighting service exhibit larger effects of the deposits channel of monetary policy transmission. When the Fed funds rate increases, banks with an image of superior service quality charge higher deposit spreads relative to banks crafting their images around emotion and trust. Correspondingly, there are larger contraction effects on the balance sheet of these "service banks." Such a result is consistent with the finding in Table 8 Panel (b) Column (3)—banks emphasizing service in their images have

higher deposit spreads and thus higher deposit market power.

The results in Table 9 are consistent with the notion of the bank deposit channel and bank franchise value. Banks use advertising to invest in their deposit franchise, through which banks sustain market power over retail deposits. Such an investment in franchise value by advertising can function by differentiating their products, increasing customer stickiness via establishing trust, lowering the willingness of depositors to switch banks, and increasing consumer awareness or attentiveness. Banks exploit this market power by charging higher deposit spreads when the Fed funds rate rises. Consistent with the predictions by the bank deposits channel, banks with higher advertising expenses and thus higher franchise value contract their balance sheet more in response to an increase in the Fed funds rate. These findings highlight the economic relevance of financial advertising and motivate our empirical study of advertising as one important dimension of bank heterogeneity in the following sections.

6. Conclusion

This paper investigates the role of financial advertising in shaping banks' strategic position, competitive advantage, and franchise value. By analyzing over a decade of TV advertising data, we uncover how banks actively use advertising to communicate their unique characteristics, align with their operational strengths, market positions, and customer demographics. Our findings provide new insights into understanding bank heterogeneity and its impact through the lens of strategic advertising strategies.

First, we document substantial heterogeneity in advertising strategies across banks, reflecting differences in market share, productivity, deposit rates, service quality, and customer demographics. Banks with higher market shares emphasize service quality and life inspiration themes, while high-productivity banks focus on pricing advantages. High-rate banks target rate-sensitive depositors with competitive pricing, whereas low-rate banks highlight trust-building and emotional appeal. Banks with high service quality highlight value-added services. Additionally, banks adapt advertising to local demographics, increasing minority representation in targeted communities. These heterogeneous approaches demonstrate how banks tailor their advertising strategies to differentiate themselves in a highly competitive

market.

Second, using robust empirical approaches—including within-county estimation and border discontinuity design—we establish the causal impact of advertising on consumer demand for financial products. Advertising intensity and style significantly influence deposit growth, mortgage origination, and small business loans. Trust-building messages prove particularly effective for deposits, while service quality emphasis drives mortgage origination. Moreover, banks with higher advertising expenditures maintain higher average deposit spreads. These findings underscore the role of advertising in sustaining market power and enhancing franchise value.

At a broader level, our findings underscore the macroeconomic implications of financial advertising and banks' strategic operations. Advertising not only shapes consumer behavior and market competition but also serves as a tool for banks to enhance their deposit franchise value, pricing power, and adaptability to evolving market dynamics. These strategic choices amplify differences in market power and financial stability across institutions, potentially shaping how banks respond to macroeconomic shocks and participate in the transmission of monetary policy. Future research could further explore interconnected roles of advertising and bank strategies in systemic financial stability, examining issues such as monetary policy transmission and the distribution of deposits across banks during times of financial stress. Furthermore, as digital marketing grows in prominence, studying the interplay between traditional advertising, digital outreach, and consumer behavior could shed light on new channels of influence in the financial sector. By integrating these perspectives, future work can provide deeper insights into the macroeconomic implications of financial advertising.

References

Argente, David, Doireann Fitzgerald, Sara Moreira, and Anthony Priolo. 2021. "How do entrants build market share? The role of demand frictions." American Economic Review: Insights.

Benmelech, Efraim, Jun Yang, and Michal Zator. 2023. "Bank branch density and bank runs." National Bureau of Economic Research.

Berger, Allen N, Nathan H Miller, Mitchell A Petersen, Raghuram G Rajan, and Jeremy C Stein. 2005. "Does function follow organizational form? Evidence from the lending practices of large and small banks." Journal of Financial economics, 76(2): 237–269.

Bertrand, Marianne, Dean Karlan, Sendhil Mullainathan, Eldar Shafir, and Jonathan Zinman. 2010. "What's advertising content worth? Evidence from a consumer credit marketing field experiment." The quarterly journal of economics, 125(1): 263–306.

Brady, Thomas F, and William F Bassett. 2002. "What Drives the Persistent Competitiveness of Small Banks?" Available at SSRN 315965.

Célérier, Claire, and Purnoor Tak. 2023. "Finance, Advertising, and Fraud: The Rise and Fall of the Freedman's Savings Bank." In Finance, Advertising and Fraud: The Rise and Fall of the Freedman's Savings Bank: Celerier, Claire— uTak, Purnoor. [Sl]: SSRN.

Chen, Qi, Itay Goldstein, Zeqiong Huang, and Rahul Vashishtha. 2022. "Bank transparency and deposit flows." Journal of Financial Economics, 146(2): 475–501.

Cole, Rebel A, Lawrence G Goldberg, and Lawrence J White. 2004. "Cookie cutter vs. character: The micro structure of small business lending by large and small banks." Journal of financial and quantitative analysis, 39(2): 227–251.

d'Avernas, Adrien, Andrea L Eisfeldt, Can Huang, Richard Stanton, and Nancy Wallace. 2023. "The Deposit Business at Large vs. Small Banks." , (31865).

Demsetz, Rebecca S, Marc R Saidenberg, Philip E Strahan, et al. 2007. Banks with something to lose: The disciplinary role of franchise value. SSRN.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2017. "The deposits channel of monetary policy." The Quarterly Journal of Economics, 132(4): 1819–1876.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl. 2021. "Banking on deposits: Maturity transformation without interest rate risk." The Journal of Finance, 76(3): 1091–1143.

Drechsler, Itamar, Alexi Savov, Philipp Schnabl, and Olivier Wang. 2024. "Deposit Franchise Runs." Available at SSRN 4411127.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos. 2017. "Deposit competition and financial fragility: Evidence from the us banking sector." American Economic Review, 107(1): 169–216.

Egan, Mark, Stefan Lewellen, and Adi Sunderam. 2022. "The cross-section of bank value." The Review of Financial Studies, 35(5): 2101–2143.

Gelman, Michael, Itay Goldstein, and Andrew MacKinlay. 2023. "Bank diversification and lending resiliency." Available at SSRN 4147790.

Gorodnichenko, Yuriy, Tho Pham, and Oleksandr Talavera. 2023. "The voice of monetary policy." American Economic Review, 113(2): 548–584.

Grundl, Serafin, and You Suk Kim. 2019. "Consumer mistakes and advertising: The case of mortgage refinancing." Quantitative Marketing and Economics, 17: 161–213.

Guitart, Ivan A, and Stefan Stremersch. 2021. "The impact of informational and emotional television ad content on online search and sales." Journal of Marketing Research, 58(2): 299–320.

Gurun, Umit G, Gregor Matvos, and Amit Seru. 2016. "Advertising expensive mortgages." The Journal of Finance, 71(5): 2371–2416.

Haddad, Valentin, Barney Hartman-Glaser, and Tyler Muir. 2023. "Bank fragility when depositors are the asset." Available at SSRN 4412256.

Haendler, Charlotte. 2022. "Keeping up in the digital era: How mobile technology is reshaping the banking sector." Available at SSRN 4287985.

Hastings, Justine, Ali Hortaçsu, and Chad Syverson. 2017. "Sales force and competition in financial product markets: the case of Mexico's social security privatization." Econometrica, 85(6): 1723–1761.

Haynes, George W, Charles Ou, Robert Berney, et al. 1999. "Small business borrowing from large and small banks." Business Access to Capital and Credit, 776: 287–327.

Honka, Elisabeth, Ali Hortaçsu, and Maria Ana Vitorino. 2017. "Advertising, consumer awareness, and choice: evidence from the U.S. banking industry." The Rand journal of economics, 48(3): 611–646.

Hu, Allen, and Song Ma. 2025. "Persuading investors: A video-based study." Journal of Finance, Forthcoming.

Iyer, Rajkamal, Shohini Kundu, and Nikos Paltalidis. 2023. "Canary in the Coal Mine: Bank Liquidity Shortages and Local Economic Activity." Available at SSRN.

Jiang, Erica Xuewei, Gloria Yang Yu, and Jinyuan Zhang. 2022. "Bank competition amid digital disruption: Implications for financial inclusion." SSRN Electronic Journal.

Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2020. "Banking without deposits: Evidence from shadow bank call reports." NBER working paper, , (w26903).

Jiang, Erica Xuewei, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2024. "Monetary tightening and US bank fragility in 2023: Mark-to-market losses and uninsured depositor runs?" Journal of Financial Economics, 159: 103899.

Jiang, Zhenling, and Donggwan Kim. 2024. "The effects of TV advertising and ad content on consumer financial decisions: Evidence from mortgage refinancing." SSRN Electronic Journal.

Kim, Donggwan, Zhenling Jiang, and R Thomadsen. 2023. "TV advertising effectiveness with racial minority representation: Evidence from the mortgage market." SSRN Electronic Journal.

Koont, Naz. 2023. "The digital banking revolution: Effects on competition and stability." Available at SSRN.

Koont, Naz, Tano Santos, and Luigi Zingales. 2024. "Destabilizing digital" bank walks"." National Bureau of Economic Research.

Liaukonyte, Jura, Thales Teixeira, and Kenneth C Wilbur. 2015. "Television advertising and online shopping." Marketing Science, 34(3): 311–330.

Loughran, Tim, and Bill McDonald. 2011. "When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks." The Journal of finance, 66(1): 35–65.

Ma, Yueran, and José A Scheinkman. 2020. "Going-concern debt of financial intermediaries." National Bureau of Economic Research.

Mendes, Bernardo. 2024. "Bank advertising and deposit demand." SSRN Electronic Journal.

Minton, Bernadette A, René M Stulz, and Alvaro G Taboada. 2019. "Are the largest banks valued more highly?" The Review of Financial Studies, 32(12): 4604–4652.

