How Do Banks Compete? Evidence from Advertising Videos*

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

Abstract

This paper studies how banks compete through a novel lens: the content of advertising videos. Using video embeddings, we identify three competitive dimensions: pricing, service quality, and trust-building emotional appeals. We build a framework connecting advertising content to franchise value and monetary policy transmission. Empirical evidence is consistent with model predictions. Banks with high local market shares compete on service and trust while downplaying pricing. New entrants compete primarily on pricing. Banks lacking pricing or service advantages lean on emotional appeals. Non-price advertising strengthens the deposit franchise, enabling banks to maintain wider spreads during monetary tightening and shaping monetary transmission.

JEL Classification: G2, M3, G5

Keywords: Banking, Competition, Advertising, Video Data, Monetary Policy

*This version: March 2026. We thank Paul Goldsmith-Pinkham, Umit Gurun, Can Huang, Naz Koont, Phil Strahan, Richard Thakor, Lulu Wang, and workshop participants at Community Banking Research Conference, Financial Intermediation in the Third Millennium: Perils and Pearls of Technology, FMA, Georgia State, HKU Summer Finance Conference, McGill, MFA, Michigan State, NBER SI (Big Data and High-Performance Computing), NUS, NTU, SMU, TAMU Young Scholars Finance Consortium, Temple, Tsinghua PBCSF, UBC, UT Austin, Yale (Finance, Marketing), and Yeshiva. All errors are our own. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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

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

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

Understanding how banks compete is central to economics and policy. The intensity and nature of bank competition shape individual banks' pricing and business strategies, households' and firms' access to financial services, financial stability, and the transmission of monetary policy.[1] The existing body of work studies bank competition through the lens of equilibrium outcomes such as prices and quantities.[2] However, it remains less well documented which specific actions and strategies banks actively use to compete for depositors and borrowers, and to build and defend franchise value. These actions include pricing and, quite importantly, non-pricing dimensions that are often omitted in existing studies.[3]

This paper studies how banks compete through a novel lens: bank advertising content. Advertising provides a rich yet underutilized window into how banks compete. Advertising videos convey detailed messages about pricing, and more importantly, about services, convenience, trust, and emotional appeal—dimensions of competition that are difficult to observe using standard balance-sheet or pricing data. Advertising is economically important: surveys of Chief Marketing Officers indicate that banks allocate, on average, 9.5% of their annual budgets to advertising, making it a first-order strategic decision rather than a residual expense (Mullainathan, Schwartzstein, and Shleifer, 2008; Bertrand, Karlan, Mullainathan, Shafir, and Zinman, 2010; Gurun, Matvos, and Seru, 2016; Célérier and Tak, 2025).

We use bank advertising content to quantify how banks compete. Our data come from Nielsen Ad Intel and contain 51,349 advertising video clips linked to 2,739 financial institutions, together with airtime schedules that capture the geographic targeting of advertisements across 210 designated market areas (DMAs), spanning 3,098 U.S. counties, from 2004 to 2020. We merge this advertising data with bank balance sheet data from U.S. Call Reports, branch-level deposit data from the FDIC Summary of Deposits, mortgage data from HMDA, and small business lending data from the CRA.

[1] See, Keeley (1990); Petersen and Rajan (1995); Jayaratne and Strahan (1996); Egan et al. (2017); Carlson et al. (2022); Drechsler et al. (2024); Haddad et al. (2023); Jiang et al. (2024a), and Carletti et al. (2024) for surveys.

[2] For instance, market concentration and local market power allow some banks to pay lower deposit rates and charge higher loan rates (Rice and Strahan, 2010; Berger and Hannan, 1989; Marquez, 2002; Boyd and De Nicolo, 2005). Moreover, banks with strong deposit franchises can keep deposit rates unusually low when policy rates rise, widening net interest margins and dampening the pass-through of monetary tightening to the real economy (Neumark and Sharpe, 1992; Drechsler, Savov, and Schnabl, 2017; Wang, Whited, Wu, and Xiao, 2022).

[3] Competition often operates beyond prices, generating heterogeneity in banks' business models, including asset composition, branch networks, service intensity, and productivity (Egan, Hortaçsu, and Matvos, 2017; Egan, Lewellen, and Sunderam, 2022; Benmelech, Yang, and Zator, 2023; d'Avernas, Eisfeldt, Huang, Stanton, and Wallace, 2023).

We develop an unsupervised video-embedding method to quantify the content of banks' television advertisements. Each clip averages 27 seconds and combines visual, verbal, and audio information. Our method represents each video as a high-dimensional embedding that captures this multimodal content, then clusters videos that share similar narratives and scenes. The clusters are chosen to maximize explained variation across videos, requiring no human coding or annotation. The method, though fully unsupervised, recovers economically interpretable categories. Each video projects onto three content types: pricing—interest rates, cashback rewards, and promotional offers; service quality—branch access, mobile banking, and convenience; and trust and emotion—relationship-building, financial advice, and aspirational narratives such as homeownership and small-business success.[4]

Banks' advertisements exhibit significant diversity in how they compete. 18% of advertisements emphasize their pricing advantages and financial benefits, and 82% on non-pricing information: 29% on customer service and support, and 53% on building trust and emotional connections. A variance decomposition reveals that advertising content is primarily explained by bank, bank×year, and bank×county fixed effects rather than product or region effects. Banks appear to choose distinct competitive positions at the local-market level and sustain them over time.

We develop a parsimonious framework to formalize how banks compete using advertising content, which in turn affects bank franchise value and monetary policy transmission. We classify advertising into three dimensions: pricing content (rate advantages), service content (verifiable attributes such as branch networks and digital tools), and trust/emotional content (emotional appeals and brand loyalty). Two banks with different characteristics—branch footprints, local market presence, brand recognition—compete for depositors who vary in how closely they monitor rates, or effectively, how sensitive they are to rates.

In equilibrium, banks with greater operational reach downplay price content and instead, emphasize service content or trust and emotional elements. The logic is intuitive: a bank with local market recognition can credibly advertise features, drawing depositors' attention toward convenience and away from rates. Having attracted less rate-sensitive depositors, the bank faces softer price competition and earns wider spreads—its franchise value makes aggressive pricing unnecessary. Banks with thinner franchises lack verifiable advantages to

[4]This clustering aligns with the marketing literature on advertising content (Resnik and Stern, 1977; Liaukonyte et al., 2015; Guitart and Stremersch, 2021; Tsai and Honka, 2021; Jiang and Kim, 2024) and the finance literature on financial intermediation (d'Avernas et al., 2023; Jiang et al., 2024b; Zhang et al., 2024).

advertise and must instead compete on price. Service advertising is most effective when backed by real operational strengths, giving it a self-reinforcing character. Advertising on trust and emotional appeals, by contrast, works through emotional attachment regardless of what the bank actually offers.

Extending the model to incorporate switching costs, we propose that non-price content also lowers deposit betas—the share of policy rate changes passed through to depositors—providing a content-based explanation for how banks sustain low pass-through, complementing the mechanisms in Drechsler et al. (2017) and Egan et al. (2025). On the lending side, trust content plays a larger role because borrowers cannot assess loan quality ex ante, weakening the informative channel.

Our empirical analysis first examines how banks' advertising content varies with local market competition. In a panel regression with county-year fixed effects, consistent with our theoretical framework, banks with higher market shares prioritize content on service quality and/or life aspiration over pricing information. Banks with an interquartile increase in mortgage market share are correlated with a 2.5% lower mentions of pricing-related content and a corresponding shift toward service and/or trust-related content. This effect is robust across a wide range of market power and competition measures, including raw county-level market share, the relative ranking of a bank compared to the leader in a region, and the bank-level Herfindahl-Hirschman index (HHI).

We find consistent evidence using alternative empirical designs exploring events that change banks' competitive environment and market power, such as bank entry into a new market (Egan et al., 2025), bank mergers (Berger et al., 1998; Erel, 2011; Liebersohn, 2024), and the arrival of FinTech competitors (Buchak et al., 2018; Gopal and Schnabl, 2022; Koont, 2023; Erel et al., 2023; Jiang et al., 2024b). When entering a new market through branch openings, these organic entrants, which have little market power, emphasize pricing advantages to attract rate-sensitive customers. They also strengthen trust-building appeals to overcome the entry barrier caused by a lack of trust (Yang, 2025). In contrast, banks entering the market via mergers and acquisitions inherit an existing customer base and shift their advertising efforts toward service quality to retain customers. In response to the expansion of FinTech lenders into local markets, incumbent banks increase their service-focused content, underscoring digital convenience and customer service to counter the technological appeal of their FinTech rivals.

Interestingly, banks compete differently for deposit and loan products. Service quality is emphasized more prominently in deposit product advertisements by banks with high market power, consistent with d'Avernas et al. (2023), who highlight 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. This aligns well with the recent literature documenting trust being an important factor in households' financial decision-making (Guiso et al., 2008; Thakor and Merton, 2024). In line with this, reputation and trust shocks also trigger adjustments to how banks compete. 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 reputation damage. Meanwhile, other banks in affected counties also increased their trust-focused messaging.

These content choices reflect genuine competitive advantages, not cheap talk, one of our theoretical implications in line with Anderson and Renault (2006). High-rate banks emphasize competitive pricing to attract rate-sensitive depositors; low-rate banks prioritize trust and emotional appeals to retain sticky customers (Zhang et al., 2024). Banks with high service quality—measured by low consumer complaint ratios—highlight value-added services in their advertising (Jiang et al., 2024b; Zhang et al., 2024). Content choices thus align with underlying bank characteristics.

Beyond these cross-sectional and quasi-experimental findings, bank competition also interacts closely with the monetary policy environment (Drechsler et al., 2017). Banks adjust advertising content across the interest rate cycle: when rates rise, advertisements shift toward trust and emotional appeals; during low-rate periods, banks emphasize pricing. In panel regressions following Drechsler et al. (2017) that incorporate both advertising content and deposit market concentration, banks emphasizing service content experience larger deposit spread increases when the Fed funds rate rises, accompanied by larger deposit outflows and sharper balance sheet contraction. These patterns are consistent with non-price content reducing deposit rate sensitivity and amplifying the deposit channel of monetary policy.

The importance of advertising lies in its ability to change demand for banks' products and their value—we provide supportive evidence in the last part of the paper. To address potential endogeneity concerns for a causal interpretation, we implement a border discontinuity design (Shapiro, 2018, 2020). 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. 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. We find that advertising content significantly influences consumer demand for deposits, mortgages, and small business loans.

Market power and franchise value are key drivers of bank value (Demsetz et al., 1996; Chen et al., 2022; Egan et al., 2022; Wang et al., 2022; Drechsler et al., 2024), and franchise value is central to monetary policy transmission and interest rate risk (Drechsler et al., 2017, 2021). Dynamic pricing and financial incentives are increasingly studied as tools to compete for depositors (Egan et al., 2025; Benetton et al., 2025). We leverage advertising content to examine how banks compete and sustain franchise value through both pricing and non-pricing messages, with competitive behaviors varying across markets, products, and monetary cycles. An emerging literature documents advertising's importance across financial markets—mortgages (Gurun et al., 2016; Grundl and Kim, 2019; Kim et al., 2023; Jiang and Kim, 2024), insurance (Shapiro, 2020), credit cards (Bertrand et al., 2010), mutual funds (Roussanov et al., 2021; Hastings et al., 2017), banking (Honka et al., 2017; Célérier and Tak, 2025; Mendes, 2024), and investor trading (Liaukonytė and Žaldokas, 2022)—and broader work emphasizes customer capital accumulated through marketing and branding (Gourio and Rudanko, 2014; He, Mostrom, and Sufi, 2024). We extend this literature by comprehensively examining advertising content in banking and documenting how content choices map to competitive strategy.

This paper also contributes to the burgeoning literature on the use of unstructured data in economics and finance (Gentzkow et al., 2019; Loughran and McDonald, 2020; Hu and Ma, 2025). Closely related to our work, previous research examines how Fed communication affects the transmission of monetary policy and financial markets, using audio (Gorodnichenko et al., 2023), text (Shapiro and Wilson, 2022; Gómez-Cram and Grotteria, 2022), and image data (Curti and Kazinnik, 2023). Our paper extends current standard approaches, such as word embeddings (Jha et al., 2025), and is among the first to use multimodal large models and video embeddings in finance, thereby adding to the broad literature on AI in finance (Eisfeldt and Schubert, 2024).

I. Data

A. *Financial Advertising*

We obtain advertising data from Nielsen's Ad Intel dataset, covering national and local television advertisements from 2004 to 2020. The dataset has two components: (i) advertising creative files—video clips of individual advertisements (the "*Creatives*" data); and (ii) airtime schedules tracking each creative's broadcast across channels, geographic regions, and time slots (the "*Schedule*" data). While prior work has employed schedule data (Shapiro, 2020, 2018; Argente et al., 2025), ours is the first to use the creative video content in academic research.

