Banks' Images: Evidence from Advertising Videos*

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Abstract

This paper examines how banks strategically develop brand images and how these efforts influence franchise value and the transmission of monetary policy. Analyzing TV advertisements via video embeddings, we measure banks' images along three dimensions: pricing advantages, service quality, and building trust and emotional connections. Banks with high local market shares highlight service and trust. Banks lacking pricing or service advantages lean on emotional appeals. Banks tailor images to demographics, increasing minority representation in targeted areas. A border discontinuity design helps identify that banks' images affect deposit growth, spreads, and loan demand, leading banks to respond differently to monetary policy.

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Keywords: Advertising Videos, Banking, Franchise Value, Market Power, Monetary Policy

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1. Introduction

Recent studies on financial intermediaries highlight significant heterogeneity across these institutions in aspects such as market share, asset composition, branch services, pricing, and productivity. These differences are central for us to understand banks' operations and competitive dynamics, with important implications for banks' franchise value and the broader economy (Egan et al., 2017; Drechsler et al., 2017; Egan et al., 2022; Benmelech et al., 2023; d'Avernas et al., 2023). For these variations to persist in equilibrium, 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 (Mullainathan, Schwartzstein, and Shleifer, 2008; Bertrand, Karlan, Mullainathan, Shafir, and Zinman, 2010; Gurun, Matvos, and Seru, 2016).

How do banks communicate with customers to build their image, and how do such image-building activities affect their business operations and the economy? In this paper, we address these questions by conducting a systematic study of financial advertising, drawing on more than a decade of data on TV advertising coverage and, importantly, content in advertising videos. Analyzing banks' image-building activities is not only new but also economically important. Surveys of Chief Marketing Officers (CMOs) indicate that, on average, banks allocate 9.5% of their annual budget to advertising efforts, making it one of the most critical operational decisions. More broadly, recent literature in economics and finance has documented the importance of building customer capital, often built through strategic advertising and marketing activities (Gourio and Rudanko, 2014; He, Mostrom, and Sufi, 2024).

The analysis leverages two novel components in our empirical design: a unique dataset of financial advertisements from Nielsen Ad Intel, and a method that quantifies banks' image-building efforts using advertising content. Our data contains information on advertisements aired on national and local TV from 2004 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, for which we develop a video-embedding method to extract the content. 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. These data are used to construct a broad set of characteristics of financial intermediaries and their business activities.

Methodologically, we develop an unsupervised high-dimensional video embedding clustering method to quantify banks' images using advertising creatives data. Each advertisement clip lasts on average 27 seconds and contains visual, verbal, and vocal information. Our quantification method creates embeddings to represent this rich and multimodal information, and provides a robust and efficient approach to extract information that represents the most variance in the video. Intuitively, our method analyzes videos by grouping similar narratives, scenes, and events without human input. By clustering, the method identifies key patterns and variations in the video, making it easier to detect meaningful moments and summarize content.

The method, though unsupervised, delivers a categorization of banks' primary images in their advertisements that aligns with economics and marketing literature. Each advertising video can be classified into three broad categories: pricing advantages and financial benefit; superior service quality; trust-building, life aspirations, and emotional connections. The first category is pricing-related information, including favorable interest rates, payment plan, special offers, and cashback rewards. The second category is service quality, including local and customer service, mobile and online banking, and daily convenience. The third category involves establishing trust with potential customers through the use of emotional appeals, including relationship-based trust-building, expert advice, and financial literacy, as well as lifestyle and aspirations, such as homeownership advantages, future lifestyle, and success stories of small businesses.[1] In addition, we identify the facial attributes of actors—such as race, gender, and emotional expressions—to assess whether a bank portrays itself as friendly

[1] This clustering aligns well with the marketing literature on coding advertising information and styles (Liaukonyte et al., 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 et al., 2024b; Zhang et al., 2024).

to minority groups or specific demographic groups.

Banks' advertisements exhibit significant diversity in how banks portray their images. 18% of advertisements focus on their pricing advantages and financial benefits, 29% on customer service and support, and 53% focus on building trust and emotional connections. In a variation decomposition exercise, we demonstrate that banks' images are primarily explained by bank-fixed effects, bank-year fixed effects, and bank-county fixed effects, while product and regional effects have significantly lower explanatory power. This is important motivating evidence, as it suggests that banks actively shape and communicate their images through persistent efforts spanning over a year or multiple years.

Our first set of analyses focuses on investigating how banks actively and strategically build their image through advertising. These analyses are organized around a central inquiry: Is image building a concrete mechanism through which banks maintain their franchise value, attract customers, and compete with other financial institutions?

We document substantial variations in banks' images, which relate to various important characteristics studied in the literature. Notably, banks with higher market shares prioritize service quality and/or life aspiration images over pricing information, leveraging their established presence to attract a broad customer base. The downplay of pricing information helps explain these banks' ability to maintain less favorable rates in the market. This result differs for deposit and loan products. Service quality is highlighted more prominently for deposit product advertisements by banks with high market power, which aligns with d'Avernas et al. (2023), who highlight the superior liquidity services but low deposit rates in the deposit business of large banks. For loan products, trust-building and emotional appeals are more widely adopted by banks with market power.

High-rate banks target rate-sensitive depositors by emphasizing competitive pricing information, while low-rate banks prioritize trust building and emotionally appealing images to retain loyal and sticky customers, reflecting the distinct behaviors of high- and low-rate banks documented in Zhang et al. (2024). Additionally, banks with high service quality, as measured by a low ratio of consumer complaints, highlight their value-added services and trustworthy image in their advertising, distinguishing themselves by targeting customers who value enhanced services and a personalized banking experience (Jiang et al., 2024b; Zhang et al., 2024). This supports an interpretation that financial advertising selectively uses information to persuade customers, and is in line with Gurun et al. (2016), which shows that advertisements for expensive mortgages highlight their low initial/introductory rates while downplaying their high reset rates.

We also find that banks strategically adapt their advertising to 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 operational 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.

We next demonstrate that banks dynamically adjust their image-building focus in response to shocks to their competitive environment, complementing the analyses thus far that exploit cross-sectional differences in banks' characteristics. We adopt an event study design to estimate the impact of four natural experiments: bank entry into new markets, the arrival of FinTech competitors, the Wells Fargo cross-selling scandal, and the Global Financial Crisis (GFC).

We find that banks strategically tailor their images in response to their competitive environment. When entering a new market through branch openings, these organic entrants emphasize pricing advantages to attract rate-sensitive customers, consistent with the previous finding that banks with low local market power tend to focus on pricing as a key competitive strategy. They also simultaneously strengthen trust-building appeals to overcome the entry barrier due to lack of trust (Yang, 2025). In contrast, banks entering the market via mergers and acquisitions inherit an existing customer base and shift their image-building efforts toward service quality to retain customers, aligning with our previous evidence that banks highlight superior service to sustain a high market share. In response to the expansion of FinTech lenders into local markets, incumbent banks increase their service-focused image, underscoring digital convenience and customer service to counter the technological appeal of their FinTech rivals.

Reputational and systemic shocks also trigger adjustments to bank image. Following the 2016 Wells Fargo scandal, a severe adverse shock to trust in the banking sector, Wells Fargo itself increased its reliance on trust-building by nearly 14 percent, a strategic attempt to repair reputational damage. Meanwhile, other banks in affected counties also increased their trust-focused messaging. During the Global Financial Crisis, banks highly exposed to Lehman Brothers reoriented their advertising toward pricing and trust themes, simultaneously reassuring depositors with favorable rates and reinforcing credibility to mitigate the heightened risk of bank runs. Together, these dynamic responses to economic shocks underscore the role of advertising as a valuable tool for banks to seize market share, build and retain customer capital, establish market power, and enhance franchise value.

In the second part of our analysis, we establish the relationship between banks' image-building efforts and the demand for their products and bank value. To address potential endogeneity concerns for a causal interpretation, we implement a border discontinuity design. This strategy leverages the natural geographic discontinuities at the borders of DMAs. Under the identifying assumption that consumers on either side of a DMA border share similar observable characteristics and product choices, variations in exposures to different levels and compositions of advertising due to DMA-specific targeting can help us to identify the effect of advertising (Shapiro, 2018, 2020). Our design effectively compares the outcomes of the same bank across counties separated by DMA borders, which we interpret as the effects of advertising on consumer demand.

Both advertising spending and image significantly influence consumer demand for deposits, mortgages, and small business loans. For example, a ten percent increase in deposit advertising spending corresponds to a 0.9 basis point increase in deposit growth rates. Similar positive effects are observed in mortgage and small business loan origination, with a ten percent increase in advertising leading to a 0.1 percent increase in mortgage origination volume and a 0.07 percent increase in small business loan origination volume.

Importantly, the specific images play a crucial role. Service quality messages prove most effective for deposits, enabling banks to retain depositors and charge higher spreads. In contrast, pricing-focused advertising is associated with contemporaneous decreases in deposit growth and deposit spreads. On the other hand, life aspirations and trust-building emphasis drive loan origination, including mortgage and small business loans.

Finally, we study how banks' images intertwine with monetary policy transmission. In a simple univariate illustration, we show that when interest rates rise, advertisements tend to lean more toward emotional and trust-based appeals, whereas during extended periods of low interest rates, banks emphasize practical financial information. This evolution in content highlights how institutions continually adjust their public image to align with both macroeconomic realities and shift consumer expectations, directly linking banks' image-building efforts to the dynamics of monetary policy.

In a more formal empirical analysis following Drechsler et al. (2017), we study whether these dynamic adjustments affect the transmission of monetary policy by incorporating both advertising expenditures and deposit market concentration into panel regressions. When the Fed funds rate rises, banks that invest heavily in advertising can command larger deposit spreads, consistent with advertising strengthening their deposit franchise and market power. Banks projecting a service-focused image experience even greater increases in deposit spreads, along with larger deposit outflows and sharper balance sheet contraction. These patterns align with the deposit channel of monetary policy, in which stronger market power enables banks to extract higher spreads but also amplifies their exposure to rate hikes.

Collectively, our empirical findings support the notion that financial institutions build their brand images to attract customers, build their deposit franchise, and strengthen market power. Additionally, by actively tailoring advertising styles to specific products and customer preferences, banks can maximize the effectiveness of their financial advertising, thereby reinforcing their competitive position and franchise value.

This paper relates to several strands of literature. This paper relates to an emerging literature studying advertising in financial markets, including studies on advertising mortgages (Gurun et al., 2016; Grundl and Kim, 2019; Kim et al., 2023; Jiang and Kim, 2024), insurance (Shapiro, 2020), credit card (Bertrand et al., 2010), mutual funds (Roussanov et al., 2021; Hastings et al., 2017), and banking (Honka et al., 2017; Célérier and Tak, 2023; Mendes, 2024). This paper extends the body of work by offering a comprehensive examination of advertising styles and images in financial advertising in practice, and by documenting how banks utilize 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.

The paper establishes that banks actively and strategically utilize image-building efforts to generate and sustain value, thereby connecting to the literature that identifies the drivers of bank value and the underlying mechanisms. A key driver of bank value identified in the literature is the franchise value of deposit businesses (Demsetz et al., 1996; Chen et al., 2022; Egan et al., 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 et al., 2017; Minton et al., 2019; Ma and Scheinkman, 2020; Gelman et al., 2023), making franchise value critical not only for individual institutions but also for systemic stability (Drechsler et al., 2024; Haddad et al., 2023; Jiang et al., 2024a; Koont et al., 2024). Additionally, franchise value plays a central role in the transmission of monetary policy and banks' exposure to interest rate risk (Drechsler et al., 2017, 2021) who emphasize the deposit market power channel as measured by deposit market concentration (HHI).

Our study provides 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 draws inspiration from the growing literature on understanding banks' evolving business models and the divergence of heterogeneous banks. Recent studies have focused on the distinction between large and small banks, which differ significantly in their funding structures (Brady and Bassett, 2002; Park and Pennacchi, 2008; Egan et al., 2017) and business strategies (Berger et al., 2005; Cole et al., 2004; Haynes et al., 1999; d'Avernas et al., 2023). Other dimensions of heterogeneity include differences in deposit rates (Iyer et al., 2023; Zhang et al., 2024), the likelihood of bank runs due to uninsured deposits (Egan et al., 2017; Benmelech et al., 2023), capital structure distinctions between traditional banks and shadow banks (Jiang et al., 2020), and variations in deposit and asset productivity (Egan et al., 2022). We add to this literature by offering a novel perspective on how these heterogeneities of banks' characteristics diffuse to consumers through their brand images.

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 DMAs for a variety of media types. We focus on advertisements occurring on national TV and local TV from 2004 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 describe how we process the advertising 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 1 Here.]

Table 1 Panel (a) presents summary statistics and coverage of the advertising data. Our sample contains 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 number of months an advertisement creative is aired is 13 months, with a median of 4 months. Most advertisements are aired on local TV, with 96% of the advertisements being broadcast on local TV and 20% on national TV, with possible overlaps. For advertisements that have at least one airing on respective channels, the average number of airings per advertisement is 1,560 on local TV and 1,340 on national TV. The average spending of an advertisement is 0.20 million USD on local TV and 3.98 million USD on national TV, although the data are less available for this variable. Personal banking and business banking accounts for 24% and 31% of the advertisement, while the personal credit product and mortgage product account for 17% and 8% 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.

2.2. Data on Financial Intermediaries

We link the advertising data to a broad set of widely used financial intermediaries data. These data include the Federal Reserve's bank balance sheet data, the Compustat bank fundamentals 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.

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 2021. 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.[2] We also obtain the deposit betas from Drechsler et al. (2017) and Drechsler et al. (2021), and deposit productivity and asset productivity from Egan et al. (2022).

On the lending side, we obtain U.S. mortgage market data using the HMDA data. HMDA data cover the near universe of U.S. mortgage applications, including both originated and rejected applications. HMDA data contain detailed loan-level information on the borrower, the loan, the property, and the lender. We use the HMDA data to construct measures of mortgage origination amount and local product share in the mortgage market. It is worth noting that these financial institutions may be beyond the banking sector, including non-bank lenders, such as fintech lenders.

We obtain small business lending data from the CRA dataset. Though this data is known to be imperfect, it has been widely used in 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 USD originated by banks with more than $1 billion in assets. Similarly, we use this data to construct the small business

[2] 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.

loan amount and local product share in the small business loan market for each financial institution.

2.3. Sample Construction and Description

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 a fuzzy-matching algorithm based on the financial institution's name. The merged sample contains 1,373 unique bank holding companies with available financial advertising data.

Table 1 Panel (b) presents the summary statistics of the financial intermediaries data at the bank-year level. The average advertising spending per bank, aggregated from Ad Intel, is 6 million USD. Among publicly listed bank holding companies from Compustat, the average amount of advertising expenses is 67 million USD, with a median value of 3 million USD. For comparison, the average non-interest expense from the U.S. Call Report is substantially larger, at 4,759 million USD. Using the data from the FDIC Summary of Deposits, banks in the sample have deposits of 15,048 million USD, provide an average savings APY of 0.62% and a time deposit APY of 1.36%, and exhibit an average deposit Herfindahl-Hirschman Index (HHI) of 0.21. Additionally, the average amount of mortgage originations from HMDA and small business loans from CRA is 2,180 million USD and 911 million USD, respectively.

We also report the summary statistics of bank activities at the bank-county-year level in Table 1 Panel (c). The average deposit amount in a county is 909 million USD, representing 31.98% of the total deposits in the county. The average saving spread and time spread are 0.70% and -0.21%, respectively. The average mortgage originations amount and average business loan amount are 19 million USD and 4.53 million USD per county, respectively, accounting for 7.36% and 9.65% of the total mortgage and business loan amounts in the county.

A natural question arises from the sample construction: Which banks advertise on TV, and more specifically, what banks are included in our sample? While virtually all banks advertise in some form, TV advertising is likely to be widely used by only a subset of banks. In the Internet Appendix (Figure A.1 and Table A.1), we provide further discussion on the sample coverage and describe the types of banks included in our sample. There is some evidence that banks are more likely to use TV advertising when the bank is larger in size, when local market competition is severe (i.e., local market concentration, measured by HHI, is low), and when a bank is in a less favorable position, as indicated by lower ROA and lower market power.

3. Method: Quantifying Banks' Images

In this section, we describe our key methodological contribution, which empirically quantifies banks' images using advertising videos. Our method is rooted in the emerging literature that exploits video as data input (Hu and Ma, 2025; Huang et al., 2023) and studies rich information from three-V dimensions: visual, verbal, and vocal. Compared to these earlier papers, the key novelty of our method is the introduction of an unsupervised video embedding clustering method that can jointly utilize the three-V information channels, and provide robust and efficient data categorization. Our design enhances replicability and is broadly adoptable to a wide range of contexts in which economists need to use video data to categorize information.