Mullainathan, Sendhil, Joshua Schwartzstein, and Andrei Shleifer. 2008. "Coarse thinking and persuasion." Quarterly Journal of Economics, 123(2): 577–619.

Park, Kwangwoo, and George Pennacchi. 2008. "Harming depositors and helping borrowers: The disparate impact of bank consolidation." The Review of Financial Studies, 22(1): 1–40.

Roussanov, Nikolai, Hongxun Ruan, and Yanhao Wei. 2021. "Marketing mutual funds." The Review of Financial Studies, 34(6): 3045–3094.

Shapiro, Bradley T. 2018. "Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants." Journal of political economy, 126(1): 381–437.

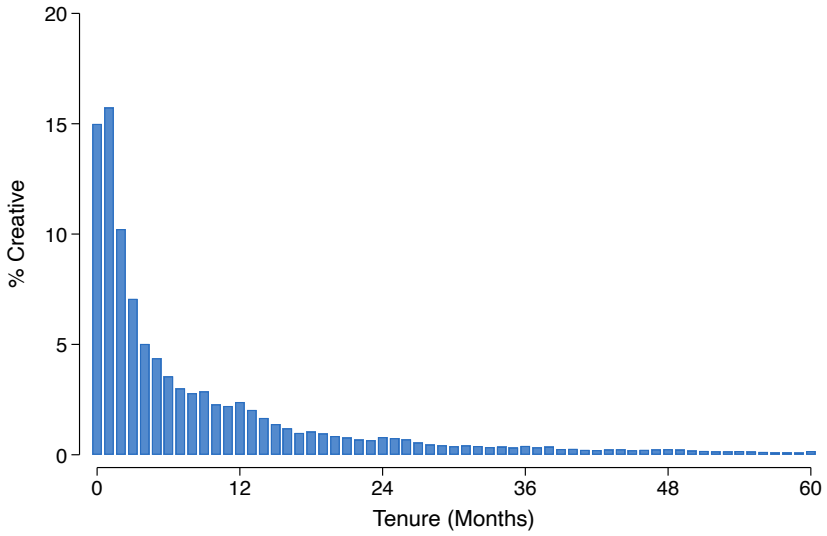
Shapiro, Bradley T. 2020. "Advertising in health insurance markets." Marketing Science, 39(3): 587–611.

Tsai, Yi-Lin, and Elisabeth Honka. 2021. "Informational and noninformational advertising content." Marketing Science, 40(6): 1030–1058.

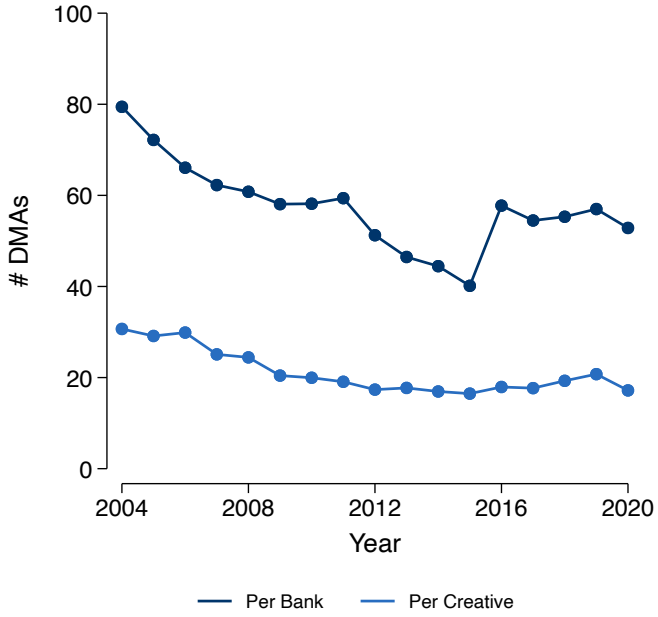
Zhang, Jinyuan, Tyler Muir, and Shohini Kundu. 2024. "Diverging banking sector: New facts and macro implications." SSRN Electronic Journal.

Figure 1. Distribution of Tenure and Geographic Coverage of Financial Advertising

Panel (a): Tenure



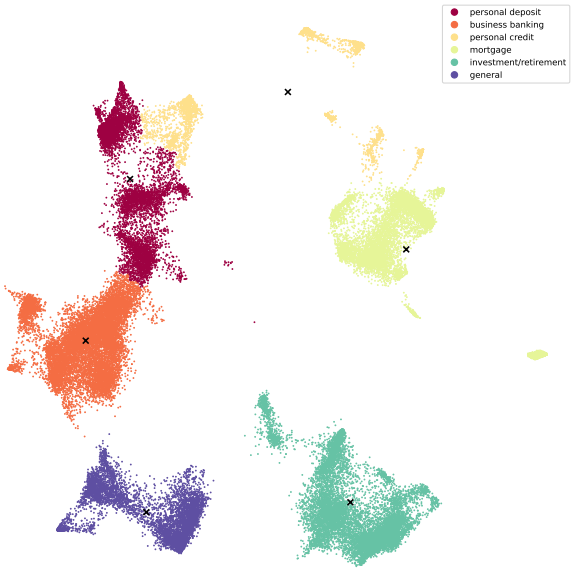
Panel (b): Geographic Coverage



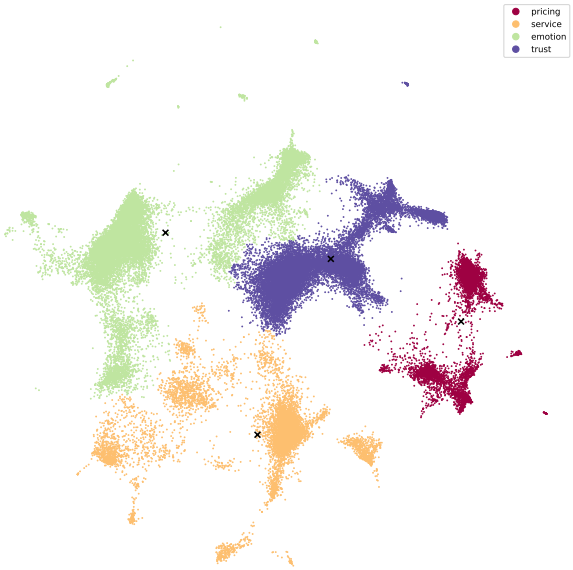
Notes. This figure shows the distribution of tenure of financial advertising in Panel (a) and geographic coverage of financial advertising in Panel (b). In Panel (a), the tenure is measured in terms of the total number of months the advertising aired on television. In Panel (b), the dark blue line is the average number of DMAs where a bank has any financial advertising in a given year, and the light blue line is the average number of DMAs for a specific financial advertising.

Figure 2. Visualization of the Video Embedding

Panel (a): Product Category

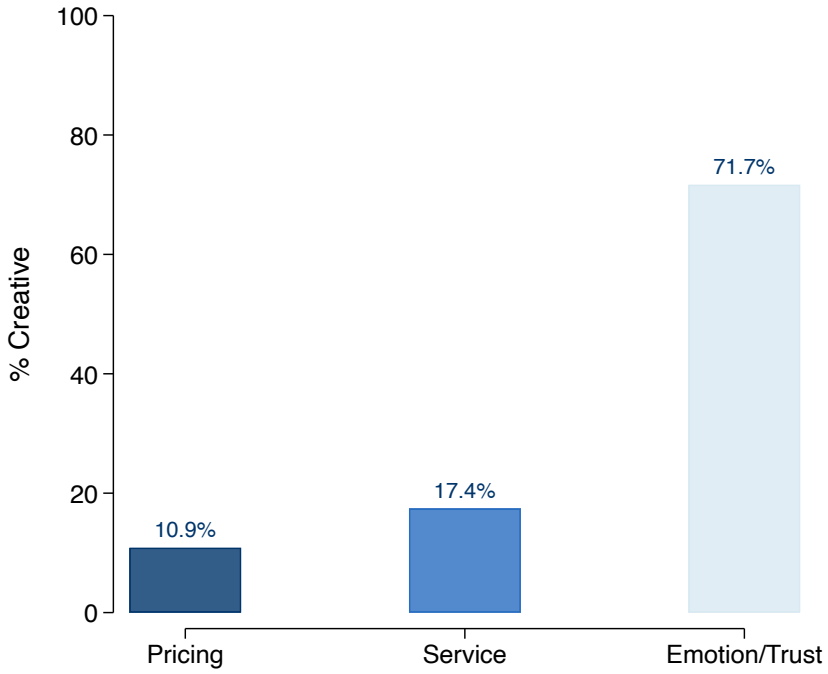


Panel (b): Persuasive Theme



Notes. This figure shows the visualization of the 2-dimensional video embedding for different product categories and persuasive themes. Panel (a) shows the visualization of the product category, as described in Section 3.1.2. Panel (b) shows the visualization of the persuasive theme, as described in Section 3.1.3.