The creatives data contain 51,349 video clips of financial product advertisements, downloaded from Nielsen's Ad Intel platform (product codes B120 and B150). A unique video ID links each creative to its schedule records. Nielsen tags each creative with the sponsoring financial institution; we manually verify these tags and use them to link advertisements to the institutional data described below. Section II describes how we process the video content.

The schedule data record each creative's airtime details. Key variables include air date and time, duration, spending, channel/program, and the designated market area (DMA) in which the advertisement aired. We use these data to measure banks' advertising strategies, including the geographic targeting of advertisements across markets.

[Insert Table 1 Here.]

Table 1 Panel (a) presents summary statistics of the advertising data. The sample contains 51,349 unique advertisements from 2,739 financial institutions, aired across 210 DMAs. Average advertisement duration is 27 seconds (median: 30), and the average creative remains in circulation for 14 months (median: 4). Most advertisements air on local TV (96%), while 20% also air nationally, with overlaps possible. Conditional on airing, the average number of broadcasts per creative is 1,560 on local TV and 1,340 on national TV. By product category, business banking accounts for 31% of advertisements, personal banking for 24%, mortgages for 17%, and personal credit for 8%. Banks may advertise multiple products across different creatives—for instance, both mortgages and business loans.

B. *Banking Data*

We merge the advertising data with five major datasets covering bank balance sheets, deposits, mortgage originations, and small business lending: the Federal Reserve's Call Reports, Compustat bank fundamentals, the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD), Home Mortgage Disclosure Act (HMDA) data, and Community Reinvestment Act (CRA) small business lending data.

We obtain quarterly bank balance sheet data from U.S. Call Reports via Wharton Research Data Services (WRDS), covering all U.S. commercial banks and their holding companies. We link bank-level figures to branch-level deposit information from FDIC's SOD, which covers the universe of U.S. bank branches annually from 1993 to 2021. We augment these deposit data with retail deposit rates from Ratewatch, which collects weekly branch-level rates by product and covers 54% of all U.S. branches as of 2013. For publicly listed bank holding companies, we supplement balance sheet data with advertising expenses from Compustat, using the linkage file provided by the Federal Reserve Bank of New York.[5] We also incorporate deposit betas from Drechsler et al. (2017) and Drechsler et al. (2021), and productivity measures from Egan et al. (2022).

On the lending side, we use HMDA data to measure mortgage originations and local market shares. HMDA covers the near universe of U.S. mortgage applications—both originated and rejected—with detailed loan-level information on borrowers, loans, properties, and lenders. These data include non-bank lenders such as fintech firms, extending coverage beyond traditional banks.

We obtain small business lending data from the CRA dataset. Despite known limitations, CRA data have been widely employed in finance research on bank lending. These data cover business loans with commitment amounts below $1 million originated by banks with more than $1 billion in assets. We use them to construct small business loan volumes and local market shares for each financial institution.

C. *Sample Construction and Description*

We link the banking datasets using standard identifiers (the Federal Reserve's RSSD ID, the FDIC's certificate number, and the HMDA's respondent ID) and merge them with the

[5] 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.

advertising data via fuzzy matching on institution names.

Table 1 Panel (b) reports summary statistics at the bank-year level. Sample banks hold average deposits of $15,048 million, with savings APY of 0.62% and time deposit APY of 1.36%, and deposit market HHI of 0.21. Average mortgage originations and small-business loan volumes are $2,180 million and $911 million, respectively.

Table 1 Panel (c) reports bank-county-year-level statistics. The average bank holds $909 million in deposits per county, representing 31.98% of local deposits. Average savings spread and time deposit spread are 0.70% and −0.21%, respectively. Average mortgage originations and business loans per county are $19 million and $4.53 million, accounting for 7.36% and 9.65% of county-level totals.

Which banks advertise on TV? While virtually all banks advertise in some form, TV advertising is concentrated among a subset. In the Internet Appendix (Figure A.1 and Table A.1), we characterize this selection. Banks that are larger, face intense local competition (low HHI), or occupy weaker market positions (lower ROA and market power) are more likely to appear in our sample.

II. Method: Quantifying How Banks Compete Using Advertising

This section describes our key methodological contribution: an empirical framework that quantifies advertising content as a measure of how banks compete. Building on recent work using video as a data input (Hu and Ma, 2025; Huang et al., 2023), our method captures rich information across three dimensions—visual, verbal, and vocal—and projects advertising videos into content categories.

Our key innovation relative to prior work is an unsupervised video-embedding clustering approach that jointly integrates all three information channels, yielding robust and efficient categorization. The approach avoids manual coding, enhances replicability, and applies broadly to other settings requiring video data categorization.

A. An Unsupervised Video Embedding Clustering Method

The method operates in two stages: (1) multimodal embedding, which generates unified vector representations of each video; and (2) hierarchical clustering, which identifies the most salient content dimensions and assigns videos to categories. We outline the method here; the Internet Appendix provides full technical details.

Step 1: High-Dimensional Multimodal Video Embedding We extract information from advertising videos using `OmniEmbed`, an open-source multimodal model built on Alibaba Cloud's `Qwen2.5-Omni-7B`. `OmniEmbed` jointly processes text, audio, and video inputs and produces a unified embedding—a numerical vector representation—for each advertisement.

In practice, we first separate the audio track and extract representative visual frames from each video. We transcribe the audio using the speech-to-text model `Whisper` (OpenAI), yielding transcripts averaging 53 words per video. The transcript, audio track, and visual frames are then jointly processed by `OmniEmbed`, which generates a 3,584-dimensional embedding for each video. These embeddings encode semantic content and cross-modal interdependencies, integrating all three information channels into a single vector space.

Step 2: Hierarchical Agglomerative Clustering Using Video Embeddings We cluster videos based on the embeddings from Step 1. The guiding principle is that the most salient variance in embedding space reflects the core distinctive features of the videos.

The clustering proceeds in three sub-steps. First, we apply PaCMAP (Pairwise Controlled Manifold Approximation Projection), a dimension reduction method that preserves both global and local structure, to project the 3,584-dimensional embedding vectors (denoted d_v) into a 2-dimensional space $\tilde{d}_v$.

Second, we apply hierarchical agglomerative clustering (HAC) to the projected embeddings $\tilde{d}_v$. HAC constructs a hierarchy of clusters, enabling interpretation at multiple levels of granularity. We measure similarity via Euclidean distance and use Ward's linkage, which minimizes within-cluster variance at each merge. Because advertisements often span multiple content dimensions, we compute soft cluster memberships using a Student's t-distribution kernel that converts distances into probabilities, yielding a probability distribution over clusters for each video.

Third, to facilitate economic interpretation, we label clusters using top keywords. We generate natural-language descriptions of each video using `Qwen2.5-Omni-7B` and apply term frequency-inverse document frequency (TF-IDF; Loughran and McDonald, 2011) to identify distinguishing terms. Applying TF-IDF to standardized descriptions rather than raw transcripts isolates distinguishing features while suppressing idiosyncratic word choices and generic banking terms.

Step 3: Quantifying and Interpreting Banks' Advertising Contents Before clustering on content, we residualize the embeddings to isolate messaging choices from product-level differences. Specifically, we regress each dimension of the 3,584-dimensional embedding on product category fixed effects and retain the residuals, removing variation attributable to the advertised product while preserving heterogeneity in how banks communicate about the same products.[6]

Applying dimension reduction and clustering (as in Step 2) to the residualized embeddings, we identify three content categories: (1) financial advantage and benefit, (2) service quality, and (3) trust-building and life aspirations. This classification balances comprehensiveness with parsimony, providing categories that are economically meaningful and reliably coded. Figure 1 shows the clustering results (Figure A.2 in the Internet Appendix provides finer detail).

[Insert Figure 1 Here.]

Table 2 summarizes the three broad content themes and their subcategories, with top keywords for each. The "financial information" cluster contains subcategories for interest rates, payment plans, and cashback rewards, identified by keywords such as "rate," "payment," and "earning." The "service quality" cluster includes local service, online service, and daily convenience, characterized by terms like "service," "online," "local," and "community."[7]

[Insert Table 2 Here.]

These clusters emerge organically from the unsupervised procedure. The categories align with frameworks in marketing for coding advertising content and styles (Liaukonyte et al., 2015; Guitart and Stremersch, 2021; Tsai and Honka, 2021; Jiang and Kim, 2024) and with the finance literature on dimensions of intermediary differentiation and consumer behavior (d'Avernas et al., 2023; Jiang et al., 2024b; Zhang et al., 2024).

Step 4: Aggregate Banks' Advertising Contents To connect video-level measures to empirical analysis, we aggregate to bank-year, bank-county-year, or other relevant units. For each bank-year, we compute a weighted average of the residualized embeddings, where weights reflect each advertisement's normalized airtime frequency. We then apply dimension reduction

[6]Product categories are identified as a preliminary step of our algorithm; see Internet Appendix A.2.2.
[7]Table A.3 compares our clustering with alternative ML methods, showing strong consistency.

and clustering (Steps 2–3) to these aggregated embeddings to obtain content category distributions at the bank-year level. This procedure extends naturally to finer aggregations—for instance, by product side (liability vs. asset) or by geography—allowing us to examine how banks tailor their messaging across markets and product lines.

B. Examples of Banks' Advertising Content and Our Method

In this section, we present examples of outcomes from these methods.[8]

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.

> *"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 advertising content is the emotional appeal and trust building. For emotional appeal, we focus on the small business support, home and future, college and education, and sports 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*

[8] We provide more related examples of advertising content in Appendix A.2.4.

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"

C. Advertising Content Distribution and Variance Decomposition

Figure 2 shows the distribution of content across creatives.[9] Emotional appeals and trust-building dominate (53%), followed by service quality (29%) and pricing/financial information (18%). The dominance of emotional and trust-based messaging is notable: Bertrand et al. (2010) show that concrete financial information can reduce consumer demand, while content appealing "peripherally" to intuition and emotions significantly increases it. Banks appear to have internalized this principle. The weight on trust-building in particular aligns with Thakor and Merton (2024) and Yang (2025), who theorize and document the importance of trust in bank entry and lending relationships.[10]

[Insert Figure 2 Here.]

Internet Appendix Figure A.3 provides finer categorizations. Within financial advantages, interest rate content is most prevalent (8%), followed by payment plans (6%) and cashback rewards (4%). Within service quality, local service leads (14%), with online service (8%) and daily convenience (7%) following. Within emotional appeals and trust-building, relationship building is the largest subcategory (23%), with emotional imagery (15%) and professional imagery (15%) equally represented.

[9] Results are similar when weighted by airtime.

[10] Content distribution may vary across media channels (Abernethy and Franke, 1996) and thus may not generalize beyond TV advertising.

We next decompose the variance in the content banks deliver in their advertisements. We do so using a bank-county-product-year panel and regressing banks' content shares on several sets of fixed effects. To assess the relative importance of each set, we employ a Shapley-Owen decomposition, which provides a principled way to attribute explanatory power in a regression with multiple, potentially overlapping sources of variation. The procedure considers all possible orderings of introducing the fixed effects into the regression and averages their incremental contributions to model fit (R^2), ensuring that no set of fixed effects receives undue priority simply because of the order in which it enters. This approach is particularly useful in our setting, where the explanatory factors—bank, geography, product, and time—are likely correlated.

Figure 3 presents a clear picture: the bulk of observed differences in banks' advertising content are attributable to bank-related dimensions, indicating that banks make persistent, strategic choices about how to compete through advertising. The baseline begins with product × year fixed effects. Only approximately 2% of advertising variation can be explained by banks using different content across different financial products. Although it is intuitive that different products may require slightly different advertising strategies, this force plays a limited role. Adding county × year fixed effects increases R^2 by about 3.6%, suggesting that differences across local markets—including local concentration and economic conditions—are not the primary drivers of banks' advertising decisions.

[Insert Figure 3 Here.]

We then examine time-invariant and time-varying bank heterogeneity. Bank fixed effects alone increase R^2 by around 5.8%. There is a substantially larger increase when time-varying bank effects are added: bank × year fixed effects produce a 31% increase in explained variation for content distributions, indicating that banks' advertising strategies evolve meaningfully over time. Finally, bank × county fixed effects, which capture the matching between banks and local markets, explain an additional 12.8% of content variation. Together, these bank-related dimensions account for the bulk of explained variation, confirming that advertising content is shaped primarily by bank-level strategic choices rather than by product or geographic characteristics.

III. A Conceptual Framework

This section develops a parsimonious framework that traces how banks' strategic choice of advertising content shapes their market power and, through depositor composition, monetary policy transmission. The mechanism operates through depositor attention: advertising content determines how attentive each bank's depositors are to rates, which in turn governs the bank's pricing power and its response to policy rate changes. We present a duopoly model extending Anderson and Renault (2006), derive equilibrium predictions, and discuss implications for deposit rate pass-through. All proofs are in the Online Appendix.