3.1. An Unsupervised Video Embedding Clustering Method

The method has two major steps: first, in the data representation stage, we leverage recent advances in multimodal machine learning to generate unified embeddings that represent the rich information; second, in the data clustering stage, we build a robust and efficient statistical method to extract the dimensions of variance most salient in each video, which leads to the formation of different categories. We provide a brief description of our method below, and a more detailed description is provided in the Internet Appendix.

Step 1: High-Dimensional Multimodal Video Embedding We begin by extracting information from advertising videos using a multimodal embedding framework. To do so, we employ `OmniEmbed`, a state-of-the-art open-sourced model built on Alibaba Cloud's `Qwen2.5-Omni-7B`, to generate unified embeddings by jointly processing text, audio, and video inputs. These embeddings are numerical vector representations of the video data.

In practice, we first separate the original audio track and extract representative visual frames from each video. We then extract the text from the advertising videos' soundtracks using the speech-to-text model `Whisper` provided by OpenAI. On average, each video contains 53 words. The transcript, audio tracks, and visual frames are jointly processed by `OmniEmbed`, which generates a 3,584-dimensional embedding for each video.

These embeddings preserve the semantic and contextual content of the advertisements, providing a unified representation that integrates all three information channels into a single vector space. This allows us to capture not only the rich content within the visual, verbal, and vocal dimensions of each advertisement, but also the interdependencies across these channels.

Step 2: Hierarchical Agglomerative Clustering Using Video Embeddings Next, we develop our clustering method using the embeddings generated in the previous step as input. The underlying intuition behind our method is that the most significant variance in the embedding space likely reflects the core and distinctive features in these videos.

The process is as follows. First, to improve efficiency, we apply `PaCMAP`, a state-of-the-art approach in dimension reduction, to project the original 3,584-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 form, ensuring that the reduced representation retains meaningful distinctions.

Second, we use hierarchical agglomerative clustering (HAC) to group the videos based on their projected embeddings, $\tilde{d}_v$. This clustering method constructs a hierarchy of clusters, which allows us to interpret the clusters at multiple levels of granularity. We measure similarity between projected embeddings using Euclidean distance and apply Ward's linkage method, which minimizes the increase in within-cluster variance at each merging step. Since advertisements often contain multiple banks' images, we compute soft cluster memberships by applying a Student's t-distribution kernel that converts distances into probabilities, providing a probability distribution of each video belonging to each cluster.

Third, to facilitate economic interpretation, we label the generated clusters by extracting top keywords from each group. We first generate natural-language descriptions for each video using `Qwen2.5-Omni-7B`, which concisely summaries of the content. We then apply the standard "term frequency-inverse document frequency" (TF-IDF, Loughran and McDonald, 2011), widely used in economics research, to assign each term a weight inversely proportional to the frequency of the term across all documents. Using TF-IDF on standardized descriptions rather than raw transcripts ensures that the labels reflect the distinguishing features while filtering out noise from idiosyncratic word choices and generic banking terms.

Step 3: Quantifying Banks' Images We quantify banks' images using the HAC method developed in step 2. The input embeddings, originally generated in step 1, are further processed in a residualization step before being entered into the HAC. This step has a simple intuition: we absorb variations that could originate from different product categories, and keep only these variations from video content unrelated to products.[3]

Applying the same `PaCMAP` + HAC clustering procedure to the residual embeddings, we uncover bank image themes generated by the method. While there are several ways to categorize them, we group them into three broad banks' images: (1) financial advantage and benefit, (2) service quality, and (3) trust-building, and life aspirations. This classification strikes a balance between the need for a comprehensive understanding of advertising content and the need for a parsimonious set of categories that can be reliably coded.

[Insert Figure 1 Here.]

Figure 1 shows these clustering, and Figure A.2 in the Internet Appendix visualizes more detailed clustering. Table 2 summarizes the broad bank image themes and their detailed subcategories, with the most important keywords for each sub-image. For example, the cluster labeled "financial information" contains three subcategories about interest rate, payment plan, and cashback rewards, characterized by the most important keywords "rate", "payment", and "earning", respectively. The "service quality" cluster includes terms such as "service", "online", "local", and "community", further dividing into local service, online service, and daily convenience.[4]

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 et al., 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 in-

[3]This step uses the product categories generated as a by-product in our algorithm, which we describe in the Internet Appendix A.2.2.

[4]In Table A.3 we show consistencies between our clustering method and alternative ML methods.

termediaries differ, potentially influencing consumer behavior (d'Avernas et al., 2023; Jiang et al., 2024b; Zhang et al., 2024).

Step 4: Aggregate Banks' Overall Images Up to this point, we have quantified the bank image of each advertisement. To connect this measure to empirical analysis, in the final step, we aggregate the video-level measure to create a comprehensive image for bank-related units, such as bank-level, bank-year-level, or bank-county-year level.

We begin by aggregating banks' images for each bank-year. We calculate the embedding representation of each bank's image annually by determining the occurrence-weighted average of the video embeddings for that bank within the same 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 a bank's image for the liability side and the asset side separately by averaging the images of the product advertisements from the respective liability and asset sides. 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

In this section, we offer some examples of outcomes of these methods.[5]

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

> *"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."*

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

[5] We provide more related examples of banks' images in Appendix A.2.4.

"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 bank image is the emotional appeal and trust building. For emotional appeal, we focus on the small business support, home and future, college and education, and sport sponsorship.

"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."

For trust building, we focus on relationship building, including brand promotion and fostering trust in the home and community, as well as professional imagery that showcases expertise and wealth management.

"We are here to talk about the recent changes in the government-insured reverse mortgage program. Making it safer for homeowners. The benefits of a 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, and need a steady income flow each month? Then call my friend"

3.3. Banks' Images: Distribution and Variance Decomposition

Figure 2 shows the distribution of the financial advertising persuasive content by creatives.[6] The most common advertising image is through emotional appeals and trust-building (53%), followed by highlighting the service quality (29%) and information on pricing and financial benefit (18%). The high weight of emotional appeal and trust-building is worth noting.

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

Bertrand et al. (2010) show that concrete information on financial products decreases consumer demand, while content appealing "peripherally" to intuition and emotions significantly increases demand. Our image distribution result suggests that this general principle is widely adopted in financial advertising practice. More specifically, the high weight on trust-building is consistent with Thakor and Merton (2024) and Yang (2025), who theorize and empirically document the importance of establishing trust in bank entry and maintaining lending relationships.

In Internet Appendix Figure A.3, we provide more detailed categorizations of banks' images. Within financial advantages, the percentage of creatives focusing on interest rate is the highest among subcategories (8%), followed by payment plan (6%), and cashback rewards (4%). Within superior service quality, the most common subcategory is local service (14%), while online service and daily convenience account for 8% and 7% of the creatives. Within emotional appeals and trust-building, relationship building accounts for the largest share (23%), and emotional (15%) and professional imagery (15%) are equally important.

[Insert Figure 2 Here.]

In Figure 3, we decompose the variances in the images banks deliver in their advertisements. We do so by using a bank-county-product-year panel and regressing log advertising spending (Panel (a)) or shares of banks' images (Panel (b)) on several sets of fixed effects. To assess the relative importance of each set of fixed effects, we rely on a Shapley-Owen decomposition, which provides a principled way of attributing explanatory power in a regression with multiple, potentially overlapping sources of variation. Intuitively, the procedure considers all possible orderings of introducing the fixed effects into the regression and averages their incremental contributions to the model fit (R^2), ensuring that no set of fixed effects is given undue priority simply because of the order in which it is added. This approach is particularly useful in our setting, where the explanatory factors—such as bank, geography, product, and time—are likely correlated and intertwined.

Figure 3 presents a clear picture of which dimensions account for the bulk of observed differences in banks' advertising content. A key takeaway from the analysis is that bank-related dimensions explain the majority of the variance, suggesting that banks take a strategic decision-making process to build their persistent image. To start with a baseline, we begin with product $\times$ year fixed effects. We find that only around 2% of the advertising variations can be explained by banks using different images for different financial products. Although it is intuitive that different products may require slightly different advertising strategies, this force plays a limited role. We then add county × year fixed effects, increasing R^2 by about 7.4% for advertising spending and 3.6% for banks' images. Such a pattern suggests that differences across local markets, including local market concentration and economic conditions, are not the primary drivers of banks' advertising decisions.

[Insert Figure 3 Here.]

We now focus on time-invariant and time-varying bank heterogeneity (i.e., bank fixed effects, bank × year fixed effects, and bank × county fixed effects). R^2 significantly increases by around 11.7% for spending when we augment bank fixed effects to the regression, and the increase for advertising images is around 5.8%. We further observe even more salient increases in R^2 when time-varying bank fixed effects are added to explain advertising choices—a 26.5% increase for spending and a 31.7% increase for banks' images. 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 and resulting image-building strategy—how they differ from each other in size, business model, product market strategy, and so on. Finally, we consider bank × county fixed effects, which capture the matching between banks and counties. Such a factor explains considerable variations in spending (a 31.3% increase) and in images (a 12.8% increase).

3.4. Demographic Profiles of Actors

We identify the facial attributes of the actors in the advertising video, including their race, gender, age, and emotional expressions. 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 is employed to extract facial embeddings. The `DeepFace` attribute model was utilized to classify facial attributes, including age, gender, and race.

The race classification categories included Asian, White, Middle Eastern, Indian, Latino or Hispanic, and Black. For the purposes of empirical analysis, we consolidated Asian, Middle Eastern, and Indian into a single "Asian" category. 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 in each advertisement.

In the Internet Appendix, we provide extensive analysis to assess the performance of this empirical framework. We compare the racial share of advertisements extracted from our framework with other sources of data (Table A.4). We then manually labeled 400 videos with race and gender information. In the step of aggregating into video-person level information, we apply two filters, including (1) keeping high-quality frames and (2) high-confidence model prediction. For these 400 videos, after these two filters, there are 270 videos with high-quality race and gender information. The performance of our model is reported in Table A.5 and Table A.6.

4. Banks' Image-Building Behaviors

In this section, we analyze the determinants of images that banks convey in their advertising. A key motivation behind our analysis is the development of theories and empirical evidence of heterogeneities in banks' business strategies and operations. Our analysis is thus organized under the guidance of this emerging literature by describing banks' image-building behaviors based on various important characteristics of banks.

These analyses help us understand a central inquiry: how do banks actively and strategically maintain their franchise value, attract customers, and compete with other financial institutions while maintaining their heterogeneous features? Can advertising and image-building strategies, given their economic significance in bank operations (Bertrand et al., 2010; Gurun et al., 2016; Drechsler et al., 2021), serve as a concrete mechanism for this to happen?

4.1. Empirical Setup

We consider a bank-county-year panel, and each observation represents a bank b in county c in year t. The dependent variable is the specific images conveyed in the creative, i.e., price advantage, superior service, or trust building and emotional appeals. This variable captures the relative weight of these image themes in bank b's advertising videos aired in county c in year t. The key independent variables are indicators of bank characteristics, which is also at the b-c-t level, and we denote them as D. We will consider a broad set of bank characteristics D, including bank local market power, as captured by local county-level market shares, deposit rate-setting behaviors, service quality, and local customer demographic characteristics. When applicable, we separately consider advertising strategies for the deposit business (liability side) and the lending business (asset side, including mortgage and business loans).

We estimate the following model:

$$\text{BankImage}_{b,c,t} = \beta \cdot D_{b,c,t-1} + \eta_{c,t} + \epsilon_{b,c,t}, \tag{1}$$

The model includes county-year fixed effects $\eta_{c,t}$, which intend to 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.

4.2. Local Market Power and Bank Images

We first examine how the financial advertising strategies of banks vary with their local market power. We compare banks with top 20 percent quantiles or bottom 80 percent quantiles of market shares in the county in the respective business, i.e., deposits or loans. Deposit shares are calculated as the share of a bank's deposits in a given county-year divided by the total deposits in that county-year. Loan shares are calculated analogously, using mortgage origination data from HMDA or small business loans from CRA.

There are no models we are aware of that provide direct predictions on how market power may shape specific image-building decisions. However, this literature has documented that banks' local market power allows them to enjoy preferred rates, i.e., lower deposit rates and higher loan rates (Drechsler et al., 2017, 2021; Sharpe, 1990; Marquez, 2002; Boyd and De Nicolo, 2005). 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 a certain bank. Image building through advertising can serve as a mechanism for market powers to sustain.

[Insert Table 3 Here.]

Table 3 presents the results on how banks with high vs. low market power advertise. Banks with higher local market shares are less likely to incorporate pricing-related content into their image. This pattern holds for all product categories. For example, in mortgage product advertising, when compared to banks with lower market shares, the images of high-market-share banks have roughly 8.7% (1.257/14.51) lower mentions of pricing advantages from the unconditional mean. The effects are also statistically significant for deposit products and small business loans, but with a smaller magnitude.

On the other hand, banks with higher market shares more heavily stress their service quality and/or incorporate life aspirations and trust-building images. In deposit services, while banks generally highlight their service quality in advertisements with an unconditional mean of 36.16%, we find that high-market-share banks emphasize service quality advertising, with 2.51 percentage points higher weights. This is 6.94% increase 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.

Banks with higher local market shares tend to incorporate more life inspirations and trust-building elements into their images for loan products. These life inspirations include success stories of small businesses obtaining credit or an inspiring lifestyle, such as homeownership. One rationale behind this finding is that banks with higher local market power can better capture increased demand for banking services, thereby incentivizing general borrowing or depositing activities more than those banks that can only capture a smaller share 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 1.54 percentage points more likely to include life inspiration content in their advertisements, a 3.03% increase from the sample mean.

The pattern of image building across market power 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 may lead to consumers having a low sensitivity to pricing.

4.3. 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 use advertising to deceive consumers? This not only helps us better understand the image-building strategies of banks, but also sheds light on the role of advertising in the financial sector. As discussed in Gurun, Matvos, and Seru (2016), a central question in financial advertising is to understand the balance between information provision and deceptive persuasion.

We investigate how financial advertising strategies differ among banks with different pricing and service quality, and examine whether their image-building is consistent with their pricing advantages and service qualities. We first focus on core retail deposit products, including $10,000 12-month CDs, $25,000 money market deposit accounts, and interest checking accounts with less than $2,500, using the data from Ratewatch. These products represent the primary types of retail deposits in banks' core offerings. To incorporate information from all three retail deposit rates, we use a weighted rank method as in Zhang et al. (2024). We first rank all banks based on the three deposit rates in each year and average these ranks. We define high-rate banks as those with average rankings above the 80th percentile within the same county for a specific year, and low-rate banks as those with average rankings below the 80th percentile.

[Insert Table 4 Here.]

Columns (1) to (3) in Table 4 show that high-rate banks tend to emphasize pricing information in their advertising for deposit products, with 3.13 percentage points higher weights than low-rate banks, representing 23% of the unconditional mean of 13.6%. In contrast, low-rate banks are more likely to incorporate either service or trust-building and emotionally appealing images in their advertising. For example, low-rate banks are 2.22 percentage points more likely to include service-related images, equivalent to 6.2% of the unconditional mean.

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 consumer complaints. 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 considered to offer a higher level of service (Egan et al., 2017, 2022).

In columns (4) to (6) of Table 4, we show that high-service-quality banks are significantly more likely to emphasize service quality images. Banks with lower complaints place 2.45 percentage points more weight on service quality in their advertising, representing 6.7% of the unconditional mean. This supports the idea that banks with higher service quality target customers who value enhanced services and a 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.[7]

Interestingly, in both analyses, 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 emphasize these advantages and downplay less substantial components.

Collectively, this table illustrates a nuanced advertising strategy employed by banks. On the one hand, they provide truthful information when they have an edge, which could potentially lead consumers to make better decisions. On the other hand, they strategically downplay their weaknesses, failing to provide a balanced view to consumers. Meanwhile, they also emphasize less substantial dimensions when they lack advantages in pricing and service. This supports the deceptive persuasion view of financial advertising.

4.4. Advertising and Customer Demographics

Our analysis so far indicates that banks 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.

[7] In Table A.7 in the Internet Appendix, we measure service quality using the branch network following Egan et al. (2017) and Zhang et al. (2024), and find similar results.

We analyze how the racial profiles of the actors in advertising videos vary according to the demographic characteristics of the counties in which banks operate. Our analysis examines the differences in actor racial profiles of advertisements from the same bank, but across counties with varying shares of minority populations. The minority population is categorized based on whether a county has an above- or below-80th percentile ranking for the Black or African American, Hispanic, and Asian populations in the same bank's respective business. The choice of the 80th percentile is based on the fact that the top 20 percent of counties roughly account for half of the African American, Hispanic, and Asian populations. The key set of controls for identification is the bank-year fixed effects, which absorb all time-varying differences between banks, allowing for comparisons within the same bank across counties.