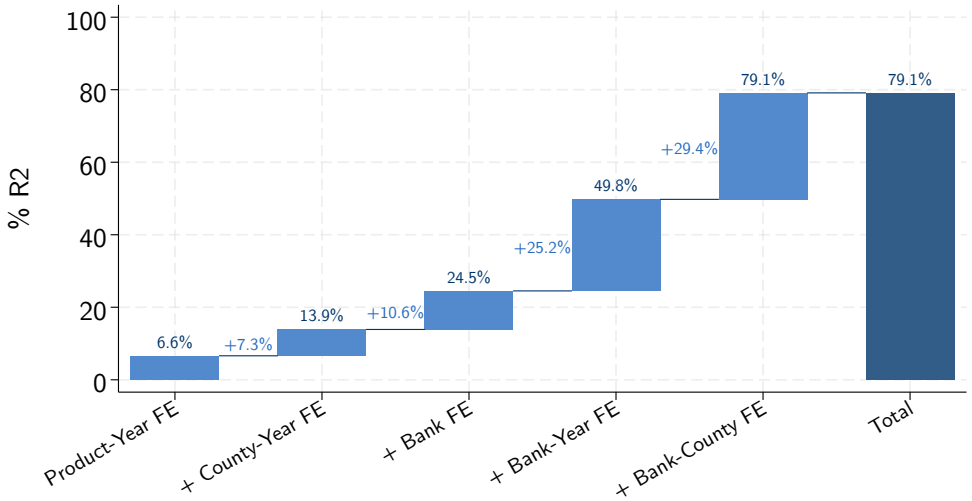
Figure 3. Overall Distribution of the Advertising Theme



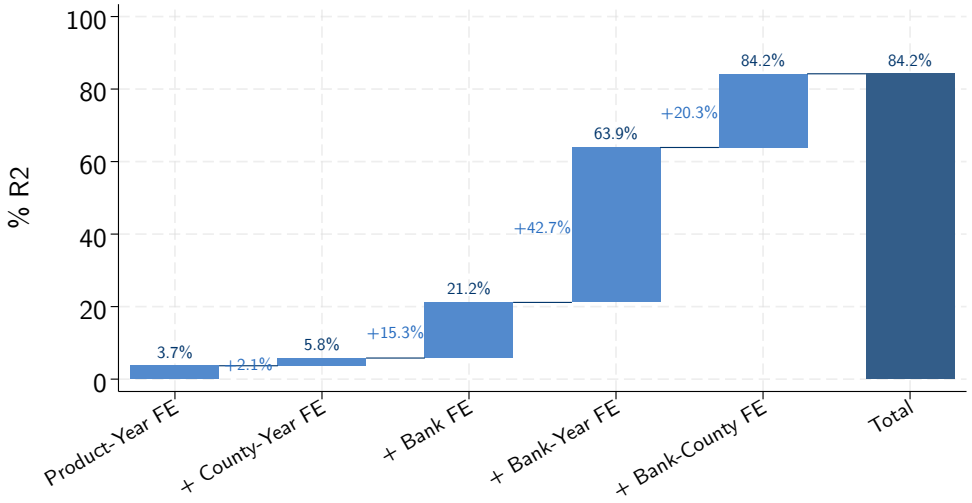
Notes. This figure shows the distribution of broad persuasive theme for financial advertising. The list of financial advertising persuasive information can be found in Table 1.

Figure 4. Decomposing Variations of Advertising Spending and Themes

Panel (a): Advertising Spending

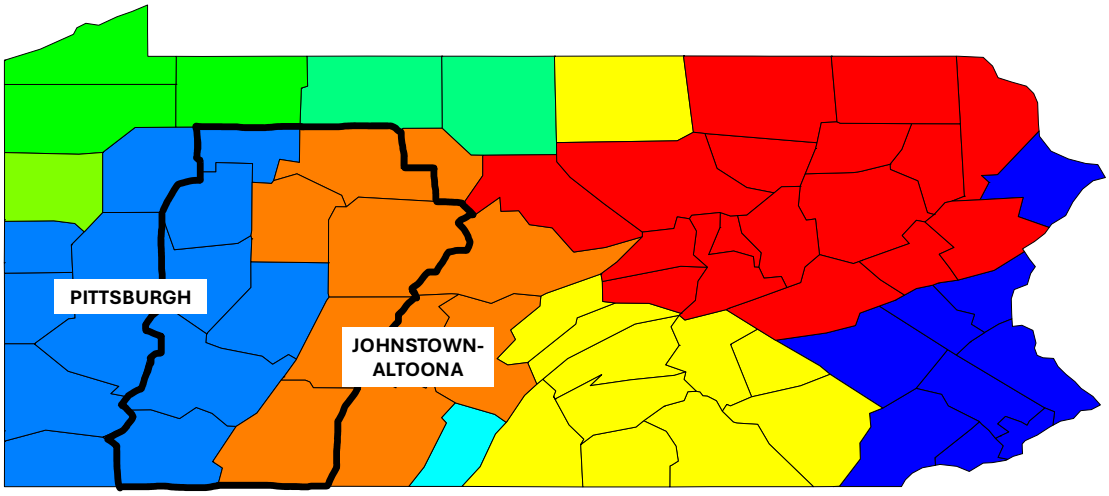


Panel (b): Advertising Theme



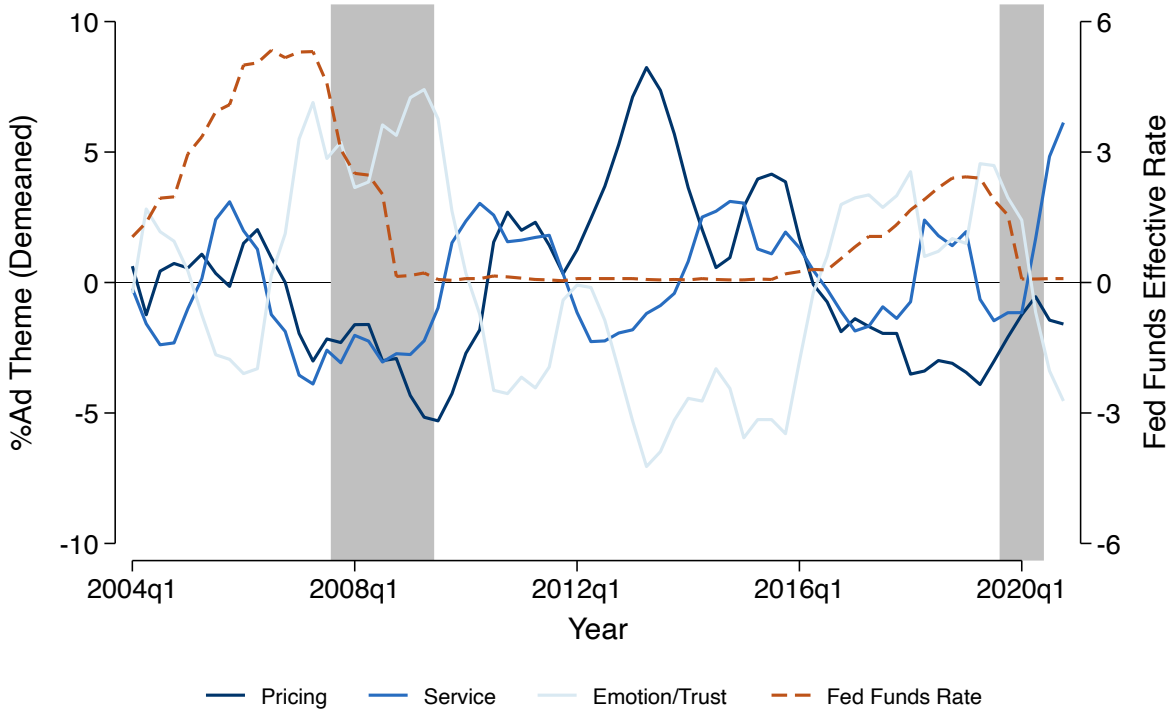
Notes. This figure shows the percentages of variations for advertising spending and theme can be explained by different specifications of fixed effects in Panel (a) and Panel (b), respectively.

Figure 5. Example of DMA Border Region



Notes. This figure shows the DMA map for Pennsylvania, highlighting the border region between Pittsburgh and Johnstown-Altoona used in border discontinuity design, as in Equation (3).

Figure 6. Advertising Theme and Monetary Policy



Notes. This figure shows the distribution of bank images in financial advertising against the Fed Funds rate over time. The distribution of persuasive themes is demeaned by the time-series average.

Table 2. Summary Statistics

	count	mean	sd	min	p25	p50	p75	max
Panel (a): Financial Advertising								
Duration	51,349	27.40	13.88	1.00	15.00	30.00	30.00	141.00
Air Months	51,349	13.86	25.92	0	1	4	14	216
First Air Year	51,349	2013	4.97	2003	2009	2014	2017	2021
# Schedule Times, Local TV	49,262	1,559.96	14,311.59	1	28	94	371	2,114,381
# Schedule Times, National TV	10,525	1,340.63	4,802.44	1.00	30.00	256.00	1,118.00	197,505.00
Total Spending, Local TV	49,262	201,195.42	2,132,026.15	0	1,728	9,495	43,545	377,648,290
Total Spending, National TV	10,525	3,983,631.69	12,979,146.01	2.00	59,482.00	630,773.00	3,231,630.00	476,271,595.00
Category: Personal Banking	48,016	14.51	35.22	0	0	0	0	100
Category: Business Banking	48,016	26.56	44.16	0	0	0	100	100
Category: Mortgage	48,016	17.80	38.25	0	0	0	0	100
Category: Credit Card	48,016	7.47	26.29	0	0	0	0	100
Category: Investment	48,016	21.66	41.20	0	0	0	0	100
Category: General Banking	48,016	12.01	32.50	0	0	0	0	100
Panel (b): Financial Intermediaries								
Total Assets (MM)	48,000	9,206.75	88,080.12	0.36	223.72	497.62	1,400.81	3,743,567.00
Advertising Expense (MM)	10,286	17.87	147.06	0.00	0.14	0.69	2.56	3,579.00
Non-interest Expense (MM)	48,770	706.57	6,368.40	-17.47	15.70	34.60	98.54	203,461.55
Deposits (MM)	133,670	1,275.96	22,933.86	0.00	53.69	117.18	279.36	1,988,464.38
# Branches	133,670	14.92	134.48	1.00	2.00	4.00	7.00	6,497.00
Bank Deposit HHI	133,664	0.23	0.13	0.05	0.15	0.20	0.28	1.00
# Mortgage Applications	82,130	3,456.39	53,480.73	1.00	58.00	168.00	501.00	4,681,350.00
Amount of Mortgage Applications (MM)	82,130	603.91	10,638.77	0.00	5.25	18.25	65.67	1,011,229.41
# Originated Mortgage	82,130	1,750.00	22,966.48	0.00	44.00	129.00	386.00	2,058,326.00
Amount of Originated Mortgage (MM)	82,130	310.41	4,633.78	0.00	3.98	14.07	50.75	355,648.98
# Small Business Loans	9,831	9,877.19	83,797.90	0.00	226.00	542.00	1,296.00	1,930,571.00
Amount of Small Business Loans (MM)	9,831	371.42	1,634.73	0.00	37.38	84.96	189.96	40,389.83