A. Model Setup

Environment Two banks $j \in \{H, L\}$ compete for a continuum of depositors (mass 1). Bank H has superior service quality q_H—we interpret this as a bank with larger local market share, denser branch networks, and established reputation. Bank L has $q_L < q_H$—think of a smaller regional bank or a new entrant. These quality differences are empirically correlated with local market share: banks with larger share tend to have denser branch networks and more established relationships, motivating our use of local share as the empirical proxy for market power in Section IV. Both banks invest deposits at the risk-free market rate r_M (taken as exogenous) and compete by setting deposit rates r_j. Following Drechsler et al. (2017), we define the deposit spread as $\mu_j \equiv r_M - r_j$, the bank's margin per dollar of deposits.

Depositor Attention Depositors are heterogeneous in their attention to rates. Motivated by the recent evidence on sleepy depositors,[11] we model each depositor's rate attention as a Bernoulli draw: when evaluating bank j, a depositor is *awake* to rates with probability λ_j and *asleep* to rates with probability $1 - \lambda_j$. An awake depositor perceives the full rate gap $\alpha(r_j - r_M)$. An asleep depositor does not perceive any rate gap, but still values quality and trust. Thus, the expected deterministic utility from bank j is:

$$\begin{aligned} V_j &= \lambda_j \cdot [\alpha(r_j - r_M) + s_j q_j + \tau_j \xi] + (1 - \lambda_j) \cdot [s_j q_j + \tau_j \xi] \\ &= \bar{\alpha}_j (r_j - r_M) + s_j q_j + \tau_j \xi \end{aligned} \tag{1}$$

[11] Egan et al. (2025) documents that depositors are "sleepy": they infrequently monitor rates and rarely switch banks. Using transaction-level data on millions of U.S. depositors, Lu and Wu (2026) show that inattention varies widely across depositors and that more inattentive depositors adjust their balances less in response to monetary policy changes.

where $\alpha > 0$ is the rate sensitivity of awake depositors, $\xi > 0$ is the marginal valuation of trust content, and $\bar{\alpha}_j \equiv \lambda_j \alpha$ is the effective rate sensitivity—the product of the wakeup probability and the common rate sensitivity.

Advertising Content and Demand Each bank allocates advertising across three normalized dimensions: $p_j + s_j + \tau_j = 1$. *Pricing content* p_j communicates rate information. *Service content* s_j highlights verifiable attributes—branch amenities, digital offerings—that convey the bank's objective product quality. *Trust content* τ_j builds emotional attachment and brand loyalty through appeals that operate independently of verifiable quality. This decomposition extends Anderson and Renault (2006) by separating their "match" category into an informative channel (service) and a persuasive channel (trust), following the information-vs.-persuasion framework of Bagwell (2007).

The central mechanism is that advertising content shifts the effective rate sensitivity $\bar{\alpha}_j$ by controlling how many depositors are awake to rates. We model this through the wakeup rate λ_j:

$$\lambda_j = \lambda_0 + \lambda_1 p_j - \lambda_2 \tilde{q}_j \, s_j - \lambda_3 \tau_j \tag{2}$$

where $\lambda_0 > 0$ is the baseline wakeup rate, $\tilde{q}_j = q_j / \bar{q}$ is normalized quality ($\tilde{q}_H > 1$, $\tilde{q}_L < 1$), and $\lambda_1, \lambda_2, \lambda_3 > 0$. Pricing content wakes depositors up ($\lambda_1 > 0$) by making depositors aware of alternatives and prompting active comparison. Service content puts depositors to sleep with respect to rates ($\lambda_2 > 0$) by redirecting attention toward quality attributes and reducing rate monitoring, and this effect is stronger for high-quality banks. Trust content also puts depositors to sleep ($\lambda_3 > 0$) by building emotional brand loyalty and reducing rate monitoring regardless of the bank's actual quality.

Thus, advertising content alters the effective rate sensitivity of bank's depositor base via:

$$\begin{aligned} \bar{\alpha}_j &= \alpha_0 + \alpha_1 p_j - \alpha_2 \tilde{q}_j \, s_j - \alpha_3 \tau_j \\ &= (\alpha_0 + \alpha_1) - (\alpha_1 + \alpha_2 \tilde{q}_j) s_j - (\alpha_1 + \alpha_3) \tau_j \end{aligned} \tag{3}$$

where $\alpha_k \equiv \lambda_k \alpha$ for $k \in \{0, 1, 2, 3\}$, and the second equation follows from substituting the budget constraint $p_j = 1 - s_j - \tau_j$. The baseline $(\alpha_0 + \alpha_1)$ represents the effective rate sensitivity when a bank devotes all advertising to pricing ($p_j = 1$), maximizing the wakeup rate. The coefficients on service and trust content each decompose into two components. The

first is the displacement effect, where each unit of non-price content displaces one unit of pricing content, eliminating the α_1 boost to rate salience. The second is the direct soporific effect, where service content actively redirects attention away from rates by $\alpha_2\tilde{q}_j$, and trust content by α_3.

Bank j's profit is $\Pi_j = \mu_j D_j - C_j$, where $C_j(s_j, \tau_j) = \frac{\gamma_s}{2}s_j^2 + \frac{\gamma_\tau}{2}\tau_j^2$ $(\gamma_s, \gamma_\tau > 0)$ is the convex cost of producing non-price advertising content. To close the demand system, we add i.i.d. type-1 extreme value taste shocks, yielding logit choice probabilities: $D_j = \exp(V_j)/[\exp(V_H) + \exp(V_L) + 1]$, where the "$+1$" represents the outside option. The outside option is investing directly at r_M (e.g., money market funds), with utility normalized to $V_0 = 0$.

B. Equilibrium Predictions

The strategic question is whether Bank H can leverage its quality advantage to compete on non-price dimensions. If Bank H emphasizes rates, it wakes depositors up, forcing rate parity with Bank L and eroding Bank H's quality premium. Alternatively, by redirecting depositor attention to non-price dimensions, Bank H can put its depositors to sleep with respect to rates and sustain a wider deposit spread. The following proposition characterizes when this non-price equilibrium exists.

Proposition 1 (Content-Driven Market Power)**.** *If quality differentiation is sufficiently large ($q_H/q_L > \theta^*$ for a threshold $\theta^* > 1$) and content costs are positive ($\gamma_s, \gamma_\tau > 0$), there exists an equilibrium in content allocations and deposit rates—unique under standard regularity conditions—with the following properties: (i) Bank H (high quality) chooses low pricing content and high non-price content, while Bank L chooses high pricing content; (ii) this content split causes Bank H's depositors to be predominantly asleep to rates (low $\bar{\alpha}_H$), while Bank L's depositors are predominantly awake (high $\bar{\alpha}_L$); (iii) within non-price content, the service share $s_j^*/(s_j^* + \tau_j^*)$ is increasing in bank quality; and (iv) equilibrium spreads satisfy $\mu_H^* > \mu_L^*$.*
Proof in Appendix A.3.2.

Bank H's quality advantage makes service advertising credible and strategically powerful. When Bank H advertises service, depositors are impressed by quality and fall asleep with respect to rates, reducing effective rate sensitivity. Bank L lacks this credibility and instead

wakes depositors up through pricing content, competing on the dimension where it offers a viable rate advantage. Bank H avoids pricing competition because making rates salient would wake its depositors up ($\bar{\alpha}_H$ rises), forcing it to match Bank L's rates and collapsing the spread from the wide inattention-based margin to the narrow logit-competitive margin. This displacement of competition to non-price dimensions is the deposit-market analogue of the "fat cat" effect (Fudenberg and Tirole, 1984): a firm relaxes price competition by investing in brand-building that makes its consumers less price-elastic.

Proposition 2 (Informative vs. Persuasive Content and Spreads)**.** *Both service (informative) and trust (persuasive) content reduce effective rate sensitivity, enabling wider equilibrium spreads. For high-quality banks ($\tilde{q}_j > \alpha_3/\alpha_2$ and $q_j \geq \xi$), service content has a larger marginal effect on rate sensitivity than trust content because the informative channel is more powerful when quality is verifiable.*
Proof in Appendix A.3.3.

The mechanism operates through a standard logit pricing relationship. Equilibrium markups satisfy $\mu_j^* = 1/[\bar{\alpha}_j(1 - D_j)]$, so any reduction in $\bar{\alpha}_j$ widens the equilibrium spread at a given market share. The model distinguishes the informative channel (service content, which leverages genuine quality to absorb attention) from the persuasive channel (trust content, which builds emotional loyalty independent of quality), following Anderson and Renault (2006) and Bagwell (2007). Service content reduces $\bar{\alpha}_j$ by $(\alpha_1 + \alpha_2\tilde{q}_j)$ and trust content reduces it by $(\alpha_1 + \alpha_3)$. The informative channel dominates when $\alpha_2\tilde{q}_j > \alpha_3$: the bank's quality advantage is large enough that quality-revealing advertising puts depositors to sleep with respect to rates more effectively than emotional appeals. For lower-quality banks, trust content dominates as the non-price strategy.

Deposit Rate Pass-Through We extend the model to two periods to trace how advertising content shapes deposit rate pass-through. In Period 1, banks choose advertising content and deposit rates, which establishes their depositor base composition. In Period 2, the Fed raises the policy rate by $\Delta r > 0$ (so $r_M \to r_M + \Delta r$), and banks re-optimize deposit rates given their inherited depositor composition. Advertising content is pre-committed: campaigns deployed in Period 1 continue to shape the wakeup rate in Period 2. Depositors who remain asleep do not observe the rate change and stay at their current bank, while awake depositors re-optimize. This stickiness is the friction that generates heterogeneous pass-through.

Define deposit beta as $\beta_j \equiv \partial r_j^*/\partial r_M$, the fraction of a policy rate increase that bank j passes through. The baseline frictionless logit model implies full pass-through ($\beta_j = 1$ for all banks). However, empirical frictions—imperfect outside-option tracking, depositor search costs, and deposit insurance (Drechsler et al., 2017)—break translation invariance and generate incomplete pass-through. Banks with predominantly awake depositors (high $\bar{\alpha}_j$) face rapid outflows if they lag the market rate and must adjust quickly, while banks with predominantly asleep depositors (low $\bar{\alpha}_j$) retain their base even when rates lag, enabling slower adjustment. These frictions imply that β_j is increasing in $\bar{\alpha}_j$.

By reducing $\bar{\alpha}_j$ (as shown in Proposition 2), non-price content lowers the deposit beta. Banks that emphasize service and trust in their advertising induce inattention among their depositors regarding interest rates, allowing these banks to adjust deposit rates more slowly when policy rates increase. This offers a strategic, content-driven explanation for why some banks accumulate predominantly "sleepy" depositors (Egan et al., 2025), extending beyond traditional explanations based on monitoring costs or deposit insurance (Drechsler et al., 2017). Whereas Drechsler et al. (2017) treat depositor composition as exogenous, our model shows that it emerges endogenously from banks' advertising strategies. Similarly, while Lu and Wu (2026) view depositor inattention as an individual characteristic, our framework attributes it to banks' strategic content decisions. Appendix A.3.4 formalizes this argument, showing that the standard logit model yields full pass-through ($\beta_j = 1$ for all j) and that a friction-augmented specification delivers the predicted increasing relationship between $\bar{\alpha}_j$ and β_j.

Although developed for deposit markets, the framework's core mechanism extends to lending: non-price advertising can reduce borrowers' attention to rates, enabling wider loan spreads. A key difference is that loan quality is harder for borrowers to assess ex ante. Borrowers cannot observe a loan's risk-adjusted return before origination, so the informative (service) channel is weaker on the asset side. This suggests that trust content plays a larger role in loan advertising than in deposit advertising, a pattern we examine via our border design in Section C.

IV. How Do Banks Compete Using Advertising Content?

This section, guided by our theoretical framework, examines how banks compete through advertising content. We study three sets of predictions from the model: (i) high-market-share

banks (proxying for high-quality Bank H) choose less pricing content and more non-price content, with service share increasing in quality (Proposition 1); (ii) content choices depend on entry mode—organic entrants, lacking service reputation, should rely on pricing content, while M&A acquirers, inheriting sticky depositor bases, should shift toward service content; and (iii) banks' content choices should align with their actual competitive advantages, with the informative (service) channel dominating for high-quality banks (Proposition 2).

A. Local Market Power and Competition Behaviors

We first examine how advertising content varies with local market power in a bank-county-year panel. We estimate the following model in a bank-county-year panel:

$$\text{AdContent}_{b,c,t} = \beta \cdot D_{b,c,t-1} + \eta_{c,t} + \epsilon_{b,c,t}. \tag{4}$$

The dependent variable is the share of content categories—pricing, service quality, and trust-building/emotional appeals—in bank b's advertising videos aired in county c in year t. These categories map to the model's three content dimensions: pricing content p_j, service content s_j, and trust content τ_j.