[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 representations of Black, Hispanic, and Asian actors in deposit-related advertising are higher when the county has a larger population in the respective racial group. The economic magnitudes are not particularly large, partially due to our restrictive empirical setup that only exploits within-bank-year variations. Given the constraints on running multiple advertisements, the room for reaction is limited.

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.

4.5. Banks' Strategic Image-Building After Economic Shocks

In the preceding sections, we explore cross-sectional variations in bank images and document how banks' images relate to important dimensions of bank heterogeneity. This section shifts the focus to the dynamics of bank images, examining how banks strategically adjust their image-building efforts in response to time-series variations captured by a broad set of economic shocks. Specifically, we use a bank (b)–county (c)–year (t) panel to study how bank images change after banks' entry into local markets, FinTech's entry into local markets, the

Wells Fargo cross-selling scandal in 2016, and the Global Financial Crisis. Our analyses reveal how image-building serves as a strategic response mechanism to changes in banks' competitive environment.

4.5.1. Bank Entry Into Local Markets. We begin by investigating market entry, an ideal setting to examine image-building dynamics in response to market competition, and its role in helping banks to accumulate customer capital (Gourio and Rudanko, 2014; He et al., 2024) and seize market share (Argente et al., 2025).

We estimate the following specification to examine how banks strategically adjust their images when entering new markets, either by new branch opening or bank M&A.[8]

$$\text{BankImage}_{b,c,t} = \beta \cdot \text{Post(Entry)}_{b,c,t} + \eta_b + \eta_{c,t} + \epsilon_{b,c,t}, \tag{2}$$

where $\text{Post(Entry)}_{b,c,t}$ is a dummy variable that takes the value of 1 if year t falls within the three-year window after bank b's entry into county c, and the value of 0 otherwise. Bank fixed effects η_b absorb bank time-invariant heterogeneity. County-year fixed effects $\eta_{c,t}$ absorb local economic shocks. Panel (a) of Table 6 presents the results.

[Insert Table 6 Here.]

Entry Through New Branch. For entry through branch expansion in columns (1)-(3), entering banks highlight pricing and emotion/trust significantly more, relative to incumbent banks in the same county. Intuitively, entrants emphasize their pricing advantages, such as high deposit rates and low mortgage rates, to accumulate the initial customer base. This is also consistent with Table 3—since the market power is low by nature after organic entry, pricing advantages become prominent in the image-building effort. Moreover, the increase in the emotion/trust image is consistent with the literature, arguing that trust can be an important entry barrier that entrants need to overcome (Thakor and Merton, 2024; Yang, 2025). As a result, banks put more effort into obtaining customers' trust when crafting their images in a previously unserved market.

[8] Data of bank M&A is downloaded from https://www.ffiec.gov/npw/FinancialReport/DataDownload.

Entry Through M&A. However, banks use different image-building strategies when they enter a county through acquiring branches of other banks, which own established customer bases. The results are presented in columns (4)-(6) of Panel (a) of Table 6. In a three-year window after a market entry via M&A, banks significantly increase the proportion of "service" theme in their image building. In terms of magnitude, the "service" theme rises by 7.83 percentage points, a 21 percent increase relative to the sample mean of 36.61 percentage points. Such an estimate aligns with our previous finding in Table 3, which documents that banks with an established market share highlight their superior service quality to retain existing customers. This strategy is also consistent with Erel (2011), who notes that merged banks can leverage increased operating efficiency to enhance higher service supply.

4.5.2. FinTech Entry Into Local Markets. Next, after studying banks' own entry activities, we investigate how traditional banks respond when FinTech lenders enter their local markets. FinTech entrants—often specializing in online mortgage or small business lending—pose a disruptive threat to traditional banks, which plausibly exogenously affects banks' competitive environment (Buchak et al., 2018; Gopal and Schnabl, 2022; Koont, 2023; Jiang et al., 2024b). To estimate the effects of FinTech entry on bank images, we estimate the following within-bank specification.

$$\text{BankImage}_{b,c,t} = \beta \cdot \text{Post(FinTech Entry)}_{c,t} + \eta_c + \eta_{b,t} + \epsilon_{b,c,t}, \tag{3}$$

$\text{Post(FinTech Entry)}_{c,t}$ is a dummy variable that takes the value of 1 if year t falls within the three-year window post the FinTech's entry into county c, and the value of 0 otherwise. We consider the set of FinTech-classified lenders following Fuster et al. (2019). We add county fixed effects η_c and bank-year fixed effects $\eta_{b,t}$, which control for regional time invariant heterogeneity and the bank's lending opportunities. As such, we compare image-building across branches of the same banks but in different counties that may or may not be affected by FinTech entry.

Panel (b) of Table 6 shows that incumbent banks respond to FinTech shocks by increasing the share of advertising devoted to service quality, such as digital and mobile banking and customer service. This shift suggests that banks perceive FinTech competition as primarily a challenge in providing better service such as quick approval and online operation, and their image building mirrors this by emphasizing tangible and verifiable service improvement rather than soft emotional appeals.

4.5.3. Wells Fargo Scandal. We now implement an event-study analysis on the 2016 Wells Fargo scandal outbreak. While the previous shocks concern market competition and market power, the Wells Fargo scandal serves as a negative shock to customers' trust in the banking sector. The Wells Fargo cross-selling scandal stemmed from the bank's creation of millions of unauthorized savings and checking accounts in customers' names, without their consent or knowledge, driven by aggressive internal sales targets. This event triggered widespread consumer skepticism toward traditional banks and prompted a reputational crisis for Wells Fargo specifically. Although most of the fraudulent behaviors dated back to as early as 2005, the revelation of this fraud is sudden and unexpected, and is also not correlated with any banking industry shock (Yang, 2025).

We first focus on a sample of Wells Fargo only and examine how Wells Fargo's image-building (or more specifically, image-recovery) strategies change after the scandal. Since there is only one bank (i.e., Wells Fargo) in this sample, the panel collapses to the county (c)-year(t) level. We use the specification below to estimate the effect of the scandal on Wells Fargo's image.

$$\text{BankImage}_{c,t} = \beta \cdot \text{Post(Scandal)}_t + \eta_c + \epsilon_{c,t}, \tag{4}$$

where $\text{BankImage}_{c,t}$ is Wells Fargo's image distribution in county c in year t. Post(Scandal)_t is a dummy variable that takes the value of 1 if year t falls within the five-year window from 2016 to 2020, and the value of 0 otherwise. η_c are county fixed effects to absorb time-invariant local market heterogeneity.

[Insert Table 7 Here.]

Columns (1)–(3) in Panel (a) of Table 7 present the results. After the scandal outbreak in 2016, Wells Fargo sharply increased trust-building and emotionally appealing content by 7.7 percentage points, a 14 percent increase relative to the sample mean of 53.37 percentage points. This pattern resonates with anecdotal evidence covered in news articles[9]. Wells Fargo launched several TV advertising campaigns to mitigate the adverse impact of the scandal. One of the campaigns was named "Re-Established" and included narratives such as "it's

[9]For example, https://www.latimes.com/business/la-fi-wells-fargo-ad-campaign-20180509-story.html

a new day at Wells Fargo." Obviously, Wells Fargo strategically responds to this negative shock to its trust level by shifting its image-building focus towards trust building. As such, crafting images in advertising can serve as an important tool for banks to maintain their customer capital, mitigate adverse shocks, and potentially enhance their value.

Moreover, we explore potential spillover effects on the images of other banks operating in counties where Wells Fargo had at least one operating branch. We estimate the specification below on a sample excluding Wells Fargo.

$$\text{BankImage}_{b,c,t} = \beta \cdot \text{Post(Scandal)}_t \times 1(\text{Wells Fargo Presence})_c + \eta_c + \eta_{b,t} + \epsilon_{b,c,t}, \tag{5}$$

where $\text{BankImage}_{b,c,t}$ is bank b's image distribution in county c in year t. Post(Scandal)_t is a dummy variable that takes the value of 1 if the year t falls within the five-year window from 2016 to 2020, and the value of 0 otherwise. $1(\text{Wells Fargo Presence})_c$ is a dummy variable which takes the value of 1 if county c has at least one Wells Fargo branch in 2016 or the value of 0 otherwise. η_c are county fixed effects. $\eta_{b,t}$ are bank-year fixed effects. By including the set of bank-year fixed effects, we are comparing image-building effort across branches of the same bank, but in different counties, with or without Wells Fargo's physical presence.

Columns (4)–(6) in Panel (a) of Table 7 present the results. These banks operating in the counties with Wells Fargo presence also increase their use of trust-building messaging, but to a lesser extent than Wells Fargo itself. This result implies that shocks to the level of trust and competitive environment can affect not only the focal bank but also competitors operating in the same region.

4.5.4. Financial Crisis. Finally, we study how macro shocks such as the Global Financial Crisis (GFC) alter bank images. Using GFC exposure measure from Chodorow-Reich (2014), we define the treatment group of banks as those cosyndicated with Lehman Brothers more prior to the crisis. We estimate the specification below and compare the image building by these "treated" banks relative to other banks operating in the same county.

$$\text{BankImage}_{b,c,t} = \beta \cdot \text{Post(GFC)}_t \times 1(\text{Lehman Cosyndication})_b + \eta_b + \eta_{c,t} + \epsilon_{b,c,t}. \tag{6}$$

Post(GFC)_t is a dummy variable that takes the value of 1 if the year t falls within the five-year window from 2007 to 2011, and the value of 0 otherwise. $1(\text{Lehman Cosyndication})_b$

is a dummy variable that takes the value of 1 if bank b has a high (i.e., above median) fraction of cosyndication loans where Lehman Brothers had a lead role, following Ivashina and Scharfstein (2010) and Chodorow-Reich (2014), and the value of 0 otherwise. As in Chodorow-Reich (2014), we focus on the 43 most active banks in the syndicated market for this analysis, resulting in a sample size of 31 banks for the final merged dataset.

Panel (b) of Table 7 shows the results. Banks more exposed to Lehman Brothers lean into providing pricing information and building trust. Intuitively, banks highlight pricing advantages as the shock likely weakens their market power. Banks also utilize the trust and emotion theme more in their advertising to counteract the rising distrust in the banking system, both during and after the financial crisis. This may help these banks mitigate the possibility of bank runs.

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

Do banks' image-building efforts have real impacts? In this section, we show that bank advertising spending and advertising styles have a significant impact on the demand for various financial products, including deposits, mortgages, and small business loans. To establish a causal interpretation, we implement a border discontinuity design (Shapiro, 2018, 2020), which leverages the discontinuities in local advertising at DMA borders, generated by the local TV market delineation. We then implement a bank-level analysis, linking bank images to bank value, deposit spreads, and market power. Finally, we employ a design at the bank-county-year level, similar to the one in Drechsler et al. (2017). We document how banks with heterogeneous images respond differently to monetary policy shocks and demonstrate how our results provide a potential mechanism for understanding banks' market power and the transmission of monetary policy.

5.1. 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. Our main empirical specification establishes the causal relationship between image-building via financial advertising and demand for financial products using a border discontinuity design, following the economics and marketing literature (Shapiro, 2018, 2020)

The design exploits the exogenous variation from geography discontinuities at the borders of DMA markets by leveraging the discrete nature of local television markets. The intuition is that consumers who live on opposite sides of DMA borders face different levels of advertising due to market factors elsewhere in their DMA. However, they share similar observable characteristics and product choice sets—an important identifying assumption. In our border discontinuity design, we control 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 4 Here.]

To illustrate, Figure 4 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. In our design, we effectively compare how demand for financial products provided by the same bank on the Pittsburgh and Johnstown-Altoona sides of the border changes when the two sides receive different advertising exposure from 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 the following specifications:

$$Y_{b,c,t} = \beta \cdot \text{AdSpend or BankImage}_{b,c,t} + \eta_{b,c} + \eta_{b,d(c),t} + \epsilon_{b,c,d(c),t}, \tag{7}$$

where $Y_{b,c,t}$ is a set of 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. Independent variables of interest can either be the advertising expenses or the bank images. $\ln(\text{Ad})_{b,c,t}$ 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. When examining differential effects of different bank images on demand for financial products, we replace the advertising variable with two measures of bank images, including pricing information $1(\text{Pricing})_{b,c,t}$ and service quality $1(\text{Service})_{b,c,t}$, effectively omitting emotional appeal and trust building $1(\text{Emotion/Trust})_{b,c,t}$ which is used as the benchmark category.

A set of fixed effects is included in the design to narrow down the variations used to identify our results. $\eta_{b,c}$ 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 counties within a border group.

The analysis uses 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.

5.2. Impacts of Bank Advertising

Table 8 presents the results of the border discontinuity design. Panel (a) shows how deposit advertising affects deposit outcomes. Column (1) reveals a strong 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 mean of 3.75 percentage points. Column (3) indicates 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 and market power.

Columns (2) and (4) focus on the impact of different bank images. Banks emphasizing service quality in their images attract 1.3 percentage points more depositors, accounting for 35% (0.0131/0.0375) of the deposit growth rate. Similarly, service-oriented banks can enjoy strong market power by charging higher spreads, with a coefficient of 1.9 percentage points. The magnitude is sizable given the unconditional mean deposit spread of -0.72 percentage points. Meanwhile, banks that highlight pricing information in their images are associated with contemporaneous decreases in deposit growth rates and deposit spreads. 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.

[Insert Table 8 Here.]

Panel (b) of Table 8 shows how loan advertising affects mortgage and small business loan origination. Columns (1) and (3) show that mortgage advertising has a significant positive effect on the dollar amount of mortgage origination and small business loan origination. Quantitatively, a one percent rise in mortgage advertising spending corresponds to a 0.01% increase in mortgage origination. As for small business loans, a one percent rise in advertising spending corresponds to a 0.007% increase in mortgage origination. Columns (2) and (4) demonstrate that banks that build emotional connection and trust with their customers (the omitted category) through their image attract higher origination on mortgage and small business loans. This result is consistent with previous evidence in Table 3.

5.3. Bank Images and Bank Value: Bank-level Analysis

Next, we build upon our detailed micro-county-level identified results and extend the analysis to the bank level. Admittedly, the analysis will be less well-identified. However, this analysis presents an opportunity to connect advertising intensity and bank images to several important dimensions of bank value that have been extensively studied in the literature but are only available at the bank level. These include bank deposit and asset productivity (Egan et al., 2022), bank market power (Drechsler et al., 2017, 2021, 2024), and franchise value (Demsetz et al., 1996).

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

$$Y_{b,t} = \beta \cdot \text{AdSpend or BankImage}_{b,t-1} + \gamma X_{b,t-1} + \eta_t + \epsilon_{b,t}, \tag{8}$$

where $Y_{b,t}$ is a set of bank value measures such as productivity, deposit spread, and Tobin's q of bank b in quarter t. $\text{AdSpend}_{b,t-1}$ is the advertising expense from Compustat scaled by total non-interest expense from Call Reports in quarter $t-1$; $\text{BankImage}_{b,t-1}$ is the bank image distribution over different images: pricing, service, emotion/trust. Since these three measures sum up to 100% by definition, we omit the emotion/trust category to avoid colinearity. As a result, estimated coefficients on pricing and service should be interpreted as relative magnitudes compared to emotion/trust. $X_{b,t-1}$ 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 et al. (2023) and Egan et al. (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. This specification leverages the cross-sectional variation of banks, as some measures, such as bank productivity, are inherently cross-sectional in nature. To mitigate the reverse causality interpretation, we lag all advertising measures (e.g., AdSpend and BankImage) for one period, relative to the dependent variables.

[Insert Table 9 Here.]

Panel (a) of Table 9 displays the results on advertising spending. Columns (1) and (2) show that banks with higher advertising expenses tend to have higher deposit and asset productivity, as measured in Egan et al. (2022). This 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 diverse demographics, establish trust, and differentiate themselves from competitors.

Columns (3) to (5) indicate that financial advertising is positively correlated with the bank deposit power and franchise value. Following Drechsler et al. (2017) and Drechsler et al. (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, greater deposit market power. In terms of magnitude, a one percentage point increase in advertising expense is associated with a 7 basis point increase in deposit spread, whose mean value is 45 basis points.

Our second measure of deposit market power is deposit beta, which is the sensitivity of a 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 et al., 2021). Column (4) shows an insignificant relationship between advertising and deposit beta. This pattern suggests that the variation in bank deposit market power can stem from multiple sources, including branches, salaries, and technology, and cannot be fully attributed to advertising alone.