Notes. This table presents summary statistics for financial advertising in Panel (a) and financial intermediaries at the bank holding company level in Panel (b). Panel (a) presents data on financial advertising derived from Nielsen's Ad Intel dataset. Duration is the length of an advertising in seconds. Air Months is the total number of months the advertising aired on television. First Air Year is the year when the advertising was first aired. # Schedule Times, Local TV / National TV is the total number of times an advertising was scheduled to air on local or national television. Total Spending, Local TV / National TV is the total expenditure on local or national television. The six categories, including Personal Banking, Business Banking, Mortgage, Credit Card, Investment, and General Banking, represent the percentage distribution of the product categories in the advertising videos. Panel (b) contains a bank holding company-year panel combining various sources of financial intermediaries data, with unavailable data for any bank-year observation recorded as missing. Total Assets (MM) is the total assets of the bank holding companies from the U.S. Call Reports. Advertising Expense (MM) is the amount expenses on advertising for the sample of publicly listed U.S. bank holding companies from Compustat. Non-interest Expense (MM) is the expense amount unrelated to interest from the U.S. Call Reports. Deposits (MM) is the amount of deposits from FDIC Summary of Deposits. # Branches is the number of branches operated by the bank holding company. Bank Deposit HHI is the bank-level market concentration, calculated as the deposit-weighted average of the county-level Herfindahl-Hirschman Index across all the counties that the bank holding company operates in. # Mortgage Applications and # Originated Mortgage is the total number of mortgage applications and originations from HMDA, respectively. Amount of Mortgage Applications (MM) and Amount of Originated Mortgage (MM) is the total value of mortgage applications and originations. # Small Business Loans is the total number of small business loans issued from CRA. Amount of Small Business Loans (MM) is the total value of small business loans issued.

Table 3. Financial Advertising by Local Market Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Product Market	SOD Deposit			HMDA Mortgage			CRA Loan		
Ad Category	Deposit			Asset			Asset		
% Ad Theme$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
Large (Product Share)$_{b,c,t-1}$	-0.554***	1.049***	-0.495	-4.773***	-0.085	4.858***	-8.240***	2.272***	5.968***
	(0.122)	(0.380)	(0.396)	(0.142)	(0.118)	(0.204)	(0.150)	(0.082)	(0.188)
Observations	71,099	71,099	71,099	273,618	273,618	273,618	322,752	322,752	322,752
R-squared	0.282	0.308	0.305	0.153	0.156	0.158	0.145	0.152	0.134
No. of Institutions	808	808	808	355	355	355	208	208	208
Mean of Y	1.793	13.12	85.09	6.243	4.492	89.27	7.781	2.621	89.60
County-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Notes. This table examines the financial advertising strategies across banks with different levels of local market power in a bank(b)-county(c)-year(t) panel. The analysis considers three different products, including deposits in Columns (1)-(3), mortgages in Columns (4)-(6), and business loans in Columns (7)-(9). % Ad Theme$_{b,c,t}$ is the share of advertising themes for that specific product used by bank b in county c in year t. Large (Product Share)$_{b,c,t-1}$ is a dummy variable for whether bank b is above median market shares in the county c in the respective product market in year $t-1$. The model includes county-year fixed effects. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Financial Advertising by High- and Low-Rate and Service Quality Banks

Panel (a): Financial Advertising by High- and Low-Rate Banks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Measure of Deposit Rate	Checking Deposit Rate			Time Deposit Rate			Saving Deposit Rate		
Ad Category	Deposit			Deposit			Deposit		
% Ad Theme$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
High Deposit Rate$_{b,c,t-1}$	0.267***	2.722***	-2.989***	0.090*	4.049***	-4.139***	0.435***	-1.634***	1.200***
	(0.044)	(0.179)	(0.187)	(0.047)	(0.106)	(0.105)	(0.036)	(0.125)	(0.125)
Observations	471,599	471,599	471,599	504,109	504,109	504,109	489,552	489,552	489,552
R-squared	0.090	0.110	0.101	0.089	0.097	0.093	0.091	0.108	0.103
No. of Institutions	891	891	891	904	904	904	891	891	891
Mean of Y	2.029	13.07	84.90	1.478	14.16	84.36	1.481	12.64	85.88
County-Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Panel (b): Financial Advertising by High- and Low-Service Quality Banks

	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Service Quality	Branch Network			CFPB Complaints		
Ad Category	Deposit			Deposit		
% Ad Theme$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
High Service Quality$_{b,c,t-1}$	-0.352***	5.568***	-5.216***	5.062***	9.012***	-14.074***
	(0.046)	(0.155)	(0.166)	(0.070)	(0.215)	(0.206)
Observations	619,956	619,956	619,956	619,956	619,956	619,956
R-squared	0.076	0.096	0.086	0.099	0.104	0.112
No. of Institutions	1,048	1,048	1,048	1,048	1,048	1,048
Mean of Y	2.341	13.68	83.98	2.341	13.68	83.98
County-Year FE	Y	Y	Y	Y	Y	Y

Notes. This table examines the financial advertising strategies across banks with different levels of deposit rate and service quality in a bank(b)-county(c)-year(t) panel. The analysis considers the deposit business. % Ad Theme$_{b,c,t}$ is the share of advertising themes used by bank b in county c in year t. Panel (a) contains High Deposit Rate$_{b,c,t-1}$, a dummy variable for whether bank b is above median level of deposit rates all the banks in the county c in year $t-1$, using chekcing deposit (i.e., interest checking accounts with less than \$2,500) in Columns (1)-(3), time deposit (i.e., \$10,000 12-month CDs) in Columns (4)-(6), and saving deposit (i.e., \$25,000 money market deposit accounts) in Columns (7)-(9). Panel (b) contains High Service Quality$_{b,c,t-1}$, a dummy variable for whether bank b is above the median level of service quality among all the banks in the county c in year $t-1$, using number of branches scaled by deposits in Columns (1)-(3) and number of CFPB consumer complaints scaled by deposits in Columns (4)-(6). The model includes county-year fixed effects. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5. Financial Advertising and Customer Demographic Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Ad Category	Deposit			Asset		
% Ad Actors$_{b,c,t}$	Black	Hispanic	Asian	Black	Hispanic	Asian
Large (County w/ % Black)$_{b,c,t-1}$	0.111**			0.172***		
	(0.046)			(0.053)		
Large (County w/ % Hispanic)$_{b,c,t-1}$		0.114***			0.144***	
		(0.011)			(0.013)	
Large (County w/ % Asian)$_{b,c,t-1}$			0.110***			0.209***
			(0.021)			(0.023)
Observations	533,517	533,517	533,517	449,917	449,917	449,917
R-squared	0.811	0.877	0.862	0.830	0.783	0.864
No. of Institutions	835	835	835	396	396	396
Mean of Y	16	1.102	5.937	21.31	0.907	5.515
Bank-Year FE	Y	Y	Y	Y	Y	Y

Notes. This table examines the financial advertising strategies of banks across counties with different customer demographic characteristics in a bank(b)-county(c)-year(t) panel. The analysis considers the liability side in Columns (1)-(3) and the asset side in Columns (4)-(6). % Ad Actors$_{b,c,t}$ is the share of minority actors used by bank b in county c in year t. Large (County w/ % Black)$_{b,c,t-1}$, Large (County w/ % Hispanic)$_{b,c,t-1}$ and Large (County w/ % Asian)$_{b,c,t-1}$ are dummy variables for whether county c is above the 80 percent quantiles of the share of Black or African American, Hispanic, and Asian population in year $t-1$, respectively. The model includes bank-year fixed effects. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Bank Images and Demand for Financial Products: Within-County Estimation

Panel (a): Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{b,c,t}$	$\Delta \ln$(Deposits)			Δ(Deposit Spread)		
$\ln(\text{Ad})_{b,c,t}$	0.0012***	0.0011***		0.0094***	0.0087***	
	(0.0002)	(0.0003)		(0.0007)	(0.0008)	
$\ln(\text{Ad})_{-b,c,t}$		−0.0022*			−0.0089***	
		(0.0013)			(0.0054)	
$1(\text{Pricing})_{b,c,t}$			−0.0154***			−0.0329**
			(0.0050)			(0.0162)
$1(\text{Service})_{b,c,t}$			0.0053**			0.0275***
			(0.0021)			(0.0068)
$1(\text{Emotion/Trust})_{b,c,t}$	Omitted					
Observations	49,502	49,502	49,502	35,938	35,938	35,938
R-squared	0.572	0.572	0.572	0.554	0.554	0.551
No. of Institutions	528	528	528	437	437	437
Mean of Y	0.0527	0.0527	0.0527	−0.0597	−0.0597	−0.0597
Bank-County FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y

Panel (b): Loans

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{b,c,t}$	ln(Mortgage Origination)			ln(Small Business Loan Origination)		
$\ln(\text{Ad})_{b,c,t}$	0.022**	0.021**		0.005***	0.008***	
	(0.008)	(0.009)		(0.002)	(0.002)	
$\ln(\text{Ad})_{-b,ct}$		−0.001			−0.031***	
		(0.028)			(0.009)	
$1(\text{Pricing})_{b,c,t}$			−0.250***			−0.151**
			(0.105)			(0.067)
$1(\text{Service})_{b,c,t}$			−0.014			−0.140***
			(0.085)			(0.016)
$1(\text{Emotion/Trust})_{b,c,t}$	Omitted					
Observations	84,648	84,648	84,648	98,996	98,996	98,996
R-squared	0.819	0.819	0.819	0.915	0.915	0.915
No. of Institutions	505	505	505	218	218	218
Mean of Y	11.988	11.988	11.988	12.753	12.753	12.753
Bank-County FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y