The key independent variables, denoted D, capture bank characteristics at the b-c-t level, including local market power (county-level market shares), deposit rate-setting behavior, and service quality. We analyze deposits and lending (mortgages and business loans) separately where relevant. County-year fixed effects $\eta_{c,t}$ absorb time-varying local demand, demographics, and competitive conditions, so the specification compares advertising strategies across banks with different characteristics within each county-year. Standard errors are clustered at the county level.

We proxy for local market power using three measures constructed at the bank–county–year level. The first is the bank's local market share in a given county and product market (i.e., separately for deposit and loan products), which captures its absolute local presence. Deposit and loan shares are calculated as each bank's share of county-year deposits and HMDA mortgage originations, respectively. The second measure scales this share by the market share of the bank with the largest share in the same county–product market, measuring the bank's position relative to the local leader. It reflects whether the bank is the dominant institution versus a smaller competitor. The last measure captures the competitiveness of the

bank's operating footprint using a bank-level Herfindahl–Hirschman index (HHI) measure (Berger and Hannan, 1989). Following Drechsler et al. (2017), we compute county-level HHI in each product market and take a product-weighted average across the counties where the bank operates. Banks that concentrate their activity in more concentrated local markets are classified as having greater market power.

[Insert Table 3 Here.]

Table 3 provides evidence consistent with Proposition 1(i): across all three market power proxies, high-market-share banks allocate significantly less advertising to pricing content. This pattern holds across products. A 10-percentage-point increase in market share (roughly interquartile) reduces mortgage pricing content by 0.368 percentage points—2.5% of the 14.51% mean—with smaller effects for deposits.[12]

High-market-share banks compete on non-price dimensions—service quality and trust-building—consistent with Proposition 1. In deposit advertising, they emphasize service quality 1.12 percentage points more per interquartile increase in market share (3.1% of the 36.16% mean). The informative (service) channel appears particularly valuable for high-quality banks: service advertising credibly conveys their quality advantage and redirects depositor attention from rates to quality attributes. This aligns with d'Avernas et al. (2023), who document that large-bank depositors disproportionately value liquidity services and exhibit lower rate sensitivity.

An important deposit–loan asymmetry emerges. While high-market-share banks emphasize service quality on the liability side, they rely more heavily on trust-building and life-inspirational content for loan products—success stories of small businesses, homeownership narratives. In mortgage advertising, a 10-percentage-point increase in market share raises life-inspiration content by 0.6 percentage points (1.2% of the sample mean). One interpretation, guided by the framework's lending extension, is that borrowers cannot assess loan quality ex ante (unlike depositors, who can verify branch amenities and service), so the informative (service) channel is weaker on the asset side. Trust content, which reduces rate sensitivity regardless of verifiable quality, plays a correspondingly larger role on loans. That said, the pattern may also reflect that loan products inherently lend themselves to aspirational messaging.

[12] Appendix Table A.5 compares banks in the top 20th percentile of market share against the bottom 80th percentile in deposit and mortgage markets separately, with consistent results.

These results are consistent with Propositions 1 and 2: high-market-power banks compete via non-price content, with service dominating on the liability side and trust on the asset side. By redirecting depositor attention from rates to quality and brand attributes, non-price advertising reduces effective rate sensitivity $\bar{\alpha}_j$, enabling wider equilibrium spreads. This content-driven mechanism complements switching-cost and deposit-insurance explanations for why high-market-share banks sustain less favorable deposit rates.

B. Alternative Designs: Bank Entry and Shocks to Trust

We complement the cross-sectional analysis with quasi-experimental designs exploiting shocks that shift content for reasons tied to entry mode or trust destruction rather than endogenous market structure. We examine three settings: bank entry (organic vs. M&A), FinTech competition, and the Wells Fargo scandal.

We begin with market entry, a setting that allows us to examine Proposition 1's prediction that content depends on bank type (Egan et al., 2025). Organic entrants, lacking established service reputation (low q_j), should emphasize pricing; M&A acquirers, inheriting customer relationships and quality, should shift toward service.[13] We estimate:

$$\text{AdContent}_{b,c,t} = \beta \cdot \text{Post(Entry)}_{b,c,t} + \eta_b + \eta_{c,t} + \epsilon_{b,c,t}, \tag{5}$$

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 4 presents the results.

[Insert Table 4 Here.]

Entry Through New Branch. For organic entry via branch expansion (columns 1–3), entrants allocate significantly more to pricing and trust content relative to incumbents in the same county-year. This pattern is consistent with Proposition 1: lacking established service reputation, new entrants tend to compete on pricing where they are credible. They offer high deposit rates and low mortgage rates to attract rate-sensitive depositors, exactly as predicted for Bank L in Proposition 1. The concurrent increase in trust content reflects

[13] M&A data downloaded from https://www.ffiec.gov/npw/FinancialReport/DataDownload.

entrants' need to overcome switching costs and depositor unfamiliarity, consistent with trust serving as an entry barrier (Thakor and Merton, 2024; Yang, 2025).

Entry Through M&A. Banks entering via acquisition inherit established customer bases and service reputations—analogous to Bank H in the model. Under Proposition 1, these banks should emphasize non-price content, with service share increasing in their inherited quality advantage.

Columns (4)–(6) of Panel (a) document this pattern. Following M&A entry, acquiring banks increase service-content weight by 7.83 percentage points (21% of the 36.61% mean), consistent with Table 3. M&A acquirers inherit sticky depositors and can immediately pivot from price competition to service emphasis, leveraging their inherited quality advantage. This also aligns with Erel (2011), who find that merged banks leverage increased operating efficiency to enhance service supply.

FinTech Entry Into Local Markets We examine how incumbent banks respond to FinTech entry, which exogenously intensifies competition in local lending markets (Buchak et al., 2018; Gopal and Schnabl, 2022; Koont, 2023; Jiang et al., 2024b).

To estimate changes in incumbent banks' advertising content after FinTech entry, we estimate the following within-bank specification.

$$\text{AdContent}_{b,c,t} = \beta \cdot \text{Post(FinTech Entry)}_{c,t} + \eta_c + \eta_{b,t} + \epsilon_{b,c,t}, \tag{6}$$

$\text{Post(FinTech Entry)}_{c,t}$ 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 also consider an intensive measure of FinTech entry by using the mortgage market share of FinTech companies in county c and year t. 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 competition strategies of the same banks, but across branches in different counties, that may or may not be affected by FinTech entry.

Panel (b) shows that incumbent banks respond by increasing service-quality advertising (digital banking, mobile access, quick approval). Banks facing a quality threat shift toward the informative (service) channel—highlighting verifiable advantages like branch networks

and relationship banking—rather than relying on persuasive (trust) appeals, consistent with Proposition 2.

Wells Fargo Scandal We analyze the 2016 Wells Fargo scandal as a distinct trust shock. Unlike the competition shocks above, this event exogenously destroys depositor trust in a specific bank. In 2016, Wells Fargo disclosed years of unauthorized account creation, triggering widespread consumer skepticism. Though fraudulent activity began in 2005, the public revelation was sudden and plausibly orthogonal to industry fundamentals (Yang, 2025).

We first focus on a sample of Wells Fargo only and examine how Wells Fargo's advertising content changes 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.

$$\text{AdContent}_{c,t} = \beta \cdot \text{Post(Scandal)}_t + \eta_c + \epsilon_{c,t}, \tag{7}$$

where $\text{AdContent}_{c,t}$ is Wells Fargo's advertising content 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.

Columns (1)–(3) in Panel (c) show that post-scandal, Wells Fargo sharply increased trust-building and emotional content by 7.7 percentage points (14% of the 53.37% mean), consistent with campaigns like "Re-Established" ("it's a new day at Wells Fargo").[14] This response is consistent with the framework: when the scandal destroyed Wells Fargo's trust capital, the bank adjusted its content mix by increasing persuasive (trust) content τ_j, which the theory predicts reduces rate sensitivity and could facilitate rebuilding depositor loyalty. The episode suggests advertising content may serve as a reputational repair tool.

We also examine spillover effects on competitors in counties with Wells Fargo branches, estimating:

$$\text{AdContent}_{b,c,t} = \beta \cdot \text{Post(Scandal)}_t \times 1(\text{Wells Fargo Presence})_c + \eta_c + \eta_{b,t} + \epsilon_{b,c,t}, \tag{8}$$

[14] See https://www.latimes.com/business/la-fi-wells-fargo-ad-campaign-20180509-story.html.

where $\text{AdContent}_{b,c,t}$ is bank b's advertising content 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 advertising content across branches of the same bank, but in different counties, with or without Wells Fargo's physical presence.

Columns (4)–(6) show that competitors in Wells Fargo counties also increase trust-building content, though by less than Wells Fargo. This spillover suggests that trust shocks affect the optimal content mix of all banks in the local market, not just the focal institution.

C. Highlighting Strengths, Substituting Toward Trust

Our framework also implies that banks with genuine advantages in pricing or service quality should highlight these verifiable strengths through informative advertising, leveraging their actual competitive edge. Banks lacking hard advantages in these dimensions should strategically shift toward trust-building and emotional appeals—substituting persuasive content where informative content would not be credible. We examine this mechanism through the lens of the informative versus persuasive advertising distinction (Anderson and Renault, 2006; Bagwell, 2007).

We investigate how financial advertising strategies differ across banks with varying pricing and service quality, and examine whether their advertising content aligns with their pricing advantages and service quality. 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 5 Here.]

High-rate banks emphasize pricing in deposit advertising: 3.13 percentage points more than low-rate banks (23% of the 13.6% mean), consistent with informative advertising—banks with genuine rate advantages make them salient. Low-rate banks compensate by allocating 2.22 percentage points more to service content (6.2% of the mean), redirecting depositor attention from their pricing disadvantage toward quality attributes. Proposition 2 explains this pattern: banks lacking pricing advantages use non-price content to reduce depositors' effective rate sensitivity.

We next examine whether high-service-quality banks employ informative advertising. We measure service quality using the complaint rate (complaints per dollar of deposits) from the CFPB Consumer Complaint Database; banks with fewer complaints are classified as higher quality (Egan et al., 2017, 2022).

High-service-quality banks allocate 2.45 percentage points more to service content (6.7% of the mean), consistent with Proposition 2: when quality is verifiable, the informative (service) channel dominates because it amplifies the bank's genuine advantage (the $\alpha_2\tilde{q}_j$ mechanism). Banks with concrete service advantages advertise them, attracting depositors who value quality over rate minimization.[15]

A revealing cross-cutting pattern: high-rate and high-service-quality banks allocate *less* to trust-building content. Proposition 2 provides a rationale: when a bank has verifiable competitive advantages, the theory predicts the informative channel dominates, making persuasive content less central to the competitive strategy.

These patterns reveal a nuanced advertising strategy that blends informative and persuasive elements. Banks with genuine advantages—competitive rates or superior service—highlight them, consistent with informative advertising. Banks lacking advantages in one dimension strategically reallocate toward other dimensions rather than highlighting their weaknesses. This selective emphasis reflects the equilibrium content allocation predicted by Propositions 1 and 2: each bank optimally emphasizes the dimension in which it holds a comparative advantage. Where genuine advantage exists, banks foreground it; where it does not, they foreground trust. This yields a bifurcated advertising market: informative content among high-quality banks, persuasive content among the rest.

[15] Appendix Table A.4 measures service quality using branch network density following Egan et al. (2017) and Zhang et al. (2024), with consistent results.

V. Advertising, Franchise Value, and Monetary Policy

A key feature of bank competition and market power is its deep connection with monetary policy through the bank deposit channel (Drechsler et al., 2017). We now examine whether advertising content serves as a mechanism through which banks build franchise value and exercise market power, with consequences for how monetary policy transmits to deposit pricing and credit supply.

Our theoretical framework predicts that non-price content—service (informative) and trust (persuasive)—enables higher deposit franchise value, manifested in wider deposit spreads and lower deposit rate sensitivity to Fed funds rate changes, with implications for the strength of the deposit channel. This section proceeds in three steps. First, we link advertising content to bank-level measures of market power and franchise value—deposit productivity, deposit spreads, deposit betas, and Tobin's q. Second, following Drechsler et al. (2017), we examine how advertising content shapes banks' heterogeneous responses to monetary policy shocks at the bank-county-year level, controlling for deposit market concentration. Third, we implement a border-discontinuity design (Shapiro, 2018, 2020) that leverages geographic discontinuities in advertising exposure at DMA borders to identify the causal effects of advertising content on demand for deposits, mortgages, and small-business loans.