In column (5), we follow Demsetz et al. (1996) to use banks' Tobin's q as a proxy for banks' franchise value. We find a significant positive correlation between banks' Tobin's q and advertising spending. Consistent with the findings on banks' deposit power in the market, effort in crafting images through advertising positively contributes to banks' franchise value.

We now turn to study the impacts of bank images in Panel (b) of Table 9. Column (1) indicates that banks highlighting their pricing advantages in advertising tend to have higher productivity in collecting deposits. This finding is consistent with Egan et al. (2022), which emphasizes rate setting and pricing technologies as an important source of variation in bank productivity. Similarly, column (2) shows a significantly positive relationship between banks' asset productivity and their image-building effort in emotion and trust, as indicated by negative coefficients on the pricing and service categories. Such an empirical pattern confirms our previous finding in Table 3 (i.e., columns (6) and (9)), that banks crafting an "emotion and trust" image are more efficient in making loans and thus have higher asset productivity. This finding is also consistent with Thakor and Merton (2024), which demonstrates that borrowers' trust is crucial for banks to maintain their business advantages in lending, but it is challenging to gain.

Columns (3) to (5) study bank market power and franchise value. Notably, Column (3) shows that banks that emphasize service tend to have higher deposit spreads and thus market power, which aligns with our previous evidence in column (2) of Table 3 and Table 4. Column (4) shows that banks focusing on pricing information in advertising have higher deposit betas. Therefore, these "pricing banks" are more sensitive to changes in interest rates and have lower market power. Such a result, again, confirms our previous finding in Table 4. Finally, the coefficients in column (5) are insignificant, suggesting that the choice of image-building themes by itself does not translate into measurable differences in 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 deposit market power, and higher franchise value. 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 the 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 illustrate the importance of this linkage, we first present the aggregate time series dynamics of bank images in relation to monetary policy cycles in Figure 5, with the NBER-dated recessions being shaded.

[Insert Figure 5 Here.]

Shifts in the Federal Funds rate coincide with adjustments in the images banks emphasize. During periods of rising interest rates, banks tend to shift their focus from 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, a time of persistently low interest rates, banks more prominently emphasized financial information. These patterns suggest that banks strategically adapt their advertising strategies and tailor their public image to align with changing economic conditions and consumer sensitivities.

To test this relation more formally, following Drechsler et al. (2017), we estimate the following within-county specification on the same bank holding company (b)-county (c)-year (t) panel as in Section 4.5:

$$
\begin{aligned}
Y_{b,c,t} = & \beta^{\mathrm{Ad}}\text{AdSpend or BankImage}_{b,c,t-1} + \gamma^{\mathrm{Ad}}\Delta\mathrm{FF}_t \times \text{AdSpend or BankImage}_{b,c,t-1} \\
& + \beta^{\mathrm{HHI}}\text{Deposit-HHI}_{b,t-1} + \gamma^{\mathrm{HHI}}\Delta\mathrm{FF}_t \times \text{Deposit-HHI}_{b,t-1} + \eta_{b,c} + \eta_{c,t} + \epsilon_{b,c,t},
\end{aligned} \tag{9}
$$

where $Y_{b,c,t}$ includes the change in deposit spread, growth rate of deposits, and mortgage and small business loan origination for bank b at quarter t. $\text{AdSpend}_{b,c,t-1}$ and $\text{BankImage}_{b,c,t-1}$ are lagged log values of advertising spending and images of bank b in county c in year $t-1$. $\Delta\mathrm{FF}_t$ is the contemporaneous change in the Fed funds rate at t. $\text{Deposit-HHI}_{b,t-1}$ is the lagged bank-level deposit concentration for bank b in year $t-1$. $\eta_{b,c}$ and $\eta_{c,t}$ are bank-county and county-year fixed effects, respectively. . We cluster standard errors at the county 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 $Y_{b,c,t}$. To isolate the effect of financial advertising from deposit market concentration studied by Drechsler et al. (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$_{b,t-1}$. We implement a within-county estimation strategy by including the county-year fixed effects ($\eta_{c,t}$), a key set of controls that absorb changes in local deposit demands and lending opportunities. Effectively, we are comparing the outcomes of different banks operating in the same county and in the same year, but with differential levels of advertising intensity and choices of image-building focus. We also include the bank-county fixed effects ($\eta_{b,c}$) to absorb time-invariant characteristics that is specific to banks' local presence, such as local brand effects.

[Insert Table 10 Here.]

Panel (a) in Table 10 presents the results on advertising spending, for bank liabilities (including the growth rate of deposits and change in deposit spread) and for bank assets (including mortgage and small business loan origination). On the liability side, column (1) shows that banks with higher advertising spending are able to charge higher deposit spreads when the Fed funds rate rises. At the same time, as column (2) indicates, banks that advertise more intensively experience larger deposit outflows. This is consistent with the prediction by the deposits channel of monetary policy (Drechsler et al., 2017), that banks with high market power experience larger increases in deposit spreads and greater deposit outflows during a Fed funds rate hike. On the asset side, columns (3) and (4) show that both mortgage and small business loan lending decline as the Fed funds rate rises. Here, as deposits are a special source of funding for banks, banks face a trade-off between maximizing profits from deposits and financing a large balance sheet. The combination of the findings from both the liability side and the asset side further supports the deposits channel.

Panel (b) in Table 10 documents differential responses to monetary policy by banks with heterogeneous images. For example, banks that highlight service exhibit larger effects through 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 that focus on emotion and trust in their images, as indicated in column (1). Correspondingly, there are larger contraction effects on the balance sheet of these "service banks"—columns (2)–(4) present a larger decline in deposit flow, mortgage, and small business lending, when the Fed funds rate increases. Such a result is consistent with the finding in Table 9 Panel (b) column (3)—banks emphasizing service in their images have higher deposit spreads and thus higher deposit market power.

The results in Table 10 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 (Drechsler et al., 2021). Banks exploit this market power by charging higher deposit spreads when the Fed funds rate rises. Consistent with the prediction of the 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 underscore the economic significance of financial advertising and motivate our empirical study of advertising as one key dimension of bank heterogeneity.

6. Conclusion

We leverage novel advertising video data and apply new empirical methods to study how banks actively use advertising to build their images, align with their operational strengths, market positions, and the demographics of target customers. These image-building efforts have significant impacts on the demand for a bank's financial products and franchise value, and the mechanism interacts with the transmission of monetary policy.

This paper is deeply connected to the banking literature, which has extensively examined bank heterogeneity and drivers of bank value. We view our study as an exploration of the operational mechanisms supporting the observed features documented in the literature. Our results essentially indicate that image-building through advertising serves as a concrete mechanism behind the equilibrium heterogeneities among banks, behind the sustainability of local market power, and behind the dynamic evolution of the banking business model.

There are several paths worth exploring based on our research findings and empirical methods, as this paper leaves many questions unanswered. For example, 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.

Perhaps most importantly, as emphasized by Bertrand et al. (2010), who pioneered financial advertising research using a field experiment, existing theories in economics and psychology offer little guidance on which advertisement content dimensions matter and through what consumer decision-making processes. We face similar challenges in our empirical work. Nonetheless, our evidence highlights concrete dimensions worth incorporating into future theoretical frameworks—particularly the categories of bank images and the distinct roles of advertising for deposit versus loan products.

Finally, from a methodological perspective, this paper contributes to the emerging literature on the use of video data in finance and economics research. A central challenge in this domain is to identify and adapt methods from data science and computer science that are suitable for economic applications. We present evidence that unsupervised video embedding clustering can robustly and efficiently encode video content, extending beyond prior work such as Hu and Ma (2025), which primarily focused on constructing measurements from individual content channels. This approach holds promise for a range of applications, including encoding political ideologies from news media, extracting managerial forecasts from interviews and calls, and classifying products from television commercials.

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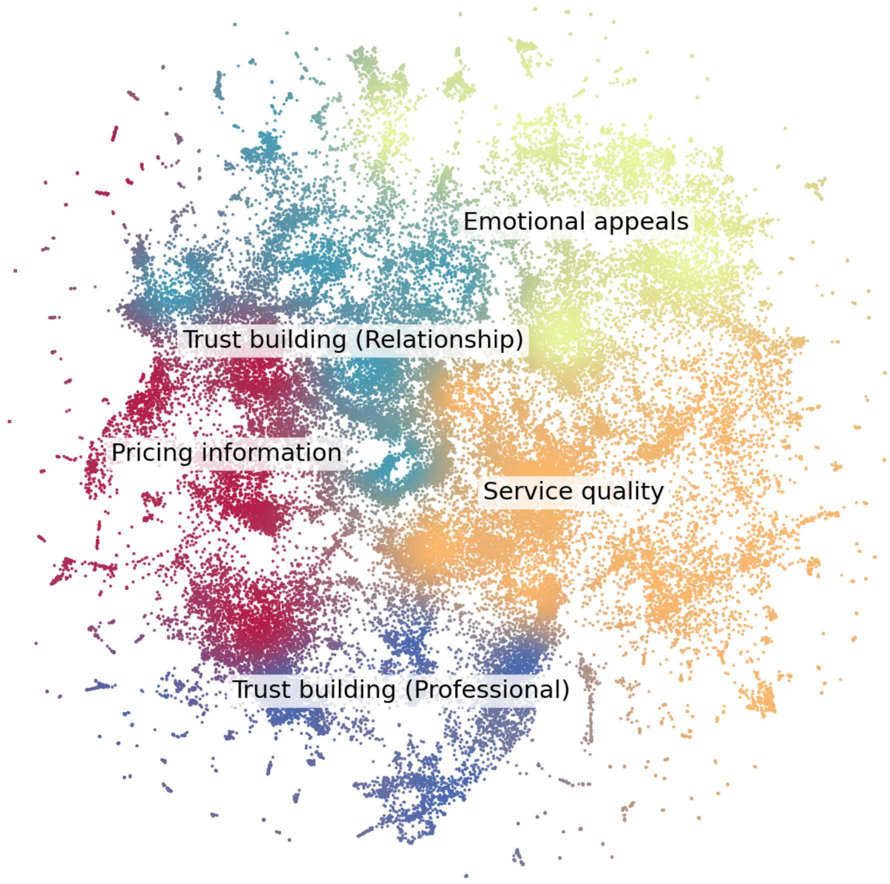
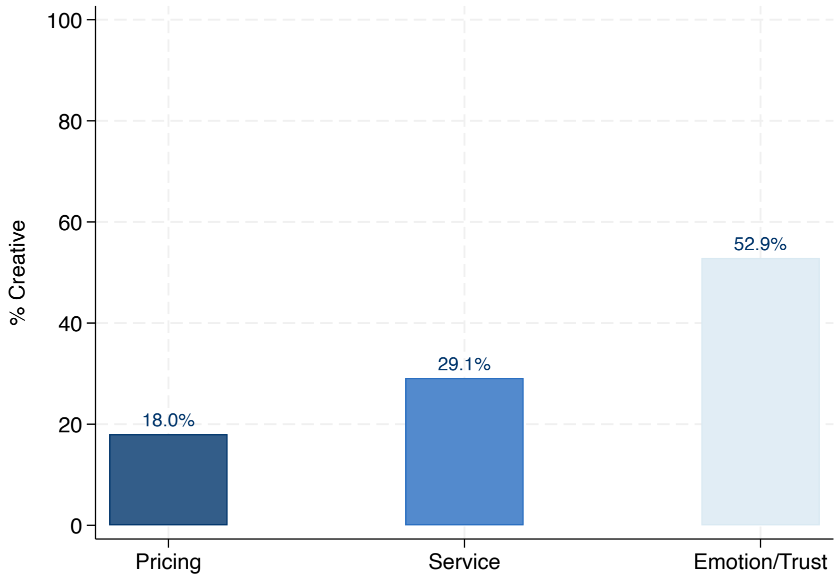
Figure 1. Visualization of the Video Embeddings and Clustered Banks' Images



Notes. This figure shows the visualization of the 2-dimensional video embedding for banks' images, as described in Section 3.1. It contains three broad banks' images, including financial information, service quality, and trust-building and life aspirations (including relationship building, professional imagery, and emotional appeal).

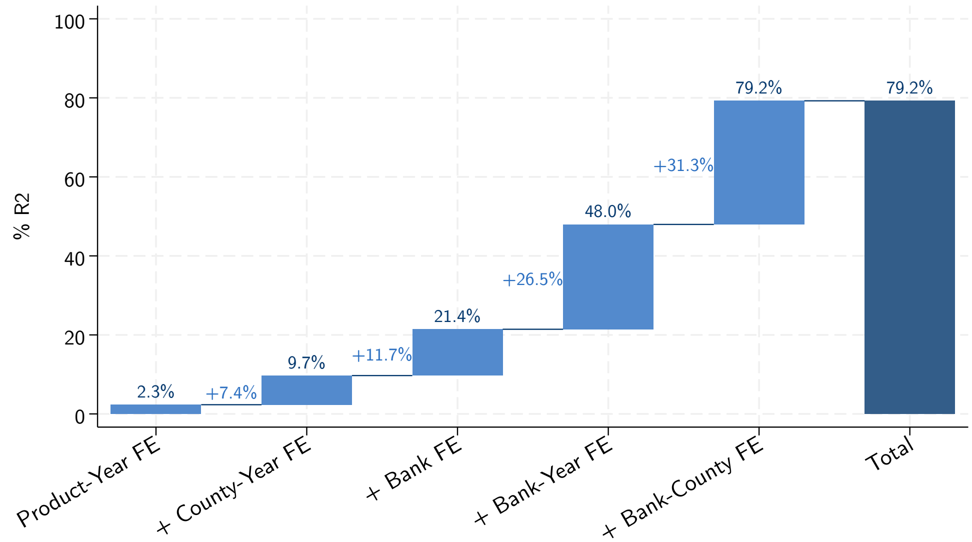
Figure 2. Distribution of Banks' Images



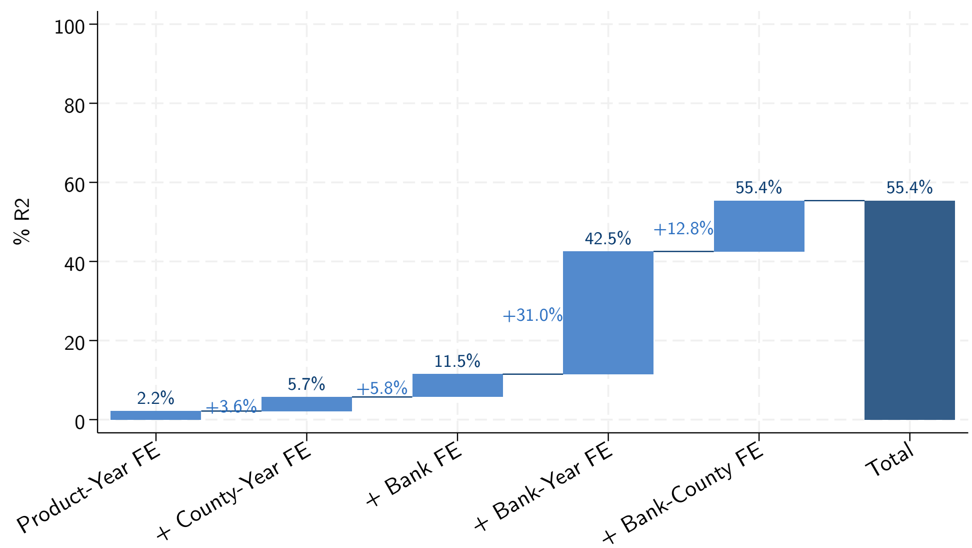
Notes. This figure shows the distribution of broad banks' images for financial advertising. It contains three broad banks' images, including financial information, service quality, and trust-building and life aspirations.