Notes. This table examines the relationship between bank images and demand for financial products in a bank(b)-county(c)-year(t) panel. The outcome variables, $Y_{b,c,t}$, include the changes in the log of deposits $\Delta \ln$(Deposits) in Columns (1)-(3) of Panel (a), changes in the deposit spread Δ(Deposit Spread) in Columns (4)-(6) of Panel (a), the log amount of new mortgage origination ln(Mortgage Origination) in Columns (1)-(3) of Panel (b), and the log amount of new small business loan origination ln(Small Business Loan Origination) from CRA in Columns (4)-(6) of Panel (b). The advertising variables include the log amount of advertising spending $\ln(\text{Ad})_{b,c,t}$ for bank b in county c in year t and the log amount of total advertising spending $\ln(\text{Ad})_{-b,c,t}$ for all other banks in county c in year t excluding the focal bank b. We use product-specific advertising spending, namely spending on deposits in Columns (1)-(6) of Panel (a), spending on mortgages in Columns (1)-(3) of Panel (b), and spending on business loans in Columns (4)-(6) of Panel (b). In Columns (3) and (6) of each panel, we include the dummy variables of bank images, including pricing information $1(\text{Pricing})_{b,c,t}$ and service quality $1(\text{Service})_{b,c,t}$, omitting emotional appeal and trust building $1(\text{Emotion/Trust})_{b,c,t}$. The specifications include bank-county fixed effects and county-year fixed effects. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Bank Images and Demand for Financial Products: Border Discontinuity Design

Panel (a): Deposits

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{b,c,t}$	$\Delta \ln$(Deposits)			Δ(Deposit Spread)		
$\ln(\text{Ad})_{bc,t}$	0.0009***	0.0007***		0.0089***	0.0082***	
	(0.0002)	(0.0002)		(0.0007)	(0.0008)	
$\ln(\text{Ad})_{-b,c,t}$		−0.0040**			−0.0154***	
		(0.0017)			(0.0087)	
$1(\text{Pricing})_{b,c,t}$			−0.0026			−0.0809**
			(0.0055)			(0.0219)
$1(\text{Service})_{b,c,t}$			0.0093**			0.0329***
			(0.0024)			(0.0078)
$1(\text{Emotion/Trust})_{b,c,t}$	Omitted					
Observations	42,144	42,144	42,144	30,918	30,918	30,918
R-squared	0.479	0.479	0.479	0.826	0.826	0.826
No. of Institutions	420	420	420	352	352	352
Mean of Y	0.0527	0.0527	0.0527	−0.0597	−0.0597	−0.0597
Bank-County FE	Y	Y	Y	Y	Y	Y
Bank-Border-Year FE	Y	Y	Y	Y	Y	Y

Panel (b): Loans

	(1)	(2)	(3)	(4)	(5)	(6)
$Y_{b,c,t}$	ln(Mortgage Origination)			ln(Small Business Loan Origination)		
$\ln(\text{Ad})_{b,c.t}$	0.030***	0.028***		0.023***	0.025***	
	(0.003)	(0.004)		(0.001)	(0.001)	
$\ln(\text{Ad})_{-b,c,t}$		−0.003			−0.017***	
		(0.017)			(0.005)	
$1(\text{Pricing})_{b,c,t}$			−0.292***			−0.040**
			(0.112)			(0.018)
$1(\text{Service})_{b,c,t}$			−0.026***			−0.196***
			(0.027)			(0.038)
$1(\text{Emotion/Trust})_{b,c,t}$	Omitted					
Observations	81,972	81,972	81,972	99,402	99,402	99,402
R-squared	0.761	0.761	0.761	0.856	0.856	0.856
No. of Institutions	493	493	493	216	216	216
Mean of Y	11.33	11.33	11.33	12.41	12.41	12.41
Bank-County FE	Y	Y	Y	Y	Y	Y
Bank-Border-Year FE	Y	Y	Y	Y	Y	Y

Notes. This table examines the relationship between bank images and demand for financial products using a border discontinuity design in a bank(b)-county(c)-border($d(c)$)-year(t) panel. The outcome variables, $Y_{b,c,t}$, include the changes in the log of deposits $\Delta \ln$(Deposits) in Columns (1)-(3) of Panel (a), changes in the deposit spread Δ(Deposit Spread) in Columns (4)-(6) of Panel (a), the log amount of new mortgage origination ln(Mortgage Origination) in Columns (1)-(3) of Panel (b), and the log amount of new small business loan origination ln(Small Business Loan Origination) from CRA in Columns (4)-(6) of Panel (b). The advertising variables include the log amount of advertising spending $\ln(\text{Ad})_{b,c,t}$ for bank b in county c in year t and the log amount of total advertising spending $\ln(\text{Ad})_{-b,c,t}$ for all other banks in county c in year t excluding the focal bank b. We use product-specific advertising spending, namely spending on deposits in Columns (1)-(6) of Panel (a), spending on mortgages in Columns (1)-(3) of Panel (b), and spending on business loans in Columns (4)-(6) of Panel (b). In Columns (3) and (6) of each panel, we include the dummy variables of bank images, including pricing information $1(\text{Pricing})_{b,c,t}$ and service quality $1(\text{Service})_{b,c,t}$, omitting emotional appeal and trust building $1(\text{Emotion/Trust})_{b,c,t}$. The specifications include bank-county fixed effects and bank-border-year fixed effects. Standard errors are clustered at the bank-county level and border-year level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Bank Images and Bank Value

Panel (a): Advertising Spending

	(1)	(2)	(3)	(4)	(5)
	Productivity		Deposit	Deposit	
$Y_{b,t}$	Deposit	Asset	Spread	Beta	Tobin Q
Ad/Expense$_{b,t-1}$	0.012*	0.063***	0.073***	0.001	0.022***
	(0.006)	(0.013)	(0.015)	(0.002)	(0.004)
Observations	11,930	11,930	19,800	16,145	19,410
R-squared	0.955	0.207	0.493	0.102	0.474
No. of Institutions	481	481	700	472	692
Mean of Y	0.0323	0.0413	0.452	0.420	1.203
Bank Controls	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y

Panel (b): Bank Images

	(1)	(2)	(3)	(4)	(5)
	Productivity		Deposit	Deposit	
$Y_{b,t}$	Deposit	Asset	Spread	Beta	Tobin Q
1(Pricing)$_{b,t-1}$	0.079***	−0.276***	0.052	−0.007**	−0.021*
	(0.018)	(0.068)	(0.036)	(0.004)	(0.011)
1(Service)$_{b,t-1}$	−0.019	−0.024	0.040*	0.001	0.008
	(0.013)	(0.048)	(0.023)	(0.002)	(0.008)
1(Emotion/Trust)$_{b,t-1}$	Omitted				
Observations	3,727	3,727	10,938	9,637	6,484
R-squared	0.930	0.214	0.509	0.148	0.345
No. of Institutions	203	203	649	553	304
Mean of Y	0.610	0.348	0.199	0.418	1.167
Bank Controls	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y

Notes. This table examines the relationship between bank images and bank value in a bank(b)-quarter(t) panel. The sample contains all the publicly listed U.S. bank holding companies with non-missing and positive Compustat item Advertising and Marketing Expenses (`xadq`). The outcome variables including bank productivity in Columns (1)-(2) from Egan, Lewellen and Sunderam (2022), deposit spread and deposit beta in Columns (3)-(4) from Drechsler, Savov and Schnabl (2021), and Tobin Q. In Panel (a), the advertising variable Ad/Expense$_{b,t-1}$ is advertising expense scaled by total non-interest expense for bank b in quarter $t-1$ obtained from Compustat and Call Reports. In Panel (b), we include the dummy variables of bank images, including pricing information 1(Pricing)$_{b,t-1}$ and service quality 1(Service)$_{b,t-1}$, omitting emotional appeal and trust building 1(Emotion/Trust)$_{b,t-1}$. The specifications include quarter fixed effects and lagged bank controls. Lagged bank controls include the log of the bank's total assets, the bank's Z-Score (the bank's ROA plus its equity ratio divided by its standard deviation of ROA), the bank's ROA, the bank's equity to assets ratio, the bank's deposits to assets ratio, and the bank's deposit and mortgage market concentration HHI, following Gelman, Goldstein and MacKinlay (2023) and Egan, Lewellen and Sunderam (2022). Standard errors are clustered at the bank level with wild cluster bootstrap procedure (1000 times). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Bank Images and Monetary Policy Transmission

Panel (a): Advertising Spending

Y_{bt}	(1) Δ(Deposit Spread)	(2) $\Delta \ln$(Total Deposits)	(3) $\Delta \ln$(Total Liabilities)	(4) $\Delta \ln$(Total Loans)	(5) $\Delta \ln$(Securities)	(6) $\Delta \ln$(Total Assets)
$\ln(\text{Ad})_{b,t-1}$,	−0.007	0.022**	0.022**	0.021*	0.014	0.021**
	(0.018)	(0.010)	(0.010)	(0.012)	(0.016)	(0.010)
$\Delta\text{FF}_t \times \ln(\text{Ad})_{b,t-1}$	0.075***	−0.005**	−0.006**	−0.005**	−0.004	−0.006**
	(0.014)	(0.002)	(0.002)	(0.002)	(0.004)	(0.002)
Observations	19,757	19,096	19,096	19,096	19,096	19,096
R-squared	0.879	0.322	0.354	0.385	0.214	0.357
No. of Institutions	654	644	644	644	644	644
Mean of Y	−0.0166	0.107	0.104	0.107	0.0903	0.104
HHI Controls	Y	Y	Y	Y	Y	Y
Bank FE	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y