A. Advertising Content and Bank Value

We first examine whether advertising content is associated with standard measures of deposit franchise value: deposit productivity, deposit spreads (the markup banks earn over the Fed funds rate), deposit betas (rate pass-through sensitivity), and Tobin's q. We use the bank holding company (b)-quarter (t) panel and estimate the following specification:

$$Y_{b,t} = \beta \cdot \text{AdContent}_{b,t-1} + \gamma X_{b,t-1} + \eta_t + \epsilon_{b,t}, \tag{9}$$

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. $\text{AdContent}_{b,t-1}$ is the advertising content measures: pricing, service, emotion/trust. Since these three measures sum to 100% by definition, we omit the emotion/trust (persuasive) category to avoid collinearity. Estimated coefficients on pricing and service should therefore be interpreted relative to emotion/trust-focused banks. $X_{b,t-1}$ 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 cross-sectional variation in banks, since some measures, such as bank productivity, are inherently cross-sectional. To mitigate reverse causality concerns, we lag all advertising measures by one period relative to the dependent variables.

[Insert Table 6 Here.]

Table 6 reports the results.[16] Column (1) shows that banks emphasizing pricing in their advertising display higher deposit productivity, echoing Egan et al. (2022), who emphasize rate-setting technology as an important source of variation in bank productivity. Column (2) reveals that banks with greater emphasis on emotion and trust achieve higher asset productivity, as indicated by negative coefficients on the pricing and service categories. This pattern mirrors our earlier evidence in Table 3 column (6): banks emphasizing the persuasive (trust) channel are more efficient in lending and achieve higher asset productivity. This finding also accords with Thakor and Merton (2024), who demonstrate that borrowers' trust is crucial for banks to maintain business advantages in lending.

Columns (3) to (5) examine bank market 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. Column (3) shows that banks emphasizing the informative (service) channel maintain significantly higher deposit spreads, corroborating our evidence in Table 3 and Table 5. Service content redirects depositor attention from rates to quality attributes, reducing effective rate sensitivity and enabling wider equilibrium spreads.

Our second measure of deposit market power is deposit beta, which captures pass-through: the sensitivity of a bank's deposit rate to changes in the Fed funds rate. Deposit beta is calculated by regressing changes in a bank's deposit rate on contemporaneous and

[16] In Table A.6, we also examine bank advertising spending using the same specification.

lagged changes in the Fed funds rate and summing the coefficients. A bank with high market power has low deposit beta—when the Fed raises rates, such a bank passes through little of the increase to depositors, preserving its spread. Conversely, a bank with weak market power, such as one reliant on rate-sensitive wholesale funding, has a beta close to 1 and earns minimal spread (Drechsler et al., 2021). Column (4) shows that banks emphasizing pricing in advertising have significantly higher deposit betas, indicating that their depositors' rates are more sensitive to Fed funds rate changes. This pattern accords with our earlier evidence in Table 5 and reflects pricing-focused advertising attracting rate-sensitive, switching-prone depositors.

Column (5) uses Tobin's q as a summary measure of franchise value (Demsetz et al., 1996). The insignificant coefficients indicate that while advertising content generates measurable deposit market power (captured by spreads and beta), these effects do not translate into sustained differences in long-run firm valuation. This may reflect that advertising-driven deposit advantages are contestable—competitors can adjust their own content strategies—or that Tobin's q is a noisy valuation measure for diversified bank holding companies with many business lines beyond retail deposits.

To summarize, advertising content is associated with measurable differences in deposit market power—captured by spreads and deposit betas—consistent with advertising serving as a mechanism through which banks invest in building a deposit franchise. Together with the advertising spending results in Table A.6, this evidence demonstrates that both the content and intensity of advertising shape deposit market power—a key dimension of bank franchise value.

B. Transmission of Monetary Policy

Having established that advertising content drives variation in deposit market power, we now ask whether this heterogeneity alters how banks transmit monetary policy shocks to the real economy. If non-price advertising reduces depositors' effective rate sensitivity, banks with strong advertising-built franchises should exhibit different deposit and lending responses to Fed funds rate changes. We begin with aggregate time-series patterns. Figure 4 plots how banks' advertising content evolves over monetary policy cycles, with NBER-dated recessions shaded.

[Insert Figure 4 Here.]

Figure 4 documents systematic cyclical patterns in advertising content. During tightening cycles, banks shift emphasis away from pricing and service messaging toward emotional appeals and trust-building—the persuasive channel. Conversely, during the zero-lower-bound period (2008Q4–2015Q3), banks prominently feature pricing and financial information. These patterns reflect banks' dynamic response to the deposit competition environment: when rates rise, trust content may help retain depositors amid intensifying rate competition; when rates are compressed, pricing content becomes more prominent as banks compete for rate-sensitive depositors in a low-spread environment. While the aggregate time series does not establish causality, it documents the timing and magnitude of these shifts, motivating the within-county analysis that follows.

To examine how advertising content shapes monetary policy transmission, we implement a within-county specification following Drechsler et al. (2017) on the same bank holding company (b)-county (c)-year (t) panel as in Section IV.B:

$$\begin{aligned} Y_{b,c,t} =& \beta^{\text{Ad}} \text{AdContent}_{b,c,t-1} + \gamma^{\text{Ad}} \Delta\text{FF}_t \times \text{AdContent}_{b,c,t-1} \\ &+ \beta^{\text{HHI}} \text{Deposit-HHI}_{b,t-1} + \gamma^{\text{HHI}} \Delta\text{FF}_t \times \text{Deposit-HHI}_{b,t-1} + \eta_{b,c} + \eta_{c,t} + \epsilon_{b,c,t}, \end{aligned} \tag{10}$$

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. $\text{AdContent}_{b,c,t-1}$ are lagged advertising content of bank b in county c in year $t-1$. ΔFF_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}, the interaction between advertising content and Fed funds rate changes, which measures whether a bank's balance-sheet response to a monetary policy shock depends on the composition of its advertising. To isolate advertising-driven heterogeneity from the deposit market concentration channel studied by Drechsler et al. (2017), we control for $\text{Deposit-HHI}_{b,t-1}$ and its interaction with ΔFF_t. County-year fixed effects ($\eta_{c,t}$) absorb time-varying local demand conditions, so we compare outcomes of different banks operating in the same county and year but with different advertising content. Bank-county fixed effects ($\eta_{b,c}$) absorb time-invariant characteristics of each bank's local presence, including historical market share, branch networks, and deposit base composition.

[Insert Table 7 Here.]

Table 7 shows that banks with different advertising content display heterogeneous balance-sheet responses to Fed funds rate increases. Banks emphasizing the informative (service) channel exhibit larger increases in deposit spreads when the Fed raises rates (column 1), reflecting their higher baseline market power and wider spread adjustment. Correspondingly, these service-focused banks experience larger deposit outflows (column 2) and greater declines in mortgage and small-business lending (columns 3–4). This pattern aligns with the bank-level evidence in Table 6 column (3): service-focused banks maintain higher deposit spreads and thus higher deposit market power, amplifying the balance-sheet contraction when rates rise.

These results accord with the bank deposit channel (Drechsler et al., 2021). In our framework, non-price advertising builds deposit franchise value by reducing depositors' effective rate sensitivity—through attention redirection (service content) or emotional attachment (trust content). Banks with strong advertising-driven franchises sustain market power over retail deposits: when the Fed raises rates, their depositors' rates adjust slowly, widening spreads and eventually triggering deposit outflows that constrain lending. Advertising content thus operates as a distinct source of bank heterogeneity in monetary policy transmission, complementing the market concentration channel documented by Drechsler et al. (2017).

C. Identifying the Impacts of Bank Advertising

The preceding analyses document associations between advertising content and deposit market power, but advertising is a bank's strategic choice, raising concerns about endogeneity. Equilibrium forces may cause advertising to correlate with demand or performance for reasons other than the direct effect of advertising. Banks may also target advertising based on anticipated rather than realized product demand, creating reverse causality. We address these concerns using a border-discontinuity design that identifies the causal effect of advertising content on financial product demand.

Our empirical specification uses a border-discontinuity design, following Shapiro (2018) and Shapiro (2020). The design exploits geographic discontinuities at the borders of Designated Market Areas (DMAs), leveraging the discrete nature of local television markets. Consumers on opposite sides of a DMA border face different advertising exposure from the same bank due to the geography of the media market, while sharing similar demographics, income

levels, and access to financial products. To verify this identifying assumption, Appendix Table A.10 reports balance tests showing that observable county characteristics—including average income, population, gender, race, age, and education—are not systematically associated with advertising content at the border.

[Insert Figure 5 Here.]

To illustrate, Figure 5 shows the Pittsburgh and Johnstown-Altoona DMAs in the state of Pennsylvania, with the border region highlighted in bold. The design compares how demand for the same bank's financial products differs between counties on opposite sides of this border, where the bank operates branches on both sides but faces different DMA-specific television advertising exposure.

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:

$$Y_{b,c,t} = \beta \cdot \text{AdContent}_{b,c,t} + \eta_{b,c} + \eta_{b,d(c),t} + \epsilon_{b,c,d(c),t}, \tag{11}$$

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. The independent variables of interest are the advertising content shares: pricing and service quality, with emotion/trust as the omitted baseline category.

The fixed effects are chosen to isolate advertising content variation from potential confounders. Bank-county fixed effects $\eta_{b,c}$ absorb all time-invariant characteristics of a bank's local presence—branch density, historical market share, deposit base composition—preventing cross-county differences in bank fundamentals from biasing the estimates. Bank-border-year fixed effects $\eta_{b,d(c),t}$ absorb bank-specific and border-specific demand trends in each year, ensuring we do not conflate time-varying bank-wide strategy shifts with local advertising effects. With both sets of fixed effects, we identify the intensive-margin effect of advertising content by comparing the same bank's product demand across counties within a border group that have differential advertising exposure. The identifying assumption is that, conditional on these fixed effects, the same bank would experience parallel trends in financial product demand on both sides of a DMA border absent differential advertising.

The analysis is restricted to bank-county observations with positive advertising spending, so the estimated coefficients capture the intensive-margin effect of advertising content conditional on the bank choosing to advertise in that market. Because counties near DMA boundaries may belong to multiple border groups, the same bank-county-year observation can appear multiple times with different border identities. To account for correlation within bank-county pairs and within border-year groups, we cluster standard errors two-way at the bank-county and border-year levels.

[Insert Table 8 Here.]

Table 8 presents the results. Columns (1) and (2) examine how advertising content causally affects deposit demand and pricing. Banks emphasizing the informative (service) channel experience 1.3 percentage-point higher deposit growth—a sizable effect representing 34% of the sample mean quarterly deposit growth of 3.8%. Service-focused advertising also enables significantly higher deposit spreads, with a coefficient of 1.9 percentage points. Given that the sample mean deposit spread is -0.72 percentage points—negative because Fed funds rates were near zero during much of the sample period—this effect is economically large. In contrast, banks emphasizing pricing in their advertising experience lower deposit growth and narrower spreads, consistent with pricing content attracting rate-sensitive depositors and eroding franchise value. These causal estimates reinforce the cross-sectional patterns documented in the preceding sections: the informative (service) channel builds deposit franchise value by redirecting depositor attention from rates to quality.

Columns (3) and (4) reveal a striking deposit–loan asymmetry. While informative (service) content drives deposit market power, it is the persuasive (trust) channel—emotion and trust-building, the omitted baseline—that drives mortgage and small-business loan origination. Banks emphasizing trust attract significantly higher loan demand. This deposit–loan asymmetry aligns with our framework's asset-side logic: borrowers cannot assess loan quality ex ante, so the informative channel is weaker, and trust content plays a larger role in reducing effective rate sensitivity and building lending relationships. Appendix Table A.8 shows that advertising *spending* also drives deposit and loan volumes, demonstrating that both content and intensity matter for financial product demand.

VI. Conclusion

This paper shows that banks compete through advertising content—pricing, service (informative), and trust (persuasive)—and that this content is a mechanism for building deposit franchise value and shaping monetary policy transmission. We develop a framework in which advertising content determines depositors' rate sensitivity through sorting. Empirically, high-market-share banks prioritize non-price content and adjust it systematically in response to entry, mergers, FinTech competition, and trust shocks. A DMA border-discontinuity design identifies causal effects: service content drives deposit growth and wider spreads, while trust content drives loan demand—reflecting our prediction that trust matters more on the asset side, where loan quality is less transparent.

Advertising content also operates as a source of heterogeneity in monetary policy transmission, complementing the market concentration channel of Drechsler et al. (2017). Banks emphasizing non-price content attract less rate-sensitive depositors and exhibit lower deposit betas, consistent with our framework. Unlike prior work that takes depositor composition as exogenous, we show that banks shape it through content choice—a mechanism through which some banks accumulate "sleepy" depositor bases (Egan et al., 2025). The border design establishes causality for deposit growth and spreads; the deposit beta channel is guided by our model and consistent with observed patterns.

Open questions remain. Our framework is deliberately parsimonious (two banks, static content) and omits dynamic adjustment and general equilibrium feedback. Welfare implications are ambiguous: service content may improve match quality while trust content may exploit behavioral biases (Anderson and Renault, 2006). As Bertrand et al. (2010) emphasize, theory offers limited guidance on which content dimensions matter; our taxonomy is a step forward, but deeper foundations are needed, especially to explain why service matters for deposits while trust matters for loans.