Figure 3. Decomposing Variations of Advertising Spending and Banks' Images

Panel (a): Advertising Spending

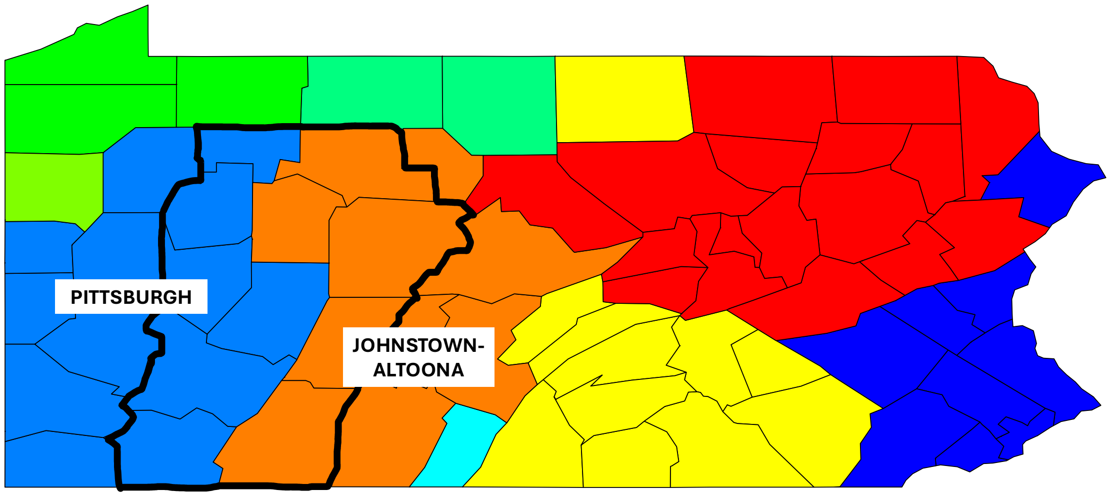


Panel (b): Banks' Images



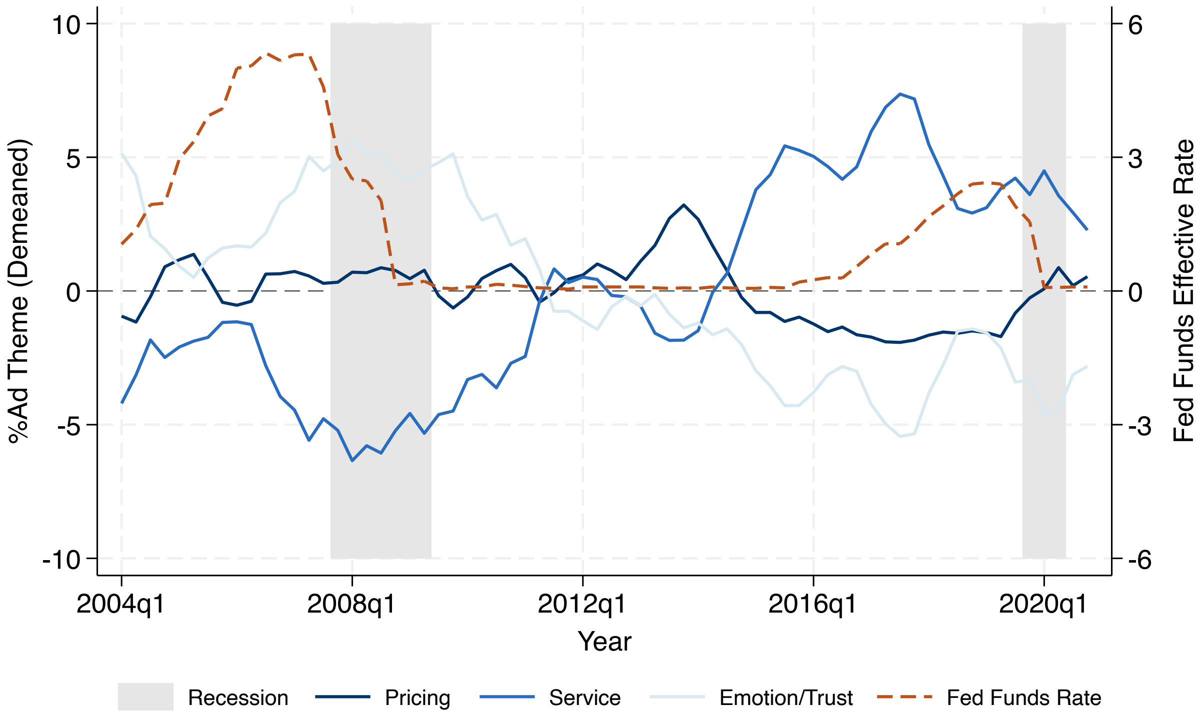
Notes. This figure shows the percentages of variations for advertising spending and banks' images can be explained by different specifications of fixed effects in Panel (a) and Panel (b), respectively. We implement a Shapley-Owen decomposition on a bank-county-product-year panel. We consider the following set of fixed effects: product-year fixed effects, county-year fixed effects, bank fixed effects, bank-year fixed effects, and bank-county fixed effects.

Figure 4. 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 (7).

Figure 5. Banks' Images and Monetary Policy



Notes. This figure plots the distribution of bank images in financial advertising alongside the Fed Funds rate over time. It contains three broad banks' images, including financial information in dark blue line, service quality in medium blue line, and trust-building and life aspirations in light blue line. The Fed Funds rate is in orange dashed line. The NBER dated-recessions are shaded. The distribution of banks' images is demeaned by the time-series average.

Table 1. Summary Statistics

	count	mean	sd	min	p25	p50	p75	max
Panel (a): Creative Level								
Duration	51,349	27.40	13.88	1	15	30	30	141
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	30	256	1,118	197,505
Total Spending (MM), Local TV	49,262	0.20	2.13	0.00	0.00	0.01	0.04	377.65
Total Spending (MM), National TV	10,525	3.98	12.98	0.00	0.06	0.63	3.23	476.27
Category: Personal Banking	50,910	24.16	41.84	0.00	0.00	0.00	22.66	100.00
Category: Business Banking	50,910	30.53	45.57	0.00	0.00	0.00	99.97	100.00
Category: Personal Credit	50,910	8.00	26.65	0.00	0.00	0.00	0.00	100.00
Category: Mortgage	50,910	17.08	37.12	0.00	0.00	0.00	0.00	100.00
Category: Investment/Retirement	50,910	20.23	39.88	0.00	0.00	0.00	0.00	100.00
Panel (b): Bank-Year Level								
Advertising Spending (MM, Ad Intel)	6,625	5.83	39.74	0.00	0.01	0.04	0.16	734.77
Advertising Spending (MM, Compustat)	1,944	67.14	311.54	0.00	0.90	3.18	10.28	3,579.00
Non-Interest Expense (MM)	3,767	4,758.59	19,904.81	1.85	68.48	182.30	740.66	203,461.55
Deposits (MM)	6,569	15,048.44	92,022.53	0.00	270.93	692.91	2,546.90	1,718,968.13
Mortgage Amount (MM)	5,998	2,180.74	14,202.02	0.00	26.44	96.87	396.72	332,987.09
Business Loan Amount (MM)	2,984	911.14	2,865.80	0.00	69.13	154.99	448.98	40,389.83
CFPB Complaints per MM Deposits	6,568	0.02	0.11	0.00	0.00	0.00	0.00	5.48
Saving APY (%)	4,807	0.62	0.74	0.01	0.14	0.29	0.89	5.04
Time APY (%)	4,903	1.36	1.36	0.03	0.31	0.66	2.26	5.36
Deposit HHI	6,568	0.21	0.10	0.05	0.14	0.19	0.24	0.96
Deposit Beta	5,924	0.40	0.11	0.02	0.34	0.39	0.44	1.45
Deposit Productivity	1,287	0.49	1.03	-1.69	-0.29	0.36	1.24	2.90
Asset Productivity	1,287	0.26	1.05	-11.72	-0.19	0.26	0.74	4.21
Tobin's q	1,739	1.18	0.37	0.40	0.97	1.12	1.32	6.59
Panel (c): Bank-County-Year Level								
Deposits (MM)	94,238	909.85	7,728.93	0.00	43.95	105.16	323.01	626,247.20
Deposits Share (%)	94,229	31.98	30.14	0.00	8.57	22.10	45.30	100.00
Saving Spread (%)	62,763	0.70	1.26	-2.09	0.01	0.10	0.95	4.92
Time Spread (%)	64,651	-0.21	0.83	-3.62	-0.43	0.01	0.20	1.20
Mortgage Amount (MM)	515,639	19.21	163.98	0.00	0.13	0.74	4.62	25,389.18
Mortgage Amount Share (%)	515,052	7.36	11.82	0.00	0.34	2.69	9.08	100.00
Business Loan Amount (MM)	468,278	4.53	27.39	0.00	0.06	0.27	1.38	3,040.95
Business Loan Amount Share (%)	468,265	9.65	14.05	0.00	1.32	4.22	11.55	100.00

Notes. This table presents summary statistics for creative-level data in Panel (a), bank-year level data in Panel (b), and bank-county-year level data in Panel (c). 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 five categories, including Personal Banking, Business Banking, Personal Credit, Mortgage, Investment/Retirement, 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. Advertising Spending (Ad Intel) is the amount expenses on advertising aggregated from Ad Intel dataset. Advertising Spending (Compustat) is the total amount expenses on advertising (Compustat item `xadq`) for the sample of publicly listed U.S. bank holding companies from Compustat. Non-interest Expense is the expense amount unrelated to interest from the U.S. Call Reports. Deposits is the amount of deposits from FDIC Summary of Deposits. Mortgage Amount is the total amount of mortgage loans originated from HMDA. Business Loan Amount is the total amount of business loans issued from CRA. CFPB Complaints per MM deposits is the number of complaints received from CFPB Consumer Complaint Database divided by the amount of deposits. Saving APY and Time APY is the average APY for savings and time deposit account, respectively. 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. Deposit Beta is obtained from Drechsler et al. (2017) and Drechsler et al. (2021). Deposit Productivity and Asset Productivity are obtained from Egan et al. (2022). Tobin's q is the market value of assets divided by the book value of assets, computed from Compustat. Panel (c) contains a bank holding company-county-year panel. Deposits Share, Mortgage Amount Share, and Business Loan Amount Share are banks' market share of deposits, mortgage loans, and business loans in the county, respectively. Saving Spread and Time Spread are the difference between the Fed Funds Rate and the average APY for savings and time deposit account, respectively.

Table 2. Categories of Banks' Images

Broad Images	Intermediate Images	Detailed Images	Related Keywords
Financial information	Interest rate	Rate & payment	rate, low, fixed, APR, payment, monthly payment
		Loan rate	rate, loan, refinance, mortgage rate, lowest
	Payment plan	Monthly payment	deposit, pay, monthly payment, fixed, low
		Loan payment	free, loan, credit, payment, income
	Cashback rewards	Account offer	free, account, rate, APY, earn, minimum balance
		Cashback rewards	earning, cash, refund, checking account
Service quality	Local service	Local service	local, community, relationship, client, team
		Customer service	customer, community bank, service, banker
		Branch service	branch, building, location, state bank, ATM
	Online service	Mobile banking	mobile, mobile banking, online, easier
		Conversational service	conversation, talk, customer, explain, representative
		Credit report	credit, score, free credit, checking credit
	Daily convenience	Eash transfer	app, send money, pay, mobile, wallet, easy
		Everyday transactions	card, ATM, store, debit card, purchase, traveling
Emotional appeal and trust building	Emotional appeals	Small business support	small business, build, grow, dream, success
		Home & future	life, home, family, moment, help, future
		College & education	college, child, education, school, plan, kid, student
		Game & sport sponsorship	game, player, team, fan, golf, basketball
		Sport sponsorship	player, sport, football, golf, basketball
	Relationship building	Investment & stock market	trade, stock, ETF, risk, fund investment, investing
		Brand promotion	trust, bank logo, member FDIC, national bank, news
		Home & community trust	home, community, dream, life, help, car, people
		Credit improvement	credit score, bad credit, financial, reward, cashback
		Family trust	family, picture, baby, kid, trust, Christmas
		Patriotism trust	veteran, new day, USA, military, hero, American
	Professional imagery	Advisory trust	firm, financial, advice, trust, planning, guidance
		Professional expertise	tax, income, money, market, strategy, social security
		Commodity market	gold, silver, capital, coin, metal, investment
		Retirement financial	senior, older, retirement, tax free, homeowner
		Wealth management	financial, planning, client, wealth, advisor, goal

Notes. This table shows the categories of banks' images and their associated keywords obtained from our unsupervised video embedding clustering method. The classification is organized hierarchically into three levels, including broad images, intermediate images, and detailed images. In the last column Related Keywords, we also report a list of representative words with the highest average TF-IDF scores for each detailed image. More details can be found in Section 3.1.

Table 3. Bank Images by Local Market Shares

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Product Market	SOD Deposit			HMDA Mortgage			CRA Loan		
Ad Category	Deposit			Mortgage			Loan		
% $\text{BankImage}_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
Large $(\text{Market Share})_{b,c,t-1}$	-0.412***	2.506***	-2.095***	-1.257***	-0.286***	1.542***	-0.293***	-0.284***	0.577***
	(0.072)	(0.117)	(0.097)	(0.037)	(0.062)	(0.059)	(0.052)	(0.095)	(0.079)
Observations	922,811	922,811	922,811	706,796	706,796	706,796	520,831	520,831	520,831
R-squared	0.054	0.068	0.068	0.064	0.067	0.067	0.075	0.087	0.096
No. of Institutions	937	937	937	721	721	721	425	425	425
Mean of Y	13.44	36.16	50.40	14.51	34.60	50.89	13.72	36.72	49.56
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). % $\text{BankImage}_{b,c,t}$ is the share of bank images for that specific product used by bank b in county c in year t. Large $(\text{Market Share})_{b,c,t-1}$ is a dummy variable for whether bank b is above the 80 percent quantiles of 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. Bank Images by High- and Low-Rate and Service Quality Banks

	(1)	(2)	(3)	(4)	(5)	(6)
Ad Category	Deposit			Deposit		
% $\text{BankImage}_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
High Deposit $\text{Rate}_{b,c,t-1}$	3.129***	-2.219***	-0.910***			
	(0.039)	(0.070)	(0.054)			
High Service $\text{Quality}_{b,c,t-1}$				-0.488***	2.448***	-1.960***
				(0.081)	(0.169)	(0.141)
Observations	665,019	665,019	665,019	987,169	987,169	987,169
R-squared	0.078	0.073	0.078	0.053	0.059	0.060
No. of Institutions	922	922	922	1,120	1,120	1,120
Mean of Y	13.63	35.98	50.38	13.30	36.41	50.28
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. % $\text{BankImage}_{b,c,t}$ is the share of images of bank b in county c in year t. In Columns (1)-(3), High Deposit $\text{Rate}_{b,c,t-1}$ is a dummy variable for whether bank b is above the 80 percent quantiles of deposit rate rankings among all the banks in the county c in year $t-1$. We rank banks based on the interest rate of time deposit (i.e., $10,000 12-month CDs), saving deposit (i.e., $25,000 money market deposit accounts), and checking deposit (i.e., interest checking accounts with less than $2,500) in each year, and then average these ranks as the overall deposit rate ranking for the bank in a given year. In Columns (4)-(6), High Service $\text{Quality}_{b,c,t-1}$ is a dummy variable for whether bank b is above the 80 percent quantiles of service quality among all the banks in the county c in year $t-1$. We measure service quality using number of CFPB consumer complaints scaled by deposits for the banks in a given year 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. Bank Images 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)$_{b,c,t-1}$	0.129***			0.082**		
	(0.040)			(0.041)		
Large (County w/ % Hispanic)$_{b,c,t-1}$		0.102***			0.117***	
		(0.010)			(0.011)	
Large (County w/ % Asian)$_{b,c,t-1}$			0.108***			0.121***
			(0.017)			(0.019)
Observations	775,701	775,701	775,701	642,864	642,864	642,864
R-squared	0.843	0.900	0.883	0.840	0.775	0.859
No. of Institutions	911	911	911	825	825	825
Mean of Y	17.58	1.628	6.236	18.82	0.912	5.558
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 After Economic Shocks: Bank and FinTech Entry

Panel (a): Bank Entry Into Local Markets

	(1)	(2)	(3)	(4)	(5)	(6)
Ad Category		All			All	
% BankImage$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
Post(Branch Entry)$_{b,c,t}$	0.318***	−0.801***	0.484***			
	(0.079)	(0.138)	(0.117)			
Post(M&A Entry)$_{b,c,t}$				−6.799***	7.833***	−1.034
				(0.538)	(1.002)	(0.767)
Observations	2,786,104	2,786,104	2,786,104	2,786,104	2,786,104	2,786,104
R-squared	0.209	0.226	0.204	0.209	0.226	0.204
No. of Institutions	2,401	2,401	2,401	2,401	2,401	2,401
Mean of Y	13.97	36.61	49.41	13.97	36.61	49.41
Bank FE	Y	Y	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y	Y	Y

Panel (b): Incumbent Responses to FinTech Entry

	(1)	(2)	(3)
Ad Category		All	
% BankImage$_{b,c,t}$	Pricing	Service	Emotion/Trust
Post(Fintech Entry)$_{c,t}$	−0.544***	0.615***	−0.071
	(0.052)	(0.094)	(0.079)
Observations	2,786,104	2,786,104	2,786,104
R-squared	0.477	0.480	0.449
No. of Institutions	2,401	2,401	2,401
Mean of Y	13.97	36.61	49.41
County FE	Y	Y	Y
Bank-Year FE	Y	Y	Y