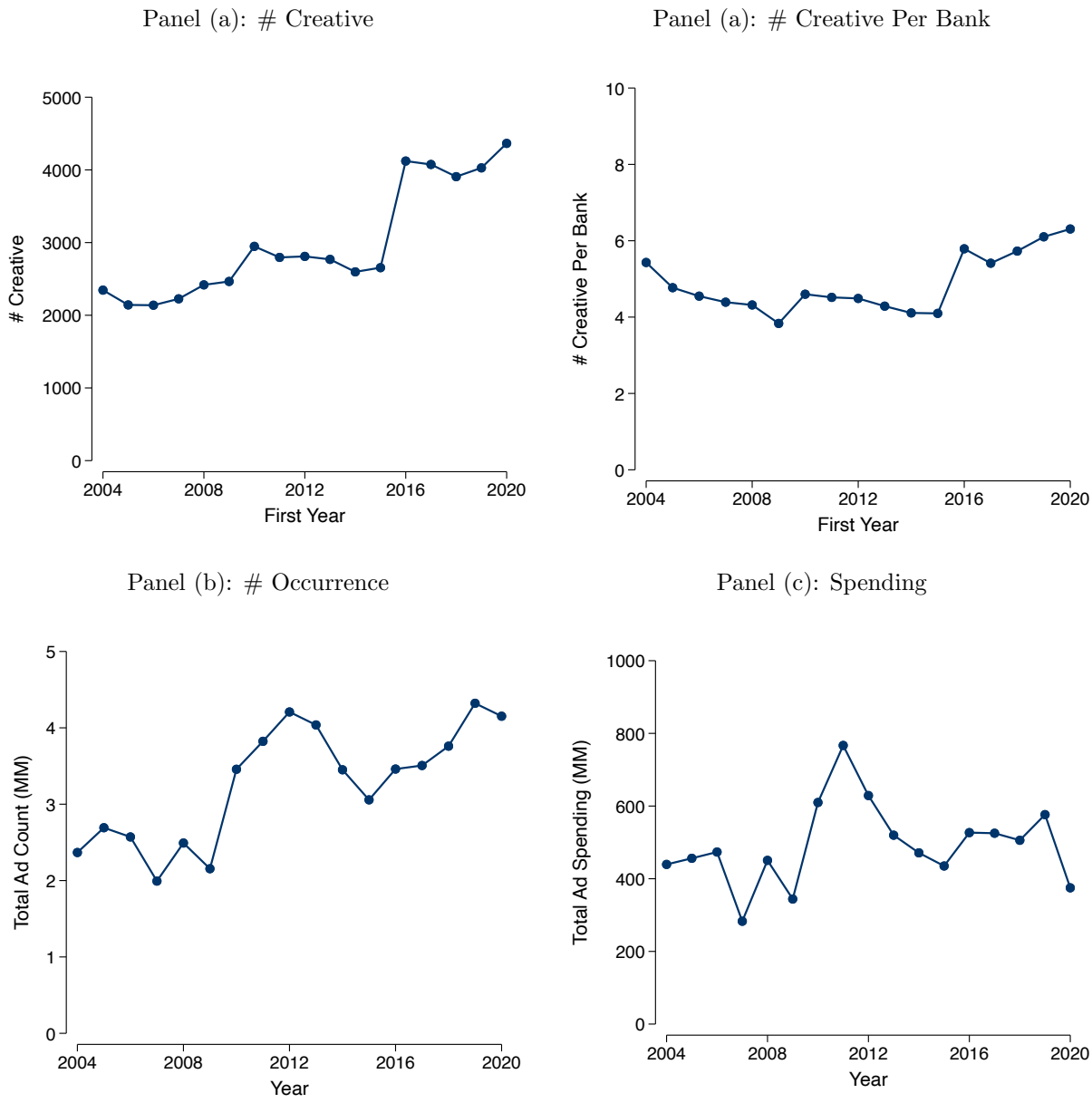
Panel (b): Bank Images

Y_{bt}	(1) Δ(Deposit Spread)	(2) $\Delta \ln$(Total Deposits)	(3) $\Delta \ln$(Total Liabilities)	(4) $\Delta \ln$(Total Loans)	(5) $\Delta \ln$(Securities)	(6) $\Delta \ln$(Total Assets)
$1(\text{Pricing})_{b,t-1}$	−0.024	0.007	0.005	0.012	0.012	0.006
	(0.024)	(0.007)	(0.007)	(0.011)	(0.014)	(0.007)
$1(\text{Service})_{b,t-1}$	−0.011	−0.013***	−0.009**	−0.013***	−0.003	−0.008*
	(0.017)	(0.004)	(0.004)	(0.005)	(0.008)	(0.004)
$\Delta\text{FF}_t \times 1(\text{Pricing})_{b,t-1}$	−0.046	−0.018	−0.024	−0.025	−0.010	−0.025
	(0.064)	(0.017)	(0.015)	(0.019)	(0.030)	(0.015)
$\Delta\text{FF}_t \times 1(\text{Service})_{b,t-1}$	0.112***	−0.008	−0.008	−0.017**	0.001	−0.010
	(0.043)	(0.007)	(0.007)	(0.007)	(0.015)	(0.007)
$1(\text{Emotion/Trust})_{b,t-1}$ and $\Delta\text{FF}_t \times 1(\text{Emotion/Trust})_{b,t-1}$ Omitted						
Observations	10,938	10,658	10,658	10,658	10,658	10,658
R-squared	0.777	0.085	0.086	0.119	0.039	0.079
No. of Institutions	649	629	629	629	629	629
Mean of Y	0.00323	0.0859	0.0771	0.0803	0.0658	0.0771
HHI Controls	Y	Y	Y	Y	Y	Y
Bank Controls	Y	Y	Y	Y	Y	Y
Quarter FE	Y	Y	Y	Y	Y	Y

Notes. This table examines the relationship between bank images and the transmission of monetary policy in a bank(b)-quarter(t) panel. The sample contains all the publicly listed U.S. bank holding companies with non-missing and positive Compustat item Advertising and Marketing Expenses (`xadq`). In Panel (a), the advertising variable $\ln(\text{Ad})_{b,t-1}$ is the log amount of overall advertising spending for bank b in quarter $t-1$ obtained from Compustat. In Panel (b), we include the dummy variables of bank images, including pricing information $1(\text{Pricing})_{b,t-1}$ and service quality $1(\text{Service})_{b,t-1}$, omitting emotional appeal and trust building $1(\text{Emotion/Trust})_{b,t-1}$. ΔFF_t is the change in the effective Fed funds rate from quarter $t-1$ to quarter t. We control for deposit market power Deposit-$\text{HHI}_{b,t-1}$, calculated as the deposit-weighted average of the county-level HHI across all the counties that the bank operates in. The specifications include bank fixed effects and quarter fixed effects in Panel (a), and lagged bank controls and quarter fixed effects in Panel (b). Standard errors are clustered at the bank level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix (For Online Publication Only)

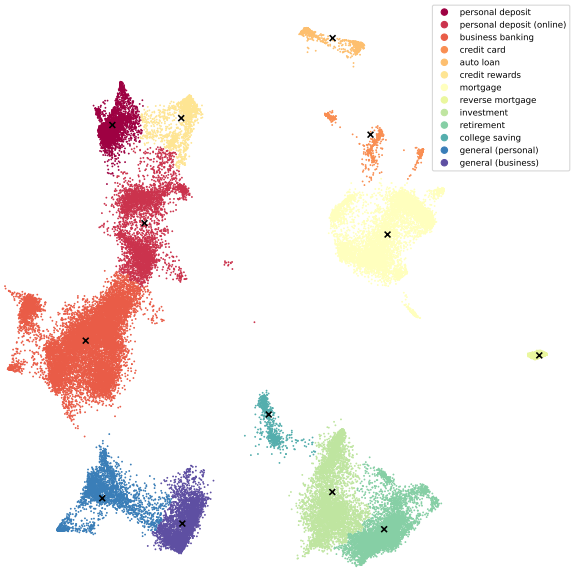
Figure A.1. Financial Advertisement Over Time



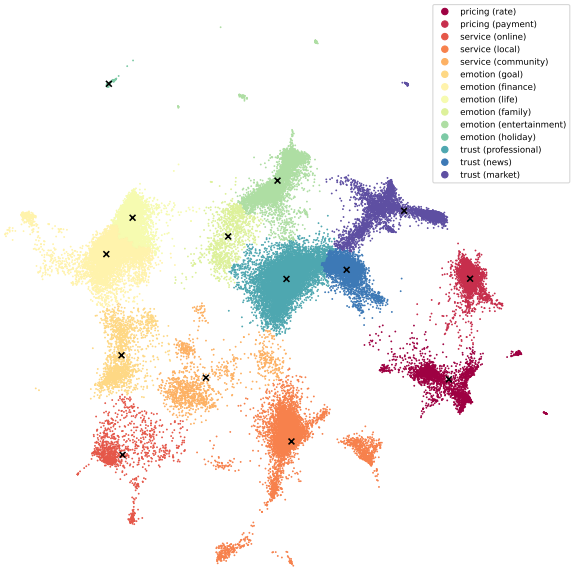
Notes. This figure presents the statistics of financial advertisement over time. Panel (a) shows the number of new creative video over year in our data, and Panel (b) shows the number of new creative video per bank over year. Panel (c) and Panel (d) show the number of occurrences and their corresponding spending over year, respectively.