Methodologically, we show that unsupervised video embedding clustering robustly encodes multimodal advertising content (Gentzkow et al., 2019). As banking competition migrates to digital channels, this framework scales to richer content data—enabling new research on how financial institutions build and defend customer franchises.

References

Abernethy, A. M., Franke, G. R., 1996. The information content of advertising: A meta-analysis. Journal of Advertising 25, 1–17.

Anderson, S. P., Renault, R., 2006. Advertising content. American Economic Review 96, 93–113.

Argente, D., Fitzgerald, D., Moreira, S., Priolo, A., 2025. How do entrants build market share? The role of demand frictions. American Economic Review: Insights 7, 160–176.

Bagwell, K., 2007. The economic analysis of advertising. Handbook of industrial organization 3, 1701–1844.

Beggs, A., Klemperer, P., 1992. Multi-period competition with switching costs. Econometrica: Journal of the Econometric Society pp. 651–666.

Benetton, M., Hébert, B., McQuade, T., 2025. Deposit competition beyond rates. Working Paper .

Benmelech, E., Yang, J., Zator, M., 2023. Bank branch density and bank runs. NBER Working Paper .

Berger, A. N., Hannan, T. H., 1989. The price-concentration relationship in banking. The Review of Economics and Statistics pp. 291–299.

Berger, A. N., Saunders, A., Scalise, J. M., Udell, G. F., 1998. The effects of bank mergers and acquisitions on small business lending. Journal of Financial Economics 50, 187–229.

Bertrand, M., Karlan, D., Mullainathan, S., Shafir, E., Zinman, J., 2010. What's advertising content worth? Evidence from a consumer credit marketing field experiment. The Quarterly Journal of Economics 125, 263–306.

Boyd, J. H., De Nicolo, G., 2005. The theory of bank risk taking and competition revisited. The Journal of Finance 60, 1329–1343.

Brown, Z. Y., Egan, M. L., Jeon, J., Jin, C., Wu, A. A., 2023. Why do index funds have market power? quantifying frictions in the index fund market. Tech. rep., National Bureau of Economic Research.

Buchak, G., Matvos, G., Piskorski, T., Seru, A., 2018. Fintech, regulatory arbitrage, and the rise of shadow banks. Journal of Financial Economics 130, 453–483.

Carletti, E., Leonello, A., Marquez, R., 2024. Market power in banking. Annual Review of Financial Economics 16, 233–251.

Carlson, M., Correia, S., Luck, S., 2022. The effects of banking competition on growth and financial stability: Evidence from the national banking era. Journal of Political Economy 130, 462–520.

Célérier, C., Tak, P., 2025. Finance, advertising, and race. The Review of Financial Studies p. hhaf038.

Chen, Q., Goldstein, I., Huang, Z., Vashishtha, R., 2022. Bank transparency and deposit flows. Journal of Financial Economics 146, 475–501.

Chodorow-Reich, G., 2014. The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. The Quarterly Journal of Economics 129, 1–59.

Curti, F., Kazinnik, S., 2023. Let's face it: Quantifying the impact of nonverbal communication in fomc press conferences. Journal of Monetary Economics 139, 110–126.

d'Avernas, A., Eisfeldt, A. L., Huang, C., Stanton, R., Wallace, N., 2023. The deposit business at large vs. small banks. NBER Working Paper .

Demsetz, R. S., Saidenberg, M. R., Strahan, P. E., 1996. Banks with something to lose: The disciplinary role of franchise value. Economic Policy Review 2.

Drechsler, I., Savov, A., Schnabl, P., 2017. The deposits channel of monetary policy. The Quarterly Journal of Economics 132, 1819–1876.

Drechsler, I., Savov, A., Schnabl, P., 2021. Banking on deposits: Maturity transformation without interest rate risk. The Journal of Finance 76, 1091–1143.

Drechsler, I., Savov, A., Schnabl, P., Wang, O., 2024. Deposit franchise runs. Available at SSRN 4411127 .

Egan, M., Hortaçsu, A., Matvos, G., 2017. Deposit competition and financial fragility: Evidence from the us banking sector. American Economic Review 107, 169–216.

Egan, M., Lewellen, S., Sunderam, A., 2022. The cross-section of bank value. The Review of Financial Studies 35, 2101–2143.

Egan, M. L., Hortaçsu, A., Kaplan, N. A., Sunderam, A., Yao, V., 2025. Dynamic competition for sleepy deposits. NBER Working Paper .

Eisfeldt, A. L., Schubert, G., 2024. Ai and finance. NBER Working Paper .

Erel, I., 2011. The effect of bank mergers on loan prices: Evidence from the united states. The Review of Financial Studies 24, 1068–1101.

Erel, I., Liebersohn, J., Yannelis, C., Earnest, S., 2023. Monetary policy transmission through online banks. NBER Working Paper .

Fudenberg, D., Tirole, J., 1984. The fat-cat effect, the puppy-dog ploy, and the lean and hungry look. American Economic Review 74, 361–366.

Fuster, A., Plosser, M., Schnabl, P., Vickery, J., 2019. The role of technology in mortgage lending. The Review of Financial Studies 32, 1854–1899.

Gelman, M., Goldstein, I., MacKinlay, A., 2023. Bank diversification and lending resiliency. Available at SSRN 4147790 .

Gentzkow, M., Kelly, B., Taddy, M., 2019. Text as data. Journal of Economic Literature 57, 535–574.

Gómez-Cram, R., Grotteria, M., 2022. Real-time price discovery via verbal communication: Method and application to fedspeak. Journal of Financial Economics 143, 993–1025.

Gopal, M., Schnabl, P., 2022. The rise of finance companies and fintech lenders in small business lending. The Review of Financial Studies 35, 4859–4901.

Gorodnichenko, Y., Pham, T., Talavera, O., 2023. The voice of monetary policy. American Economic Review 113, 548–584.

Gourio, F., Rudanko, L., 2014. Customer capital. Review of Economic Studies 81, 1102–1136.

Grundl, S., Kim, Y. S., 2019. Consumer mistakes and advertising: The case of mortgage refinancing. Quantitative Marketing and Economics 17, 161–213.

Guiso, L., Sapienza, P., Zingales, L., 2008. Trusting the stock market. The Journal of Finance 63, 2557–2600.

Guitart, I. A., Stremersch, S., 2021. The impact of informational and emotional television ad content on online search and sales. Journal of Marketing Research 58, 299–320.

Gurun, U. G., Matvos, G., Seru, A., 2016. Advertising expensive mortgages. The Journal of Finance 71, 2371–2416.

Haddad, V., Hartman-Glaser, B., Muir, T., 2023. Bank fragility when depositors are the asset. Available at SSRN 4412256 .

Hastings, J., Hortaçsu, A., Syverson, C., 2017. Sales force and competition in financial product markets: The case of mexico's social security privatization. Econometrica 85, 1723–1761.

He, B., Mostrom, L. I., Sufi, A., 2024. Investing in customer capital. Working Paper .

Honka, E., Hortaçsu, A., Vitorino, M. A., 2017. Advertising, consumer awareness, and choice: evidence from the U.S. banking industry. The Rand Journal of Economics 48, 611–646.

Hu, A., Ma, S., 2025. Persuading investors: A video-based study. The Journal of Finance 80, 2639–2688.

Huang, X., Ivković, Z., Jiang, J. X., Wang, I. Y., 2023. Angel investment and first impressions. Journal of Financial Economics 149, 161–178.

Ivashina, V., Scharfstein, D., 2010. Bank lending during the financial crisis of 2008. Journal of Financial Economics 97, 319–338.

Jayaratne, J., Strahan, P. E., 1996. The finance-growth nexus: Evidence from bank branch deregulation. Quarterly Journal of Economics 111, 639–670.

Jha, M., Liu, H., Manela, A., 2025. Does finance benefit society? A language embedding approach. The Review of Financial Studies p. hhaf012.

Jiang, E. X., Matvos, G., Piskorski, T., Seru, A., 2024a. Monetary tightening and us bank fragility in 2023: Mark-to-market losses and uninsured depositor runs? Journal of Financial Economics 159, 103899.

Jiang, E. X., YU, Y. G., Zhang, J., 2024b. Bank competition amid digital disruption: Implications for financial inclusion. Working Paper .

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

Keeley, M. C., 1990. Deposit insurance, risk, and market power in banking. American Economic Review 80, 1183–1200.

Kim, D., Jiang, Z., Thomadsen, R., 2023. TV advertising effectiveness with racial minority representation: Evidence from the mortgage market. SSRN Electronic Journal .

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

Liaukonyte, J., Teixeira, T., Wilbur, K. C., 2015. Television advertising and online shopping. Marketing Science 34, 311–330.

Liaukonytė, J., Žaldokas, A., 2022. Background noise? tv advertising affects real-time in-

vestor behavior. Management Science 68, 2465–2484.

Liebersohn, J., 2024. How does competition affect retail banking? quasi-experimental evidence from bank mergers. Journal of Financial Economics 154, 103797.

Loughran, T., McDonald, B., 2011. When is a liability not a liability? textual analysis, dictionaries, and 10-Ks. The Journal of Finance 66, 35–65.

Loughran, T., McDonald, B., 2020. Textual analysis in finance. Annual Review of Financial Economics 12, 357–375.

Lu, X., Wu, L., 2026. Banking on inattention. Tech. rep., National Bureau of Economic Research.

Marquez, R., 2002. Competition, adverse selection, and information dispersion in the banking industry. The Review of Financial Studies 15, 901–926.

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

Mullainathan, S., Schwartzstein, J., Shleifer, A., 2008. Coarse thinking and persuasion. Quarterly Journal of Economics 123, 577–619.

Neumark, D., Sharpe, S. A., 1992. Market structure and the nature of price rigidity: evidence from the market for consumer deposits. The Quarterly Journal of Economics 107, 657–680.

Petersen, M. A., Rajan, R. G., 1995. The effect of credit market competition on lending relationships. The Quarterly Journal of Economics 110, 407–443.

Resnik, A., Stern, B. L., 1977. An analysis of information content in television advertising. Journal of Marketing 41, 50–53.

Rice, T., Strahan, P. E., 2010. Does credit competition affect small-firm finance? The Journal of Finance 65, 861–889.

Roussanov, N., Ruan, H., Wei, Y., 2021. Marketing mutual funds. The Review of Financial Studies 34, 3045–3094.

Shapiro, A. H., Wilson, D. J., 2022. Taking the fed at its word: A new approach to estimating central bank objectives using text analysis. The Review of Economic Studies 89, 2768–2805.

Shapiro, B. T., 2018. Positive spillovers and free riding in advertising of prescription pharmaceuticals: The case of antidepressants. Journal of Political Economy 126, 381–437.

Shapiro, B. T., 2020. Advertising in health insurance markets. Marketing Science 39, 587–611.

Thakor, R. T., Merton, R. C., 2024. Trust in lending. Review of Economics and Statistics pp. 1–45.

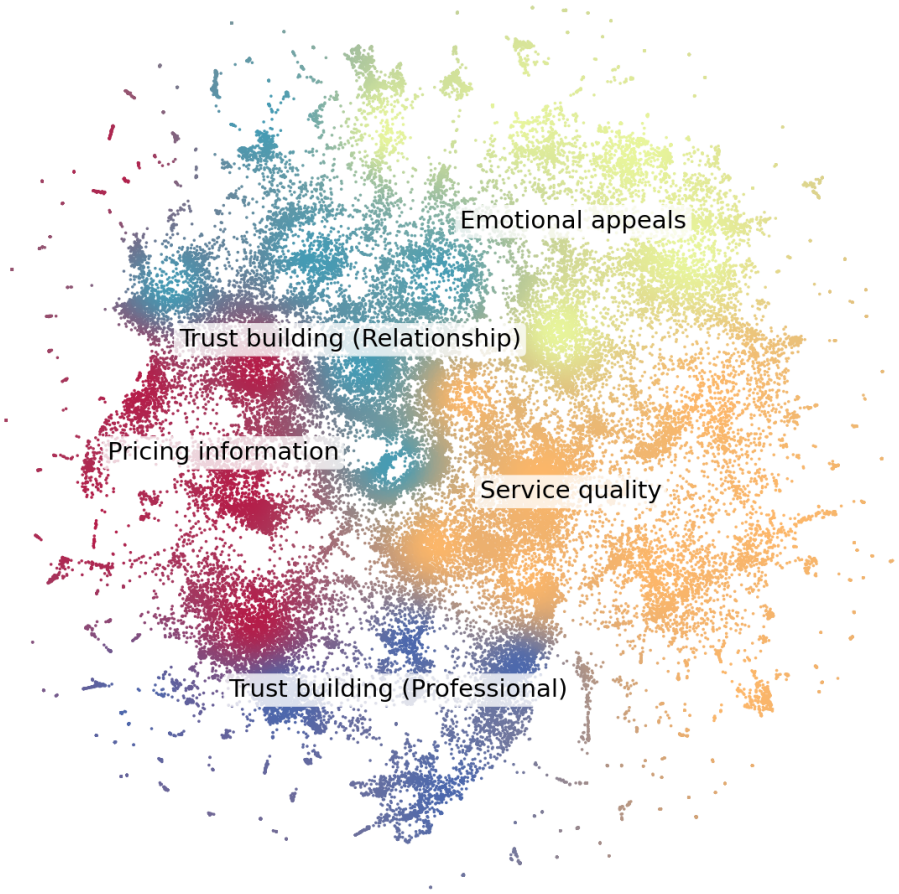
Tsai, Y.-L., Honka, E., 2021. Informational and noninformational advertising content. Marketing Science 40, 1030–1058.