Notes. This table examines how bank image building responds to bank and FinTech entry into local markets, using a bank(b)-county(c)-year(t) panel. Panel (a) reports effects of bank's entry into local markets, through opening a new branch in Columns (1)-(3) or M&A in Columns (4)-(6). Post(Branch Entry)$_{b,c,t}$ and Post(M&A Entry)$_{b,c,t}$ are dummy variables for whether year t falls within the three-year window post bank b's entry into county c through opening a new branch and through M&A, respectively. Panel (b) reports effects of FinTech's entry into local markets, where Post(FinTech Entry)$_{c,t}$ is a dummy variable for whether the year t falls within the three-year window post the FinTech's entry into county c. Fixed effects are denoted at the bottom. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Bank Images After Economic Shocks: Scandal and Financial Crisis

Panel (a): Wells Fargo Scandal

	(1)	(2)	(3)	(4)	(5)	(6)
Ad Category	All			All		
% BankImage$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
Post(Scandal)$_t$	−2.781***	−4.915***	7.697***			
	(0.102)	(0.159)	(0.188)			
Post(Scandal)$_t$				−0.079***	−0.055	0.133***
×1(Wells Fargo Presence)$_c$				(0.027)	(0.047)	(0.044)
Sample	Wells Fargo	Wells Fargo	Wells Fargo	Other Banks	Other Banks	Other Banks
Observations	55,612	55,612	55,612	2,730,492	2,730,492	2,730,492
R-squared	0.067	0.046	0.059	0.483	0.485	0.452
No. of Institutions	1	1	1	2,400	2,400	2,400
Mean of Y	12.77	33.86	53.37	14	36.67	49.33
County FE	Y	Y	Y	Y	Y	Y
Bank-Year FE	N	N	N	Y	Y	Y

Panel (b): Financial Crisis

	(1)	(2)	(3)
Ad Category	All		
% BankImage$_{b,c,t}$	Pricing	Service	Emotion/Trust
Post(GFC)$_t$	1.680***	−5.236***	3.556***
×1(Lehman Cosyndication)$_b$	(0.069)	(0.136)	(0.117)
Observations	502,925	502,925	502,925
R-squared	0.194	0.163	0.150
No. of Institutions	31	31	31
Mean of Y	12.95	37.94	49.11
Bank FE	Y	Y	Y
County-Year FE	Y	Y	Y

Notes. This table examines how bank image building responds to bank scandal and financial crisis, using a bank(b)-county(c)-year(t) panel. Panel (a) reports effects of Wells Fargo scandal in 2016. Columns (1)–(3) focus on Wells Fargo itself and Columns (4)–(6) examine all other banks excluding Wells Fargo. Post(Scandal)$_t$ is a dummy variable for whether year t falls in the range of 2016 to 2020. 1(Wells Fargo Presence)$_c$ is a dummy variable for whether county c has at least one Wells Fargo branch in 2016. Panel (b) reports effects of the Global Financial Crisis (GFC). Post(GFC)$_t$ is a dummy variable for whether year t falls in the range of 2007 to 2011. 1(Lehman Cosyndication)$_b$ is a dummy variable for whether bank b had an above-median share of cosyndication loans where Lehman Brothers had a lead role, following Chodorow-Reich (2014). Fixed effects are denoted at the bottom. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Bank Images and Demand for Financial Products: Border Discontinuity Design

Panel (a): Deposits

	(1)	(2)	(3)	(4)
Ad Category	Deposit		Deposit	
$Y_{b,c,t}$	Δ ln(Deposits)		Δ(Deposit Spread)	
$\ln(\text{Ad})_{b,c,t}$	0.0009**		0.0017***	
	(0.0004)		(0.0006)	
$1(\text{Pricing})_{b,c,t}$		−0.0190		−0.1706***
		(0.0139)		(0.0220)
$1(\text{Service})_{b,c,t}$		0.0131*		0.0194**
		(0.0080)		(0.0087)
$1(\text{Emotion/Trust})_{b,c,t}$	Omitted			
Observations	48,709	48,709	48,709	48,709
R-squared	0.284	0.356	0.954	0.954
No. of Institutions	352	352	352	352
Mean of Y	0.0375	0.0375	-0.0072	-0.0072
Bank-County FE	Y	Y	Y	Y
Bank-Border-Year FE	Y	Y	Y	Y

Panel (b): Loans

	(1)	(2)	(3)	(4)
Ad Category	Mortgage		Loan	
$Y_{b,c,t}$	ln(Mortgage)		ln(Small Business Loan)	
$\ln(\text{Ad})_{b,c,t}$	0.010**		0.007***	
	(0.004)		(0.001)	
$1(\text{Pricing})_{b,c,t}$		−0.847***		−0.067**
		(0.099)		(0.028)
$1(\text{Service})_{b,c,t}$		−0.810***		−0.018
		(0.060)		(0.017)
$1(\text{Emotion/Trust})_{b,c,t}$	Omitted			
Observations	335,171	335,171	401,296	401,296
R-squared	0.680	0.681	0.784	0.784
No. of Institutions	930	930	418	418
Mean of Y	11.64	11.64	12.35	12.35
Bank-County FE	Y	Y	Y	Y
Bank-Border-Year FE	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 Δ ln(Deposits) in Columns (1)-(2) of Panel (a), changes in the deposit spread Δ(Deposit Spread) in Columns (3)-(4) of Panel (a), the log amount of new mortgage origination ln(Mortgage) in Columns (1)-(2) of Panel (b), and the log amount of new small business loan origination ln(Small Business Loan) from CRA in Columns (3)-(4) 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. We use product-specific advertising spending, namely spending on deposits in Columns (1)-(4) of Panel (a), spending on mortgages in Columns (1)-(2) of Panel (b), and spending on business loans in Columns (3)-(4) of Panel (b). In Columns (2) and (4) of each panel, we include the measures 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 model includes 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 9. Bank Images and Bank Value

Panel (a): Advertising Spending

	(1)	(2)	(3)	(4)	(5)
$Y_{b,t}$	Deposit TFP	Asset TFP	Deposit Spread	Deposit Beta	Tobin's q
$\text{Ad}_{b,t-1}$	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
Year FE	Y	Y	Y	Y	Y

Panel (b): Bank Images

	(1)	(2)	(3)	(4)	(5)
Ad Category	Deposit	Asset	Deposit	Deposit	All
$Y_{b,t}$	Deposit TFP	Asset TFP	Deposit Spread	Deposit Beta	Tobin's q
$1(\text{Pricing})_{b,t-1}$	0.389**	−0.903***	0.035	0.018**	0.041
	(0.181)	(0.266)	(0.098)	(0.009)	(0.056)
$1(\text{Service})_{b,t-1}$	−0.168	−0.445***	0.101*	0.005	−0.012
	(0.108)	(0.163)	(0.058)	(0.005)	(0.023)
$1(\text{Emotion/Trust})_{b,t-1}$	Omitted				
Observations	2,638	2,638	8,053	9,348	6,239
R-squared	0.930	0.214	0.509	0.148	0.345
No. of Institutions	165	165	537	810	325
Mean of Y	0.793	0.528	0.169	0.408	1.157
Bank Controls	Y	Y	Y	Y	Y
Year 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 Advertising and Marketing Expenses (Compustat item `xadq`). The outcome variables are bank deposit productivity (Deposit TFP) and asset productivity (Asset TFP) in Columns (1)-(2) from Egan et al. (2022), deposit spread and deposit beta in Columns (3)-(4) from Drechsler et al. (2021), and Tobin's q. In Panel (a), $\text{Ad}_{b,t-1}$ is Compustat advertising expense scaled by Call Reports total non-interest expense for bank b in quarter $t-1$. In Panel (b), we include the measures 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 $1(\text{Emotion/Trust})_{b,t-1}$. The model includes 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 et al. (2023) and Egan et al. (2022). Standard errors are clustered at the bank level with a wild cluster bootstrap procedure (1000 times). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Bank Images and Monetary Policy Transmission

Panel (a): Advertising Spending

	(1)	(2)	(3)	(4)
$Y_{b,c,t}$	Δ(Deposit Spread)	$\Delta\,\ln$(Deposits)	ln(Mortgage)	ln(Small Business Loan)
$\ln(\text{Ad})_{b,c,t-1}$	0.0004	0.0001	0.0064***	0.0009
	(0.0004)	(0.0002)	(0.0018)	(0.0008)
$\Delta\text{FF}_t \times \ln(\text{Ad})_{b,c,t-1}$	0.0086***	−0.0002*	−0.0077***	−0.0042***
	(0.0007)	(0.0001)	(0.0012)	(0.0007)
Observations	51,516	86,829	684,850	485,658
R-squared	0.915	0.491	0.643	0.830
No. of Institutions	603	809	1,019	351
Mean of Y	0.140	0.0567	11.89	12.48
$\text{HHI}_{b,t-1}$ and $\Delta\text{FF}_t \times \text{HHI}_{b,t-1}$	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Bank-County FE	Y	Y	Y	Y

Panel (b): Bank Images

	(1)	(2)	(3)	(4)
Ad Category	Deposit			
$Y_{b,c,t}$	Δ(Deposit Spread)	$\Delta\,\ln$(Deposits)	ln(Mortgage)	ln(Small Business Loan)
$1(\text{Pricing})_{b,c,t-1}$	−0.0544***	0.0020	−0.1071**	0.2939***
	(0.0128)	(0.0039)	(0.0479)	(0.0182)
$1(\text{Service})_{b,c,t-1}$	0.0411***	0.0078***	−0.3597***	0.1268***
	(0.0060)	(0.0025)	(0.0293)	(0.0101)
$\Delta\text{FF}_t \times 1(\text{Pricing})_{b,c,t-1}$	0.0753***	0.0078**	−0.2371***	−0.1610***
	(0.0250)	(0.0038)	(0.0449)	(0.0193)
$\Delta\text{FF}_t \times 1(\text{Service})_{b,c,t-1}$	0.0991***	−0.0088***	−0.3645***	−0.0660***
	(0.0106)	(0.0023)	(0.0241)	(0.0102)
$1(\text{Emotion/Trust})_{b,c,t-1}$ and $\Delta\text{FF}_t \times 1(\text{Emotion/Trust})_{b,c,t-1}$ Omitted				
Observations	51,516	86,829	684,850	485,658
R-squared	0.915	0.492	0.643	0.830
No. of Institutions	603	809	1,019	351
Mean of Y	0.140	0.0567	11.89	12.48
$\text{HHI}_{b,t-1}$ and $\Delta\text{FF}_t \times \text{HHI}_{b,t-1}$	Y	Y	Y	Y
County-Year FE	Y	Y	Y	Y
Bank-County FE	Y	Y	Y	Y

Notes. This table examines the relationship between bank images and the transmission of monetary policy in a bank(b)-county(c)-year(t) panel. Panel (a) includes $\ln(\text{Ad})_{b,c,t-1}$, the lagged log advertising spending for bank b in county$c$ in year $t-1$. Panel (b) includes the lagged measures of bank images for bank b in county$c$ in year $t-1$, such as pricing information $1(\text{Pricing})_{b,c,t-1}$ and service quality $1(\text{Service})_{b,c,t-1}$, omitting emotional appeal and trust building $1(\text{Emotion/Trust})_{b,c,t-1}$. ΔFF_t is the contemporaneous change in the Fed funds rate. Following Drechsler et al. (2017), we control for bank-level Deposit-$\text{HHI}_{b,t-1}$ and its interaction term $\Delta\text{FF}_t \times \text{HHI}_{b,t-1}$. Bank-level Deposit-$\text{HHI}_{b,t-1}$ is calculated as the deposit-weighted average of the county-level HHI across all the counties where the bank b operates in year $t-1$. The model includes county-year fixed effects and bank-county fixed effects. Standard errors are clustered at the county level. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix (For Online Publication Only)

A.1. Additional Results

A.1.1. Additional Sample Descriptions

This appendix provides additional descriptions of our sample of financial advertisements.

Figure A.1 shows that bank commercials have relatively short life cycles, and banks use different commercials in different DMAs. Panel (a) of Figure A.1 shows the distribution of air months for each creative video. 48% of creative videos were only shown on TV for less than three months. The median and average air months of financial commercials is four and fourteen months, respectively. This is robust for the sample of standard thirty-second commercials, both banks and non-banks, and different types of banks (such as those with different sizes, deposit rates, and HHIs). Panel (b) of Figure A.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 A.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.

Table A.1 investigates which banks select into running advertising campaigns, and thus enter our sample of analysis. We use a bank(b)-quarter(t) sample of all the publicly listed U.S. bank holding companies at the quarterly frequency. The selection variable $1(\text{Advertising})_{b,t}$ is defined as whether bank b has non-missing and positive Compustat item Advertising and Marketing Expenses (`xadq`) in quarter t. We then use a comprehensive set of lagged bank characteristics to explain banks' selection into advertising, controlling for quarter fixed effects η_t. Therefore, our design exploits cross-sectional variations across banks to explain the sample selection. The explanatory variables are lagged one period and include log total assets, Z-Score (the bank's ROA plus its equity ratio divided by its standard deviation of ROA), ROA, Tobin's q, deposit spread, deposit and asset productivity from Egan et al.

(2022), and the bank's deposit and mortgage market concentration HHI, calculated as the volume-weighted average of the county-level HHI across all the counties where the bank operates.

The results indicate that there is no single variable that can consistently explain banks' decision to advertise, except for the deposit market HHI, whose coefficient is significantly negative. One potential interpretation is that when a bank faces more intense competition in the deposit market, as indicated by low market concentration and HHI, it chooses to run advertisements to attract customers and capture market share. There is some weaker evidence that larger banks are more likely to use advertising campaigns. ROA and Tobin's q seem to have negative correlations with the selection, suggesting that slightly weaker banks are more likely to use TV advertising campaigns, although the statistical significance is fragile. Deposit spread has a negative correlation with the selection, suggesting that banks with lower market power are more active in TV advertising.

A.1.2. Additional Results on Banks' Images

Figure A.2 and Figure A.3 provide detailed cluster visualization and distributions of banks' images. Banks may use different images for different products because they have different target customers and different marketing strategies. Figure A.4 shows the image distribution across product categories. Table A.2 studies the transition probability of a bank's images from one year to the next. The high probability of staying within the same image category (as indicated by the large diagonal terms in the transition matrix) suggests that banks often adhere to a fixed image-building strategy in consecutive years.

A.2. Appendix on Method

This appendix provides additional details of our method and presents additional analysis to validate the method and show its robustness.

A.2.1. Technical Details on the Unsupervised Video Embedding Method

A.2.1.1. Representation of Video Using High-Dimensional Multimodal Embedding. The foundation of our method is the construction of video embeddings that capture the rich multimodal content of advertisements. For this purpose, we employ `OmniEmbed`,[10] a state-of-the-art open-source model built on Alibaba Cloud's `Qwen2.5-Omni-7B`. `OmniEmbed` generates unified embeddings by jointly processing text, audio, images, and video inputs. This allows us to capture not only the rich content within the visual, verbal, and vocal dimensions of each advertisement, but also the interdependencies across these channels.

In practice, we first separate the original audio track and extract representative visual frames from the video using `moviepy`.[11] We then apply the open-sourced speech-to-text model `Whisper`[12] provided by OpenAI to convert the audio track into text. Since some advertisements are in non-English languages, we translate the transcripts into English using the Google Translate API through deep-translator.[13] The transcript, audio features, and visual frames are then provided simultaneously to `OmniEmbed`, which outputs a single 3,584-dimensional embedding for each advertisement.

A.2.1.2. Dimension Reduction Using `PaCMAP`. The raw video embeddings generated by `OmniEmbed` are 3,584-dimensional vectors, which are too high-dimensional for direct visualization or intuitive interpretation. To address this, we apply Pairwise Controlled Manifold Approximation Projection (`PaCMAP`),[14] a state-of-the-art nonlinear dimension reduction algorithm, to project these embeddings into a two-dimensional space. `PaCMAP` is designed to preserve both global and local structures of the data, meaning that points that are similar in

[10] https://huggingface.co/Tevatron/OmniEmbed-v0.1
[11] https://github.com/Zulko/moviepy
[12] https://github.com/openai/whisper
[13] https://github.com/nidhaloff/deep-translator
[14] https://github.com/YingfanWang/PaCMAP

the original high-dimensional space remain close in the reduced space, while broader clusters of dissimilar points are also kept well separated.