Figure A.2. Visualization of the Video Embedding at the Detailed Level

Panel (a): Product Category

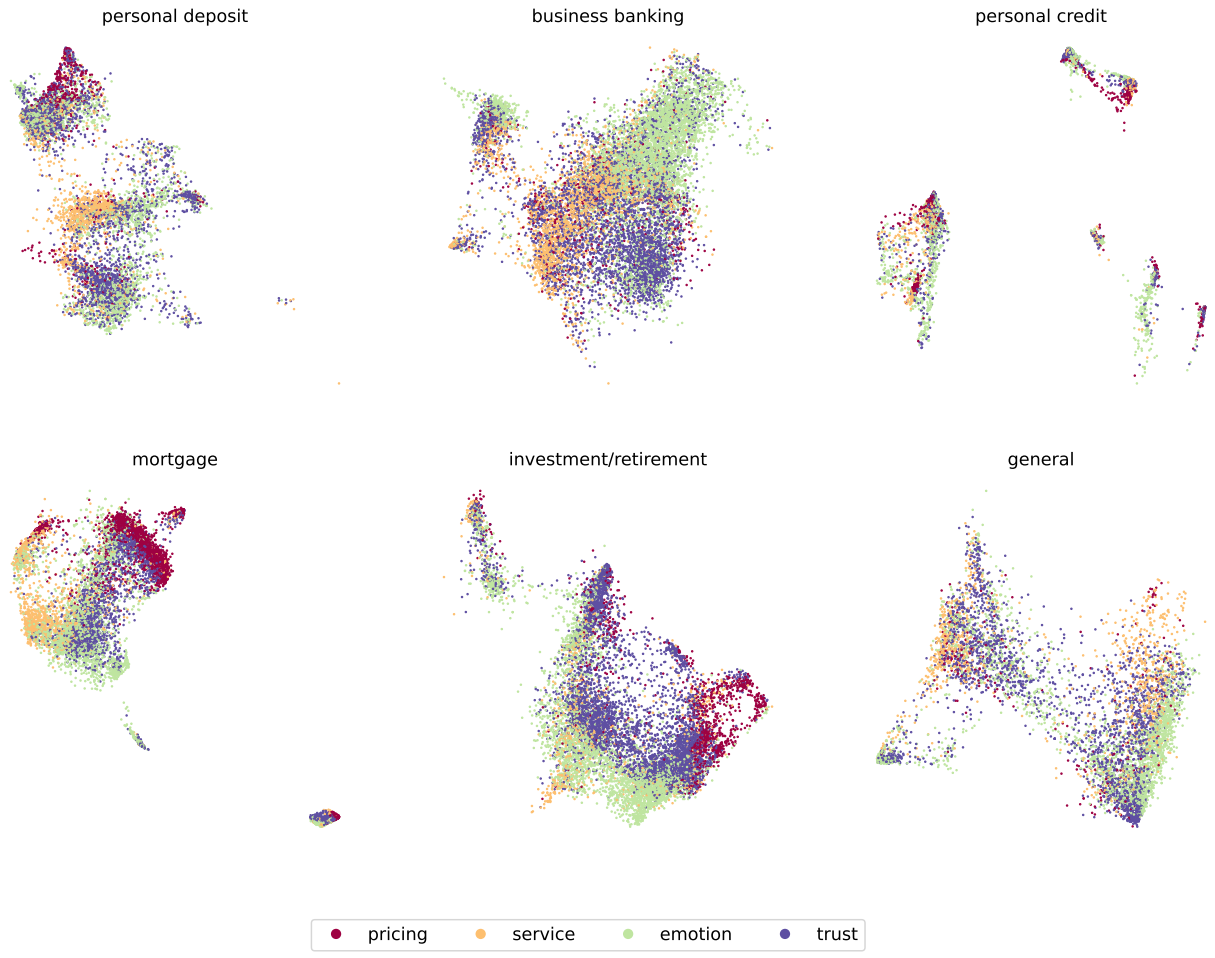


Panel (b): Persuasive Theme



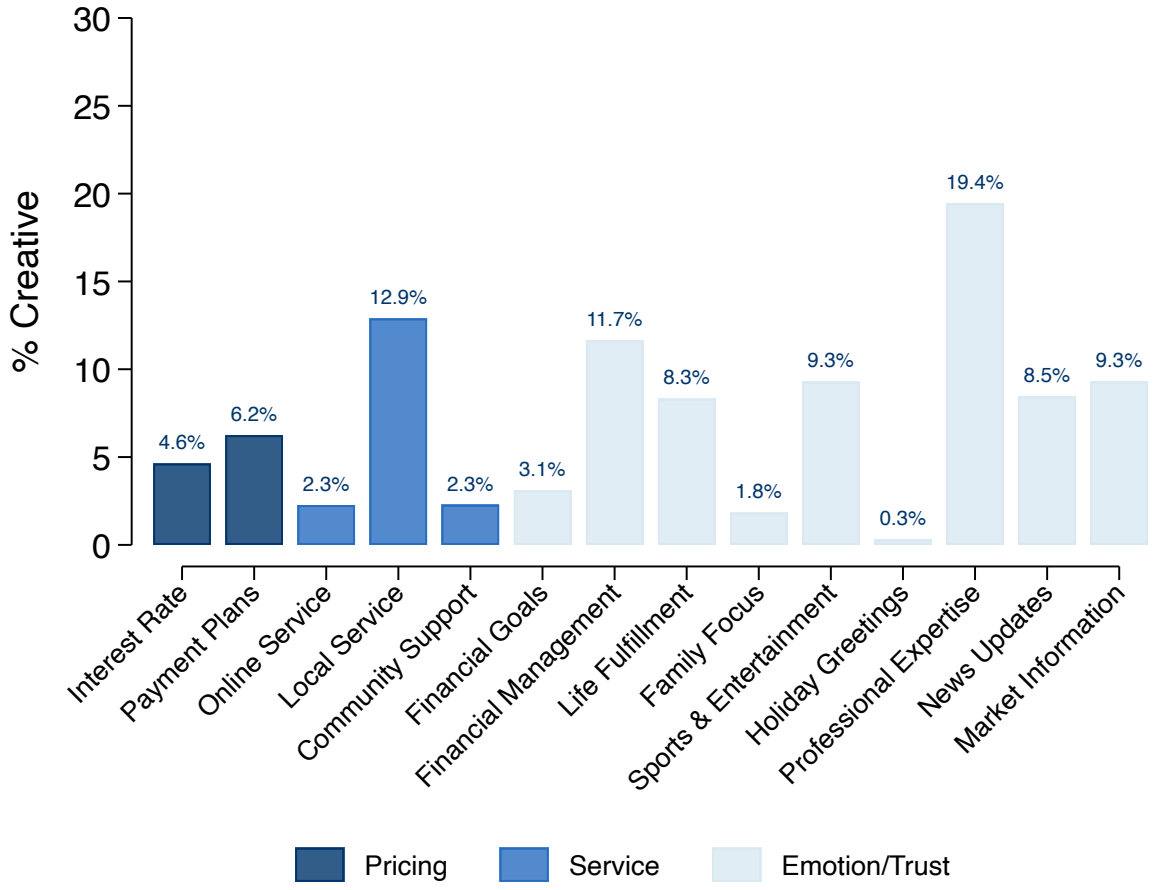
Notes. This figure shows the visualization of the 2-dimensional video embedding for different product categories and persuasive themes at the more detailed level. Panel (a) shows the visualization of the product category, as described in Section 3.1.2. Panel (b) shows the visualization of the persuasive theme, as described in Section 3.1.3.

Figure A.3. Visualization of the Video Embedding by Product Category



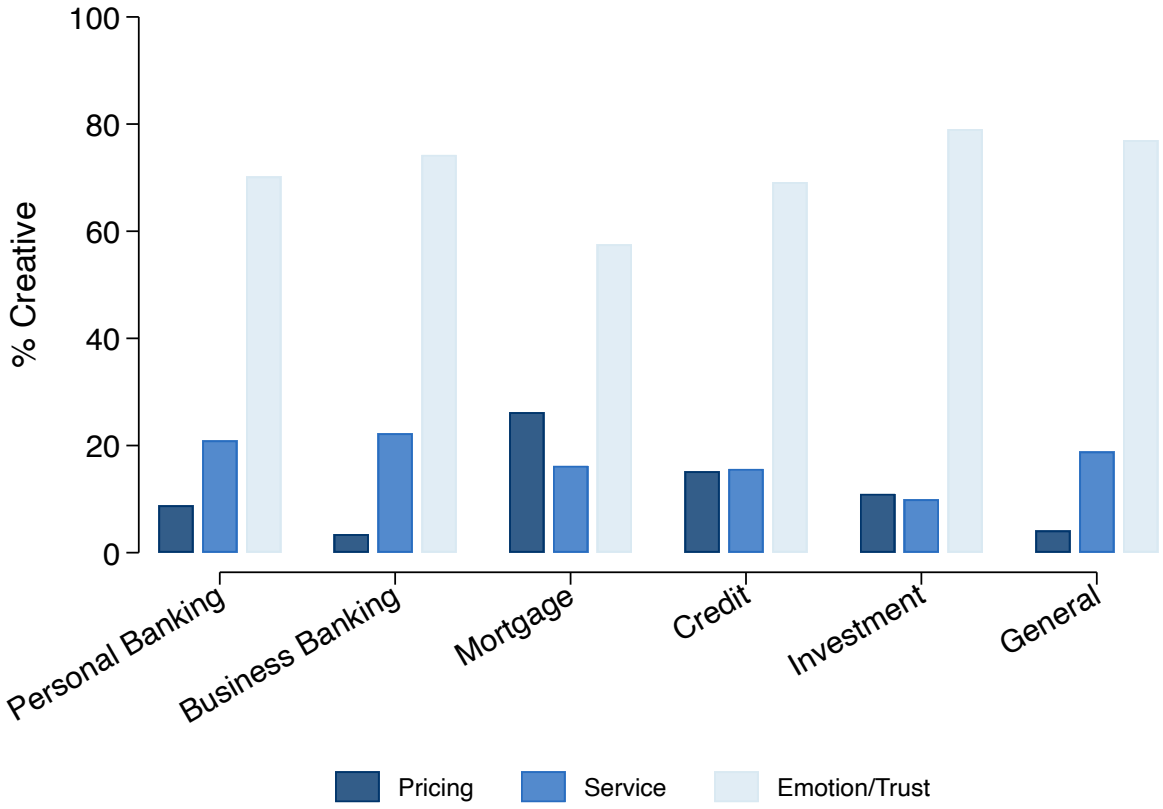
Notes. This figure shows the visualization of the 2-dimensional video embedding for persuasive themes by various product categories, as described in Section 3.1.