Wang, Y., Whited, T. M., Wu, Y., Xiao, K., 2022. Bank market power and monetary policy transmission: Evidence from a structural estimation. The Journal of Finance 77, 2093–2141.

Yang, K., 2025. Trust as an entry barrier: Evidence from fintech adoption. Journal of Financial Economics 169, 104062.

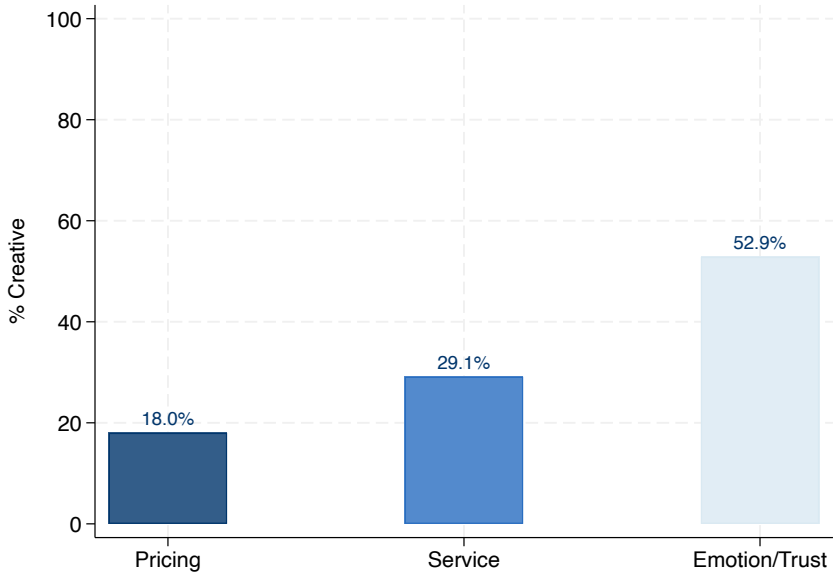
Zhang, J., Muir, T., Kundu, S., 2024. Diverging banking sector: New facts and macro implications. SSRN Electronic Journal .

Figure 1. Visualization of Video Embeddings and Advertising Content Clusters



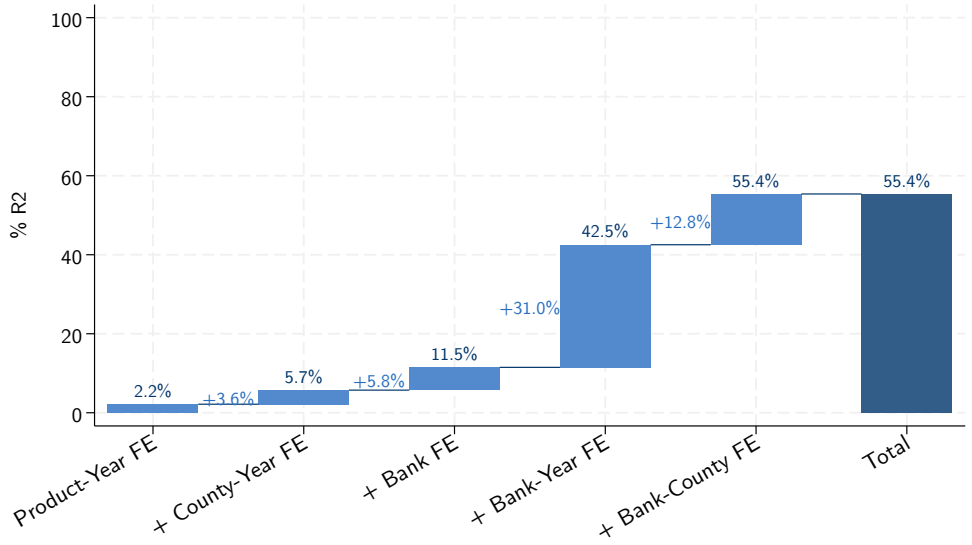
Notes. This figure shows the visualization of the two-dimensional embeddings of bank advertising videos, as described in Section A. It shows three categories of advertising content: financial information, service quality, and trust-building and life aspirations (including relationship building, professional imagery, and emotional appeal).

Figure 2. Distribution of Bank Advertising Content



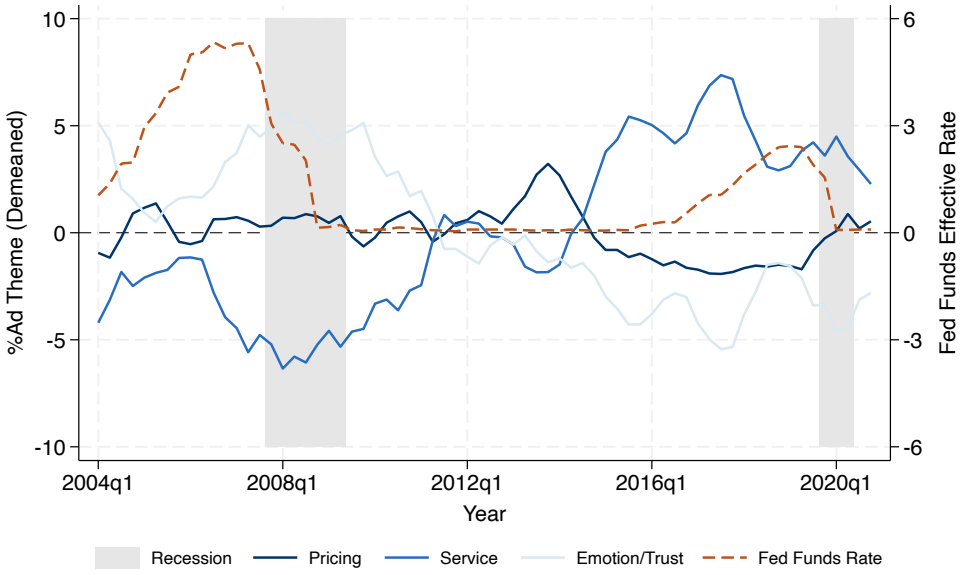
Notes. This figure shows the distribution of bank advertising content, including financial information, service quality, and emotional appeal/trust-building.

Figure 3. Decomposing Variations of Advertising Content



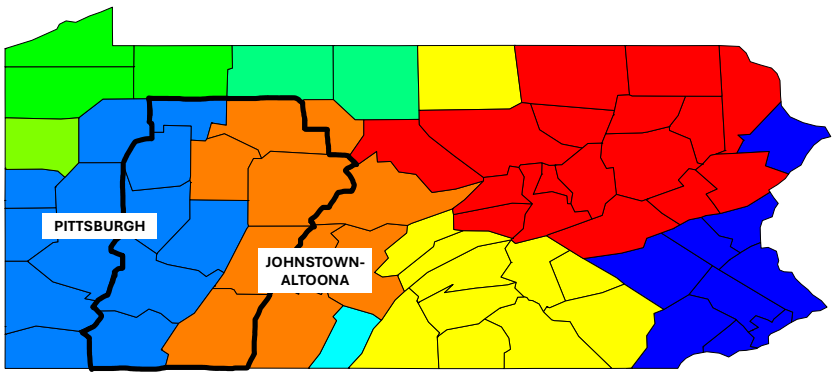
Notes. This figure shows the percentages of variations for advertising content can be explained by different specifications of fixed effects. We implement a Shapley-Owen decomposition on a bank-county-product-year panel. We consider the following set of fixed effects: product-year fixed effects, county-year fixed effects, bank fixed effects, bank-year fixed effects, and bank-county fixed effects.

Figure 4. Advertising Content and Monetary Policy



Notes. This figure plots the distribution of bank advertising content (e.g., financial information, service quality, and trust-building) alongside the Fed Funds rate over time. The NBER dated-recessions are shaded. The advertising content variables are demeaned by the sample average.

Figure 5. Example of DMA Border Region



Notes. This figure shows the DMA map for Pennsylvania, highlighting the border region between Pittsburgh and Johnstown-Altoona used in border discontinuity design, as in Equation (11).

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
# 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
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								
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 bank 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. # Schedule Times, Local TV / National TV is the total number of times an advertising was scheduled to air 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. 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 accounts, respectively.

Table 2. Categories of Bank Advertising Content

Broad	Intermediate	Detailed	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	Cash 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 bank advertising content and their associated keywords obtained from unsupervised clustering of video embeddings. The classification hierarchy has three levels: broad, intermediate, and detailed. The last column (Related Keywords) reports representative words with the highest average TF-IDF scores for each detailed category. Refer to Section A for more details.

Table 3. Advertising Content by Local Market Power

	(1)	(2)	(3)	(4)	(5)	(6)
Ad Category	Deposit			Mortgage		
% AdContent$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
Panel (a): Local Market Share as Measure of Market Power						
Local Market Share$_{b,c,t-1}$	-0.355**	3.058***	-2.703***	-3.678***	-2.326***	6.003***
	(0.141)	(0.218)	(0.175)	(0.135)	(0.230)	(0.213)
R-squared	0.053	0.068	0.067	0.063	0.067	0.068
Panel (b): Market Share/Top Share as Measure of Market Power						
Market Share/Top Share$_{b,c,t-1}$	-0.351***	2.674***	-2.323***	-1.922***	-0.568***	2.490***
	(0.097)	(0.157)	(0.127)	(0.057)	(0.102)	(0.096)
R-squared	0.053	0.068	0.068	0.064	0.067	0.067
Panel (c): Bank HHI as Measure of Market Power						
Bank HHI$_{b,c,t-1}$	-5.354***	7.512***	-2.157***	-2.736***	-8.401***	11.137***
	(0.060)	(0.104)	(0.098)	(0.524)	(0.849)	(0.689)
R-squared	0.061	0.072	0.067	0.062	0.067	0.067
Observations	922,811	922,811	922,811	706,796	706,796	706,796
No. of Institutions	937	937	937	721	721	721
Mean of Y	13.44	36.16	50.40	14.51	34.60	50.89
County-Year FE	Y	Y	Y	Y	Y	Y

Notes. This table examines the advertising content across banks with different levels of local market power in a bank(b)-county(c)-year(t) panel. The analysis considers two different products, including deposits in Columns (1)-(3), and mortgages in Columns (4)-(6). % Ad Content$_{b,c,t}$ is the share of advertising content for that specific product used by bank b in county c in year t. The analysis considers three measures of local market power in the county c in the respective product market in year $t-1$, including local market share in Panel (a), the ratio of local market share divided by the maximum market share in Panel (b), and bank-level HHI calculated as the product-weighted average of the county-level HHI across all the counties in year $t-1$ in Panel (c). 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. Advertising Content After Economic Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
Ad Category	All			All		
% AdContent$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
Panel (a): Bank Entry Into Local Markets						
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						
Post(FinTech Entry)$_{c,t}$	−0.544***	0.615***	−0.071			
	(0.052)	(0.094)	(0.079)			
FinTech Market Share$_{c,t}$				−0.382**	0.981***	−0.598**
				(0.176)	(0.310)	(0.281)
Observations	2,786,104	2,786,104	2,786,104	2,786,104	2,786,104	2,786,104
R-squared	0.477	0.480	0.449	0.477	0.480	0.449
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
County FE	Y	Y	Y	Y	Y	Y
Bank-Year FE	Y	Y	Y	Y	Y	Y
Panel (c): Wells Fargo Scandal						
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

Notes. This table examines how bank advertising content changes after bank and FinTech entry into local markets and a bank scandal, 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. 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. FinTech Market Share$_{c,t}$ is the mortgage market share of FinTech companies in county c and year t. Panel (c) reports the effects of the 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. 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 5. Advertising Content by High- and Low-Rate and Service Quality Banks

	(1)	(2)	(3)	(4)	(5)	(6)
Ad Category	Deposit			Deposit		
% AdContent$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
High Deposit Rate$_{b,c,t-1}$	3.129***	-2.219***	-0.910***			
	(0.039)	(0.070)	(0.054)			
High Service 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 advertising content 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. % AdContent$_{b,c,t}$ is the share of advertising content of bank b in county c in year t. In Columns (1)-(3), High Deposit 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 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 6. Advertising Content and Bank Value

	(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(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(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(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 advertising content 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. The measures of advertising content include pricing information 1(Pricing)$_{b,t-1}$ and service quality 1(Service)$_{b,t-1}$, omitting emotional appeal and trust building 1(Emotion/Trust)$_{b,t-1}$. The 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 7. Advertising Content and Monetary Policy Transmission

	(1)	(2)	(3)	(4)
$Y_{b,c,t}$	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 advertising content and the transmission of monetary policy using a bank(b)-county(c)-year(t) panel. The lagged measures of advertising content for bank b in county$c$ in year $t-1$ are 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.