There are three key parameters in `PaCMAP`. The number of nearest neighbors, `n_neighbors`, controls the extent to which local structure is preserved by defining how many close neighbors are considered when constructing the low-dimensional representation. The ratio of the number of mid-near pairs to the number of neighbors, `MN_ratio`, adjusts the weight given to moderately close points, thereby helping to balance local and global geometry. The ratio of the number of further pairs to the number of neighbors, `FP_ratio`, determines the weight given to distant points, ensuring that broad cluster structures are maintained. In identifying the product categories, we set `n_neighbors` to 10, `MN_ratio` to 5, and `FP_ratio` to 20. In identifying the image themes, we set `n_neighbors` to 10, `MN_ratio` to 10, and `FP_ratio` to 10. These parameters were chosen to optimize visualization clarity, and our framework and results are robust to alternative parameter choices.

By default, the `PaCMAP` algorithm applies a Principal Component Analysis (PCA) preprocessing step, reducing the original embeddings to 100 dimensions before applying the manifold learning procedure. This step substantially accelerates computation while retaining nearly all relevant information from the high-dimensional data.

A.2.1.3. Unsupervised Clustering Using Hierarchical Agglomerative Clustering. We next apply hierarchical agglomerative clustering (`HAC`) to the two-dimensional embeddings produced by `PaCMAP`. `HAC` is a bottom-up clustering method that recursively merges pairs of clusters based on a chosen linkage criterion. In our case, we use Euclidean distance together with Ward's linkage method, which minimizes the increase in within-cluster variance at each step. This combination is widely used in the clustering literature and is particularly effective for producing compact, interpretable clusters.

A key advantage of `HAC` is that it naturally generates a hierarchy of clusters. This structure enables us to "cut" the tree at different levels, yielding clusterings of varying granularity. In our analysis, we cut the tree at the level of 30 clusters to obtain the most detailed product categories and image themes. We then move to higher levels of the hierarchy to recover more aggregated clusters, which correspond to broader product categories and banks' images.

While HAC provides only hard cluster assignments, advertisements may naturally overlap in images (e.g., an advertisement can simultaneously emphasize pricing information and service quality). To account for this, we compute a soft assignment between each embedding and the cluster centroids. Following the soft clustering literature, we use the Student's t-distribution as a kernel to measure the probability of assigning embedding $\tilde{d}_v$ to cluster $\tilde{\mu}_j$:

$$\Pr(v \in j) = \frac{\left(1 + ||\tilde{d}_v - \tilde{\mu}_j||^2/\alpha\right)^{-\frac{\alpha+1}{2}}}{\sum_{j'} \left(1 + ||\tilde{d}_v - \tilde{\mu}_{j'}||^2/\alpha\right)^{-\frac{\alpha+1}{2}}},$$

where α is the degrees of freedom of the Student's t-distribution. We use $\alpha = 0.5$ to compute the soft assignment, and our results are robust to alternative choices of α. The resulting soft assignment can be interpreted as the probability of each video belonging to each cluster.

A.2.1.4. Interpretation of Clusters Using Generative Description and TF-IDF. To systematically interpret the clusters, we generate natural-language descriptions of each advertisement using `Qwen2.5-Omni-7B`, a state-of-the-art multimodal generative model. Each full video is provided to the model, including its transcript, audio track, and visual frames. We then prompt the model with the following instruction:

> *"Combining all the materials (including text, audio, and video) from the advertisement of financial products from a financial firm, describe this advertisement."*

The model outputs a concise description that summarizes the advertisement's content in a standardized format. These generated descriptions provide consistency across ads, reduce noise from idiosyncratic transcripts or incidental details, and create a comparable text corpus for interpretation.

We next apply the term frequency-inverse document frequency (TFIDF, Loughran and McDonald, 2011) method to the set of descriptions. Each video is represented as a TF-IDF vector, and the average of the TF-IDF vectors for all videos within it represents each cluster. The words with the highest average TF-IDF scores within each cluster serve as interpretable labels, highlighting the distinguishing features of each cluster.

A.2.2. Product Categorizations

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 helpful 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 is likely very different from a general banking service advertisement.

Our clustering method identifies five primary product categories: personal deposits, business banking, personal credit (including credit card, auto loan, and veteran finance), mortgages, investment and retirement services. These categories are well separated in the embedding space, as shown in Panel (a) of Figure A.5. A more granular level of clusters, shown in Panel (b) of Figure A.5, reveals thirty subcategories. For example, the personal credit category contains three sub-products, including credit card, auto loan, and veteran finance. 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 "money", while the "mortgage" cluster includes top keywords like "mortgage", "home", and "loan".

A.2.3. Cross-Validation Using LLM

Cross-Validating Product Categories Using LLM We use a large language model (LLM) to identify the product categories by submitting the extracted transcript text to ChatGPT. Specifically, we ask ChatGPT to classify the text into one of the following categories: banking services, business loans, personal credit, mortgage and real estate, investment and brokerage, retirement financial services, and insurance. To ensure the reliability of GPTis response, we fixed the random seed and set the temperature to 0, making 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.3, 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, 70.8% are also categorized as personal deposit by LLM. Intuitively, the two methods should be very similar, as both are based on the exact text that has been extracted. This further validates the robustness of our results in extracting advertising categories.

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 and the transcript of the advertisement, and in response, GPT generates a string of text containing the probability distribution of the list of categories in Table 2. In Panel (b) of Table A.3, we show that image categorization extracted from the LLM is highly consistent with the clustering method.

A.2.4. More Examples of Banks' Images

In this subsection, we provide additional examples of how financial institutions shape their public image.

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

> *"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."*
>
> *"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 local and community service, online and mobile applications, and daily convenience.

> *"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."*

Example of Emotional Appeal and Trust Building Our last broad banks' images is the emotional appeal and trust building. For emotional appeal, we focus on the small business support, home and future, college and education, and sport sponsorship.

> *"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."*

> *"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."*

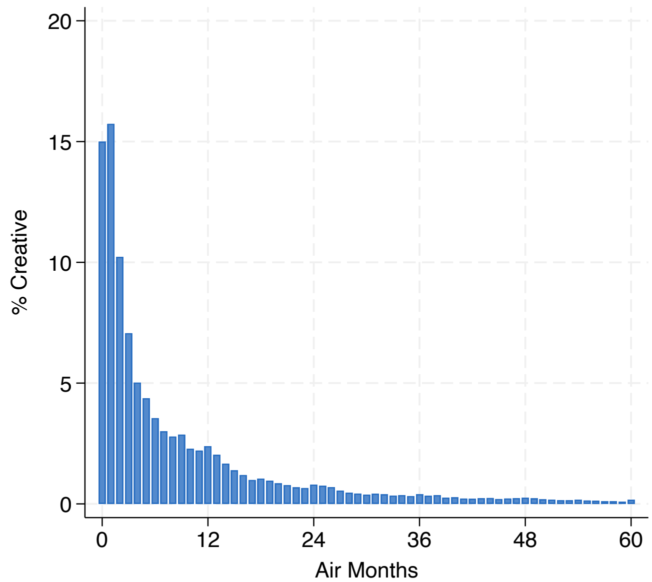
For trust building, we focus on the relationship building, such as brand promotion and home and community trust, and professional imagery, such as professional expertise and wealth management.

> *"We share our world with billions of people, each going through unique experiences, 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 partner. For those times, trust us. Now in your corner and proud to be part of this community."*

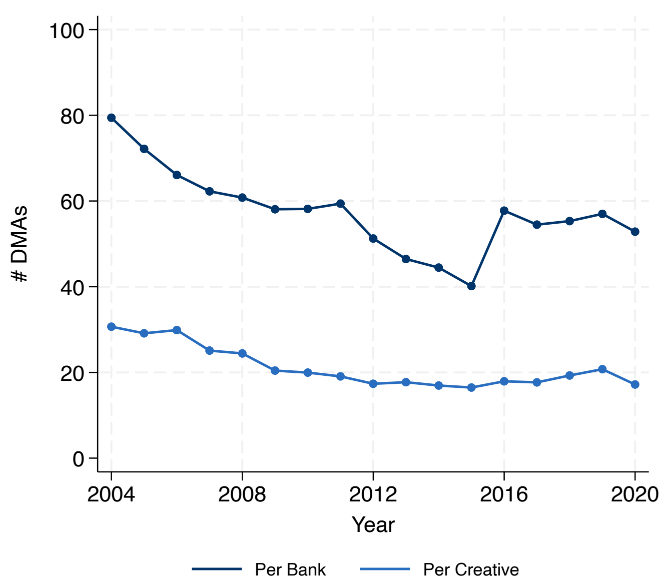
> *"Are you in good hands? At any minute, you could be a victim of fraud. Fraud could mean lower credit scores and higher interest rates when you apply for a credit card. It's a problem waiting to happen. Check your credit score. "*

Figure A.1. Distribution of Air Months and Geographic Coverage of Financial Advertising

Panel (a): Air Months

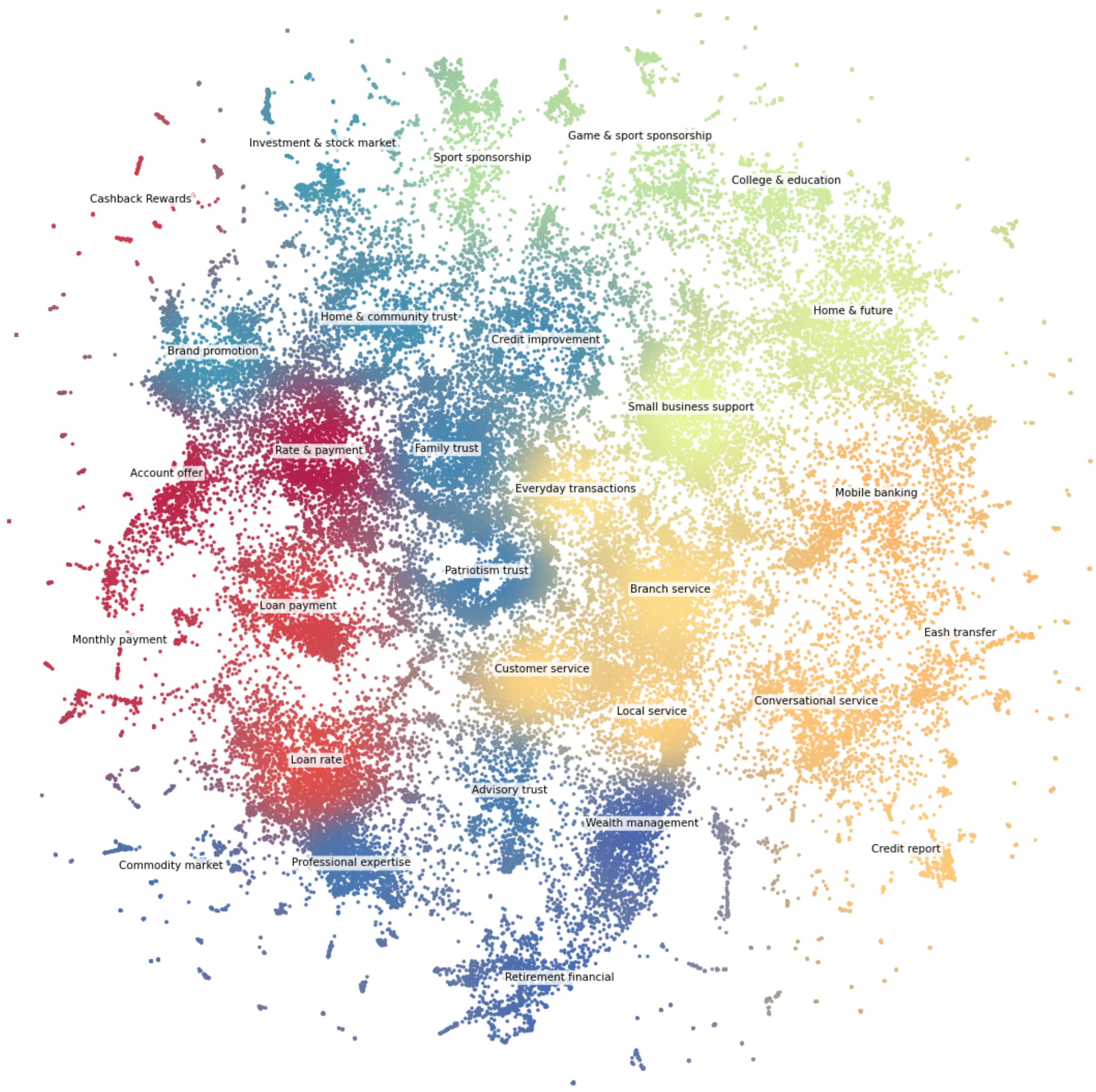


Panel (b): Geographic Coverage



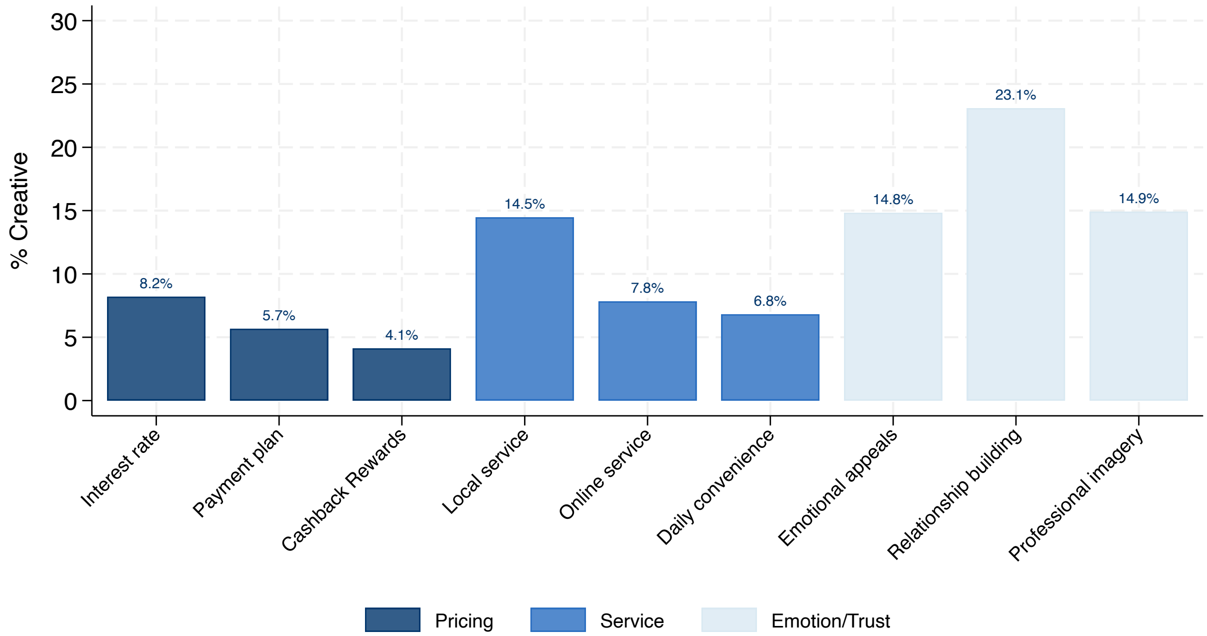
Notes. This figure shows the distribution of air months of financial advertising in Panel (a) and geographic coverage of financial advertising in Panel (b). In Panel (a), the tenure is measured in terms of the total number of months the advertising aired on television. In Panel (b), the dark blue line 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 A.2. Visualization of the Video Embedding for Detailed Banks' Images



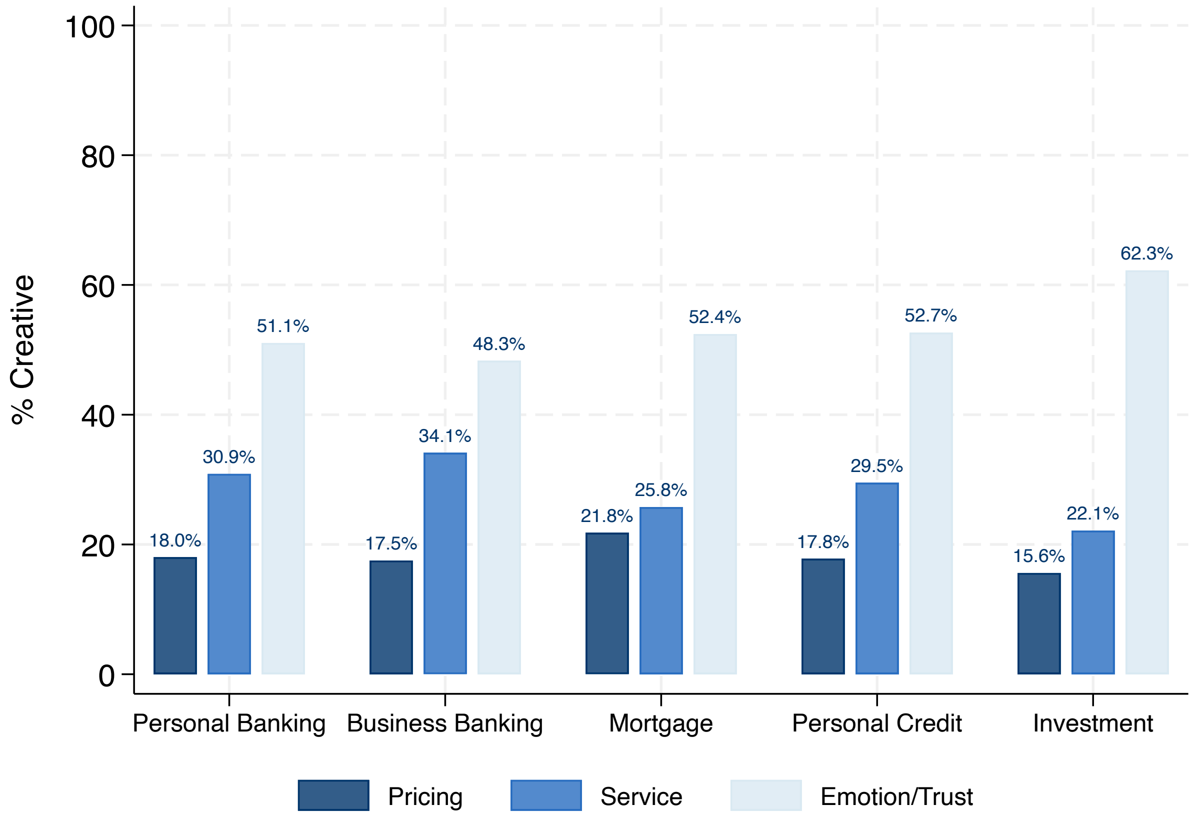
Notes. This figure shows the visualization of the 2-dimensional video embedding for detailed banks' images.