Figure A.4. Overall Distribution of the Advertising Detailed Theme



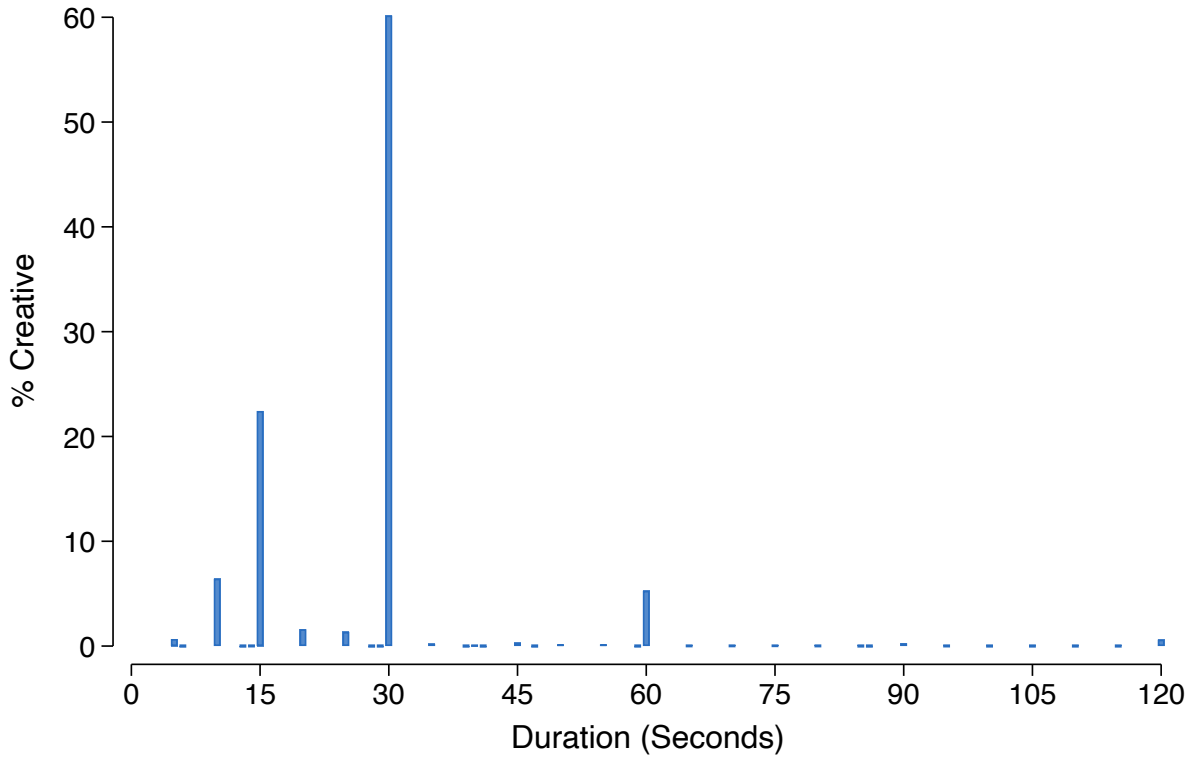
Notes. This figure shows the distribution of detailed persuasive theme for financial advertising. The list of financial advertising persuasive information can be found in Table 1.

Figure A.5. Distribution of the Advertising Themes by Product Categories



Notes. This figure shows the distribution of theme for different specific products. The list of financial advertising broad persuasive information can be found in Table 1.

Figure A.6. Distribution of Duration for Financial Advertisement



Notes. This figure shows the distribution of duration of financial advertisement, where duration is the length of an advertisement in seconds.

Table A.1. Alignment of Product Categories and Persuasive Themes Between Clustering Method and LLM

Panel (a) Product Category

	Product Category (Clustering)					
	personal deposit	business banking	personal credit	mortgage	investment/retirement	general banking
# Videos	7,593	13,417	4,968	9,697	11,917	6,457
Distribution of Product Categories Through LLM						
% Banking	0.836	0.786	0.247	0.165	0.081	0.585
% Business loan	0.014	0.084	0.007	0.004	0.003	0.022
% Personal credit	0.078	0.033	0.652	0.037	0.029	0.107
% Mortgage	0.010	0.027	0.073	0.767	0.014	0.045
% Investment and brokerage	0.055	0.060	0.015	0.015	0.542	0.189
% Retirement financial services	0.003	0.007	0.000	0.011	0.301	0.029
% Insurance	0.004	0.004	0.005	0.001	0.029	0.023
Distribution of Product Categories Through LLM (Standardized)						
% Banking	**0.965**	**0.838**	-0.518	-0.723	-0.935	**0.332**
% Business loan	-0.112	**0.465**	-0.168	-0.196	-0.199	-0.044
% Personal credit	-0.111	-0.295	**2.245**	-0.278	-0.311	0.009
% Mortgage	-0.448	-0.399	-0.261	**1.803**	-0.436	-0.346
% Investment and brokerage	-0.387	-0.370	-0.523	-0.524	**1.270**	0.069
% Retirement financial services	-0.351	-0.332	-0.365	-0.314	**1.124**	-0.221
% Insurance	-0.099	-0.100	-0.078	-0.132	**0.231**	0.159

Panel (a) Product Category

	Persuasive Theme (Clustering)			
	Pricing	Service	Emotion	Trust
# Videos	6,007	9,251	18,669	20,122
Distribution of Persuasive Themes Through LLM				
% Pricing	0.426	0.254	0.197	0.193
% Service	0.294	0.474	0.342	0.362
% Emotion	0.049	0.076	0.129	0.076
% Trust	0.231	0.197	0.332	0.369
Distribution of Persuasive Themes Through LLM (Standardized)				
% Pricing	**0.416**	0.123	-0.110	-0.079
% Service	-0.042	**0.212**	-0.124	0.030
% Emotion	-0.199	-0.119	**0.191**	-0.063
% Trust	-0.210	-0.228	0.086	**0.087**

Notes. This table compares the alignment of product categories and persuasive themes obtained specifically through the clustering method and LLM. Panel (a) and Panel (b) shows the distribution of product categories and persuasive themes, respectively. In each panel, the standardized distribution is computed by subtracting the mean and dividing by the standard deviation of the distribution.

Table A.2. Markov Transition Matrix of Bank Theme

Panel (a): For All Financial Advertising

	Ad Theme$_{b,t+1}$		
Ad Theme$_{b,t}$	Pricing	Service	Emotion/Trust
Pricing	51.32%	10.58%	38.10%
Service	3.67%	57.75%	38.58%
Emotion/Trust	4.71%	9.27%	86.01%

Panel (b): For Financial Advertising Related to Deposit Business

	Ad Theme$_{b,t+1}$		
Ad Theme$_{b,t}$	Pricing	Service	Emotion/Trust
Pricing	35.90%	15.38%	48.72%
Service	2.45%	59.00%	38.55%
Emotion/Trust	3.21%	12.19%	84.60%

Panel (c): For Financial Advertising Related to Asset Business

	Ad Theme$_{b,t+1}$		
Ad Theme$_{b,t}$	Pricing	Service	Emotion/Trust
Pricing	70.86%	10.00%	19.14%
Service	6.35%	74.15%	19.50%
Emotion/Trust	7.28%	6.71%	86.01%

Notes. This table presents the Markov transition matrix of bank theme over year. Panel (a) contains persuasive theme at the bank-year level using all the financial advertising. Panel (b) and Panel (c) contains persuasive theme at the bank-year level using financial advertising related to deposit business and asset business, respectively. To estimate the transition matrix, we only consider banks with at least 5 year sample of financial advertising data.

Table A.3. Race/Gender Share from Different Sources at the Video Level

Data source:	DeepFace			Extreme Reach	Census
	All Years	2019	Manual Check	2019	2019
% White Actors	82.3%	86.5%	69.5%	73.6%	61.2%
% Black Actors	9.6%	7.5%	19.3%	12.3%	12.7%
% Hispanic Actors	1.5%	0.4%	6.3%	6.2%	19.8%
% Asian Actors	6.6%	5.6%	4.9%	8.0%	6.3%
% Male Actors	76.4%	74.1%	46.9%	67.8%	49.5%
% Female Actors	23.6%	25.9%	53.1%	32.2%	50.5%

Notes. This table compare the racial and gender share of advertisement extracted from our framework with other sources of data, including the DeepFace framework that we rely on, the statistics on the actors in financial advertisement obtained from Extreme Reach, and the 2019 census data.

Table A.4. The Performance of DeepFace Framework at Video Level

	Unconditional Average		Conditional Average	
	True value	Prediction	True value	Prediction
Race				
% White Actors	64.70%	16.12%	69.53%	73.95%
% Black Actors	18.00%	2.49%	19.34%	11.42%
% Hispanic Actors	5.82%	1.32%	6.26%	6.04%
% Asian Actors	4.54%	1.87%	4.87%	8.58%
% Other Actors	6.95%	78.20%		
Gender				
% Male Actors	45.32%	15.48%	46.93%	71.02%
% Female Actors	51.26%	6.32%	53.07%	28.98%
% Other Actors	3.43%	78.20%		

Notes. This table reports the video-level performance of the DeepFace framework that we use to identify the facial attributes of the actors in the advertising video. The sample contains 400 videos that we manually labeled with true labels of race and gender.

Table A.5. The Performance of DeepFace Framework at Person Level

Panel (a) Race

Prediction True value	White	Black	Hispanic	Asian	Recall
White	566	4	25	11	93.40%
Black	14	131	8	8	81.37%
Hispanic	15	1	14	15	31.11%
Asian	6	0	0	54	90.00%
Precision	94.18%	96.32%	29.79%	61.36%	**87.73%**

Panel (b) Gender

Prediction True value	Male	Female	Recall
Male	468	3	99.36%
Female	130	271	67.58%
Precision	78.26%	98.91%	**84.75%**

Notes. This table reports the person-level performance of the DeepFace framework that we use to identify the facial attributes of the actors in the advertising video. The sample contains 400 videos that we manually labeled with true labels of race and gender.