Figure A.3. Distribution of the Detailed Banks' Images



Notes. This figure shows the distribution of detailed banks' images for financial advertising. The list of financial advertising persuasive information can be found in Table 2. The financial information category contains detailed images including the interest rates, payment plans, and cashback rewards. The service quality category includes the local and community service, online and mobile applications, and daily convenience. The emotional appeal and trust building contains the emotional appeal, relationship building, and professional imagery.

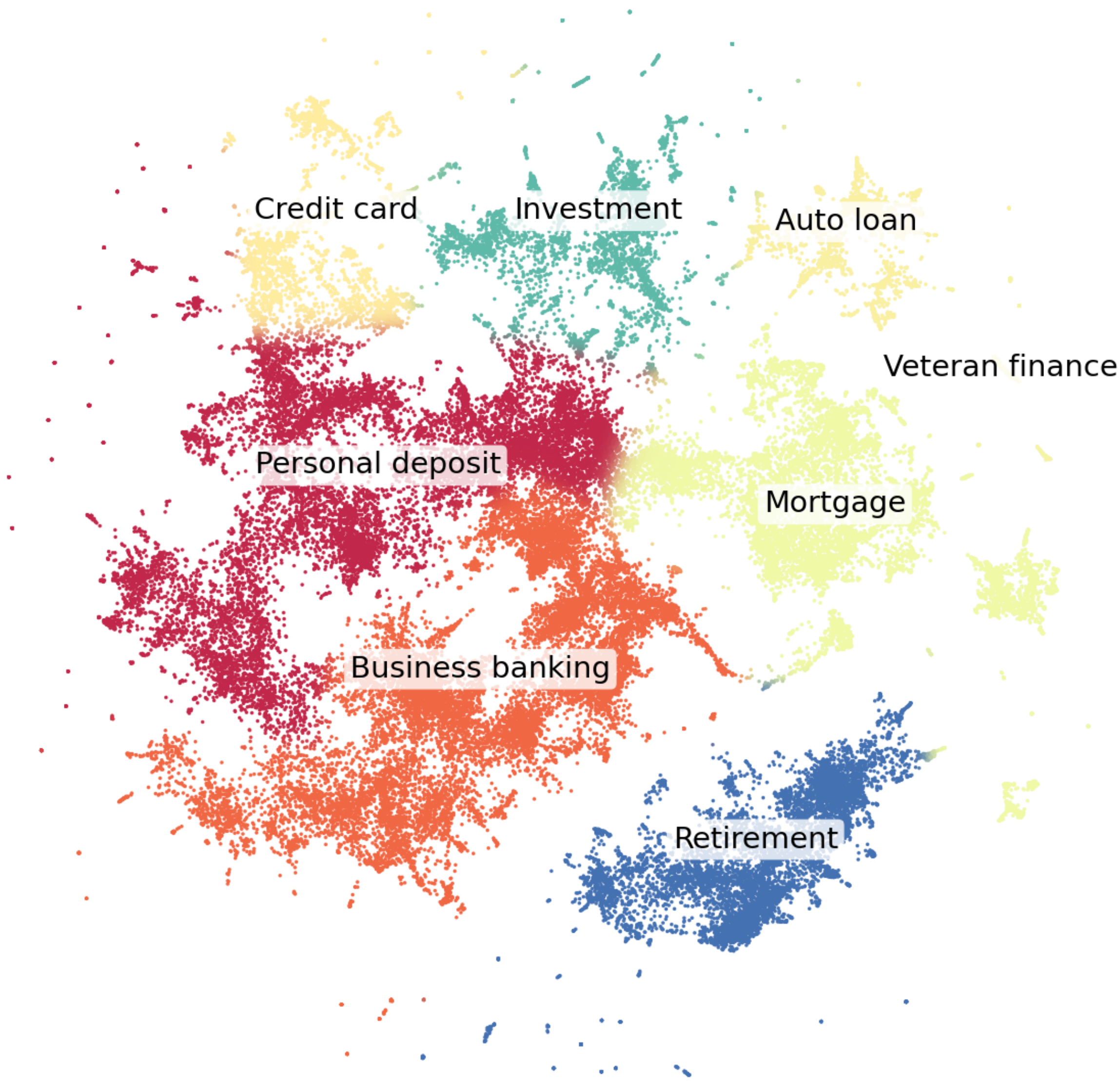
Figure A.4. Distribution of the Banks' Images by Product Categories



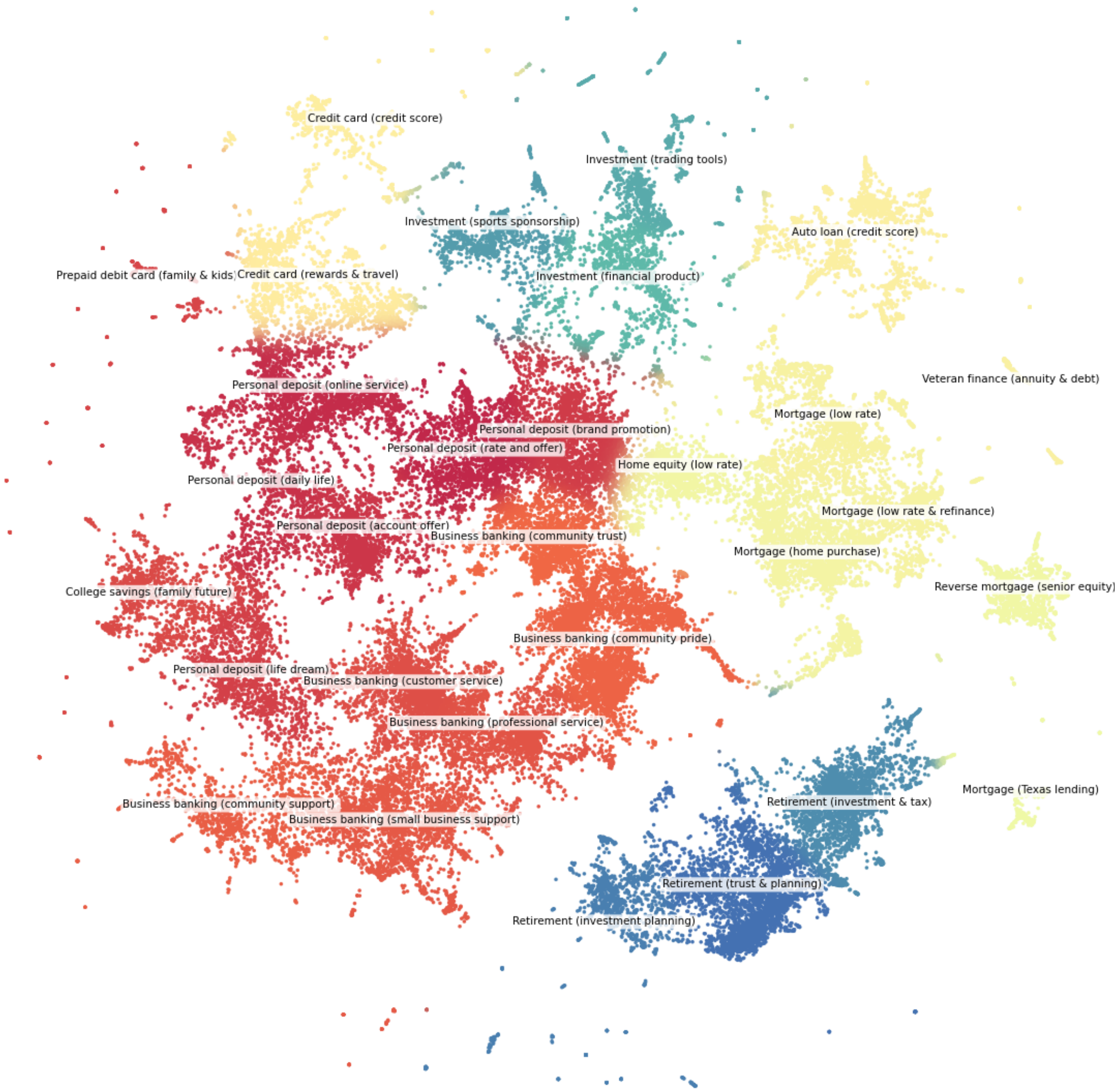
Notes. This figure shows the distribution of banks' images for different specific products. The list of financial advertising broad persuasive information can be found in Table 2.

Figure A.5. Visualization of the Video Embedding for Product Category

Panel (a): Broader Product Category



Panel (b): Detailed Product Category



Notes. This figure shows the visualization of the 2-dimensional video embedding for broader product categories in Panel (a) and detailed product categories in Panel (b).

Table A.1. Bank Selection Into Advertising

	(1)	(2)	(3)	(4)
	$1(\text{Advertising})_{b,t}$			
$\ln(\text{Asset})_{b,t-1}$	0.028***			0.021
	(0.010)			(0.037)
Z-Score$_{b,t-1}$	-0.002			−0.002
	(0.002)			(0.002)
ROA$_{b,t-1}$	−0.059*			−0.020
	(0.032)			(0.024)
Tobin's $q_{b,t-1}$		−0.130*		−0.125*
		(0.073)		(0.074)
Deposit Spread$_{b,t-1}$		−0.039**		−0.026*
		(0.016)		(0.016)
Deposit Productivity$_{b,t-1}$		0.040**		0.007
		(0.019)		(0.068)
Asset Productivity$_{b,t-1}$		0.006		0.012
		(0.012)		(0.012)
Deposits HHI$_{b,t-1}$			−0.905***	−0.913***
			(0.313)	(0.309)
Mortgage HHI$_{b,t-1}$			−1.179	−1.078
			(0.734)	(0.720)
Observations	12,125	12,125	12,125	12,125
R-squared	0.132	0.136	0.156	0.176
No. of Institutions	520	520	520	520
Mean of Y	0.729	0.729	0.729	0.729
Quarter FE	Y	Y	Y	Y

Notes. This table examines which banks select into advertising. The sample contains quarterly information of all the publicly listed U.S. bank holding companies. The outcome variable $1(\text{Advertising})_{b,t}$ is a dummy variable for whether bank b has non-missing and positive Compustat item Advertising and Marketing Expenses (`xadq`) in quarter t. The explanatory variables are lagged one period and include log total assets, Z-Score (the bank's ROA plus its equity ratio divided by its standard deviation of ROA), ROA, Tobin's q, deposit spread, deposit and asset productivity from Egan et al. (2022), and the bank's deposit and mortgage market concentration HHI, calculated as the volume-weighted average of the county-level HHI across all the counties where the bank operates. Standard errors are double-clustered at the levels of bank and quarter. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.2. Markov Transition Matrix of Banks' Images

Panel (a): For All Financial Advertising

	$\text{BankImages}_{b,t+1}$		
$\text{BankImages}_{b,t}$	Pricing	Service	Emotion/Trust
Pricing	22.08%	31.63%	46.28%
Service	4.16%	64.37%	31.47%
Emotion/Trust	6.40%	34.97%	58.63%

Panel (b): For Financial Advertising Related to Deposits

	$\text{BankImages}_{b,t+1}$		
$\text{BankImages}_{b,t}$	Pricing	Service	Emotion/Trust
Pricing	22.91%	30.45%	46.65%
Service	3.70%	68.33%	27.97%
Emotion/Trust	6.61%	34.64%	58.75%

Panel (c): For Financial Advertising Related to Loans

	$\text{BankImages}_{b,t+1}$		
$\text{BankImages}_{b,t}$	Pricing	Service	Emotion/Trust
Pricing	31.47%	25.10%	43.43%
Service	3.04%	73.60%	23.36%
Emotion/Trust	6.33%	31.78%	61.89%

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

Table A.3. Alignment of Product Categories and Banks' Images Between Clustering Method and LLM

Panel (a) Product Category

	Product Category (Clustering)				
	Personal deposit	Business banking	Personal credit	Mortgage	Investment/retirement
# Videos	13,746	16,410	5,466	10,093	11,866
Distribution of Product Categories Through LLM					
% Banking	0.708	0.737	0.227	0.185	0.126
% Business loan	0.017	0.066	0.009	0.006	0.006
% Personal credit	0.101	0.042	0.568	0.049	0.035
% Mortgage	0.044	0.048	0.050	0.692	0.027
% Investment and brokerage	0.096	0.084	0.107	0.044	0.517
% Retirement financial services	0.026	0.014	0.028	0.019	0.265
% Insurance	0.008	0.009	0.009	0.004	0.024
Distribution of Product Categories Through LLM (Standardized)					
% Banking	**0.625**	**0.698**	-0.582	-0.688	-0.836
% Business loan	-0.076	**0.340**	-0.141	-0.168	-0.174
% Personal credit	-0.019	-0.261	**1.887**	-0.231	-0.289
% Mortgage	-0.338	-0.324	-0.318	**1.613**	-0.387
% Investment and brokerage	-0.253	-0.294	-0.216	-0.428	**1.164**
% Retirement financial services	-0.229	-0.287	-0.215	-0.260	**0.982**
% Insurance	-0.038	-0.031	-0.018	-0.095	**0.176**

Panel (a) Product Category

	Banks' Images (Clustering)			
	Pricing	Service	Emotion	Trust
# Videos	10,535	16,585	8,512	21,948
Distribution of Banks' Images Through LLM				
% Pricing	0.271	0.211	0.190	0.220
% Service	0.378	0.420	0.354	0.350
% Emotion	0.077	0.086	0.139	0.086
% Trust	0.273	0.282	0.317	0.344
Distribution of Banks' Images Through LLM (Standardized)				
% Pricing	**0.166**	-0.039	-0.110	-0.008
% Service	0.007	**0.140**	-0.069	-0.083
% Emotion	-0.075	-0.030	**0.228**	-0.030
% Trust	-0.098	-0.073	0.021	**0.094**

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

Table A.4. 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.5. 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.6. 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.

Table A.7. Bank Images by Service Quality Banks: Alternative Measure

	(1)	(2)	(3)
Measure of Service Quality	Branch Network		
Ad Category	Deposit		
% $\text{BankImages}_{b,c,t}$	Pricing	Service	Emotion/Trust
High Service $\text{Quality}_{b,c,t-1}$	-0.748***	0.523***	0.226***
	(0.042)	(0.091)	(0.069)
Observations	987,169	987,169	987,169
R-squared	0.053	0.059	0.060
No. of Institutions	1,120	1,120	1,120
Mean of Y	13.30	36.41	50.28
County-Year FE	Y	Y	Y

Notes. This table examines the financial advertising strategies across banks with different levels of service quality in a bank(b)-county(c)-year(t) panel. The analysis considers the deposit business. % $\text{BankImages}_{b,c,t}$ is the share of images used by bank b in county c in year t. High Service $\text{Quality}_{b,c,t-1}$ is a dummy variable for whether bank b is above the 80 percent quantiles of service quality among all the banks in the county c in year $t-1$, using number of branches scaled by deposits as the measure of service quality. 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.