Table 8. Advertising Content and Financial Product Demand: Border Discontinuity Design

	(1)	(2)	(3)	(4)
Ad Category	Deposit		Mortgage	Loan
$Y_{b,c,t}$	$\Delta \ln$(Deposits)	Δ(Deposit Spread)	ln(Mortgage)	ln(Small Business Loan)
$1(\text{Pricing})_{b,c,t}$	−0.019	−0.171***	−0.847***	−0.067**
	(0.014)	(0.022)	(0.099)	(0.028)
$1(\text{Service})_{b,c,t}$	0.0131*	0.0194**	−0.810***	−0.018
	(0.008)	(0.009)	(0.060)	(0.017)
$1(\text{Emotion/Trust})_{b,c,t}$			*Omitted*	
Observations	48,709	48,709	335,171	401,296
R-squared	0.356	0.954	0.681	0.784
No. of Institutions	352	352	930	418
Mean of Y	0.038	−0.007	11.64	12.35
Bank-County FE	Y	Y	Y	Y
Bank-Border-Year FE	Y	Y	Y	Y

Notes. This table examines the relationship between advertising content and demand for financial products using a border discontinuity design in a bank(b)-county(c)-border($d(c)$)-year(t) panel. The outcome variables, $Y_{b,c,t}$, include the changes in the log of deposits $\Delta \ln$(Deposits) in Column (1), changes in the deposit spread Δ(Deposit Spread) in Column (2), the log amount of new mortgage origination ln(Mortgage) in Column (3), and the log amount of new small business loan origination ln(Small Business Loan) from CRA in Column (4). The measures of advertising content include pricing information $1(\text{Pricing})_{b,c,t}$ and service quality $1(\text{Service})_{b,c,t}$, omitting emotional appeal and trust building $1(\text{Emotion/Trust})_{b,c,t}$. We use product-specific advertising measures, namely deposits in Column (1)-(2), mortgages in Column (3), and business loans in Column (4). 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.

Internet Appendix (For Online Publication Only)

How Do Banks Compete?
Evidence from Advertising Videos

Xugan Chen Allen Hu Song Ma

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 Advertising Content

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

A.1.3. Additional Results on Advertising Spending

Table A.6 examines the relationship between bank advertising spending and bank market power and franchise value. We use the bank holding company (b)-quarter (t) panel and estimate the following specifications:

$$Y_{b,t} = \beta \cdot \text{AdSpend}_{b,t-1} + \gamma X_{b,t-1} + \eta_t + \epsilon_{b,t}, \tag{A1}$$

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 $t-1$. $X_{b,t-1}$ 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 for one period, relative to the dependent variables.

Table A.6 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. 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. 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.

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 advertising is an important way through which banks invest in building a deposit franchise, which gives them market power.

Table A.7 follows Drechsler et al. (2017) and shows how advertising spending affects monetary policy transmission. We estimate the following within-county specification on the same bank holding company (b)-county (c)-year (t) panel.

$$\begin{aligned} Y_{b,c,t} =& \beta^{\text{Ad}} \text{AdSpend}_{b,c,t-1} + \gamma^{\text{Ad}} \Delta \text{FF}_t \times \text{AdSpend}_{b,c,t-1} \\ &+ \beta^{\text{HHI}} \text{Deposit-HHI}_{b,t-1} + \gamma^{\text{HHI}} \Delta \text{FF}_t \times \text{Deposit-HHI}_{b,t-1} + \eta_{b,c} + \eta_{c,t} + \epsilon_{b,c,t}, \end{aligned} \tag{A2}$$

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. $\text{AdSpend}_{b,c,t-1}$ is lagged log values of advertising spending of bank b in county c in year $t-1$. ΔFF_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.

Table A.7 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.

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:

$$Y_{b,c,t} = \beta \cdot \text{AdSpend or AdContent}_{b,c,t} + \eta_{b,c} + \eta_{b,d(c),t} + \epsilon_{b,c,d(c),t}, \tag{A3}$$

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.

Table A.8 presents the results of the border discontinuity design. 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 (2) 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 (3) and (4) 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.

A.1.4. Financial Crisis

We study how macro shocks such as the Global Financial Crisis (GFC) alter bank advertising content. 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 advertising content from these "treated" banks relative to other banks operating in the same county.

$$\text{AdContent}_{b,c,t} = \beta \cdot \text{Post(GFC)}_t \times 1(\text{Lehman Cosyndication})_b + \eta_b + \eta_{c,t} + \epsilon_{b,c,t}. \quad \text{(A4)}$$

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.

Table A.9 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.

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

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`,[17] 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`.[18] We then apply the open-sourced speech-to-text model `Whisper`[19] 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.[20] The transcript, audio features, and visual frames are then provided simultaneously to `OmniEmbed`, which outputs a single 3,584-dimensional embedding for each advertisement.

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`),[21] 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 the original high-

[17] https://huggingface.co/Tevatron/OmniEmbed-v0.1
[18] https://github.com/Zulko/moviepy
[19] https://github.com/openai/whisper
[20] https://github.com/nidhaloff/deep-translator
[21] https://github.com/YingfanWang/PaCMAP

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 advertising content, 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.

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 advertising content. We then move to higher levels of the hierarchy to recover more aggregated clusters, which correspond to broader product categories and advertising

content.

While HAC provides only hard cluster assignments, advertisements may naturally overlap in advertising content (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.

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 advertising content 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 Advertising Content 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 categorization extracted from the LLM is highly consistent with the clustering method.

A.2.4. More Examples of Advertising Content

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 advertising content 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."

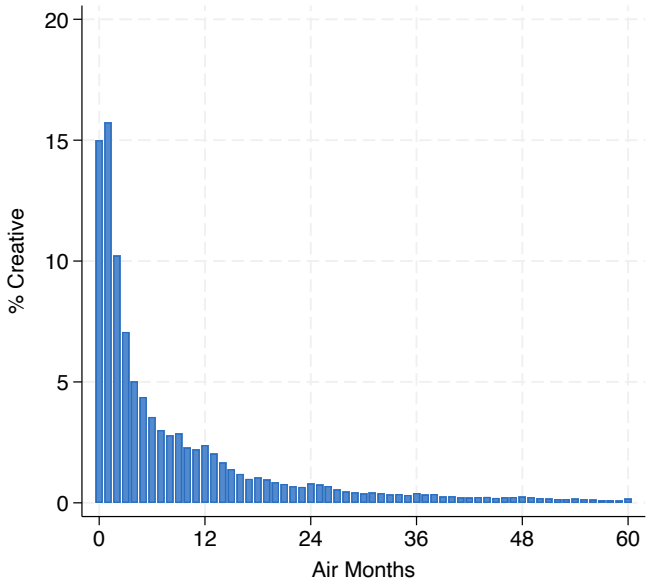
For trust building, we focus on the relationship building, such as brand promotion and home and community trust, and professional imagery, such as professional expertise and wealth management.

"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."

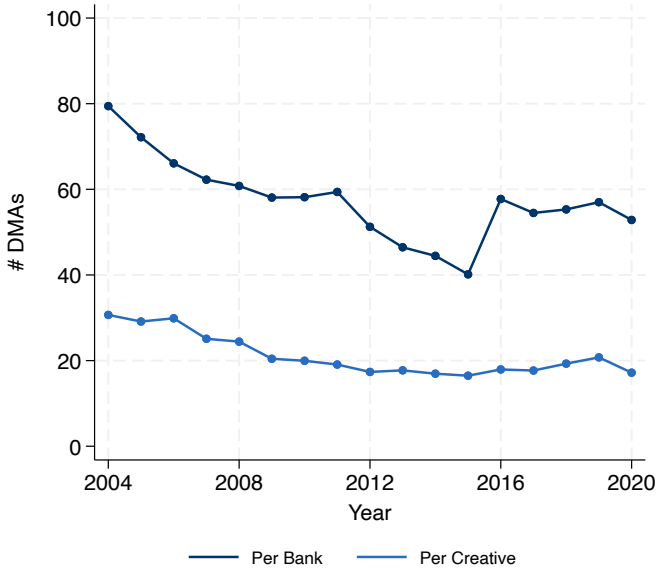
"Are you in good hands? At any minute, you could be a victim of fraud. Fraud could mean lower credit scores and higher interest rates when you apply for a credit card. It's a problem waiting to happen. Check your credit score. "

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

Panel (a): Air Months

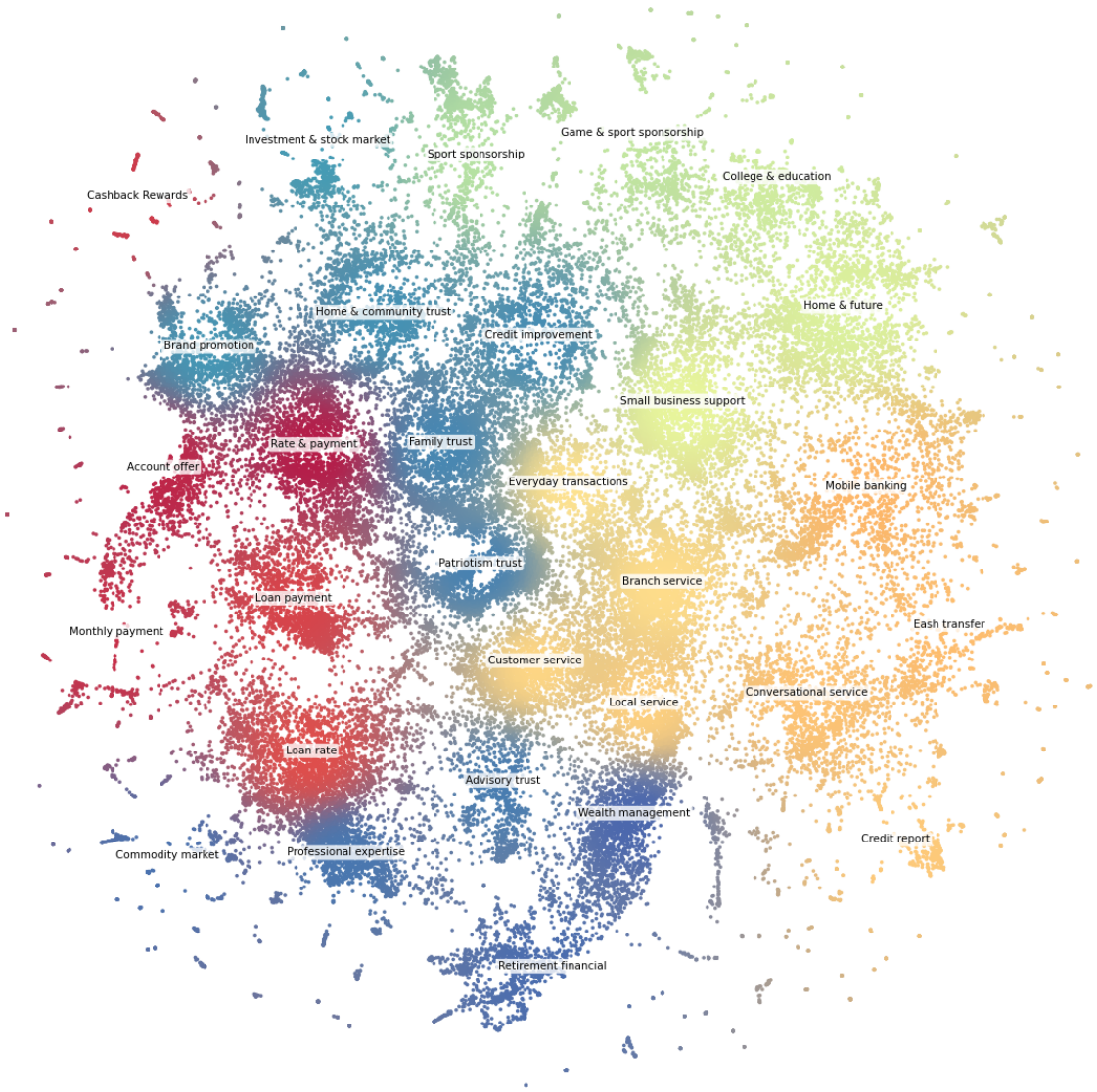


Panel (b): Geographic Coverage



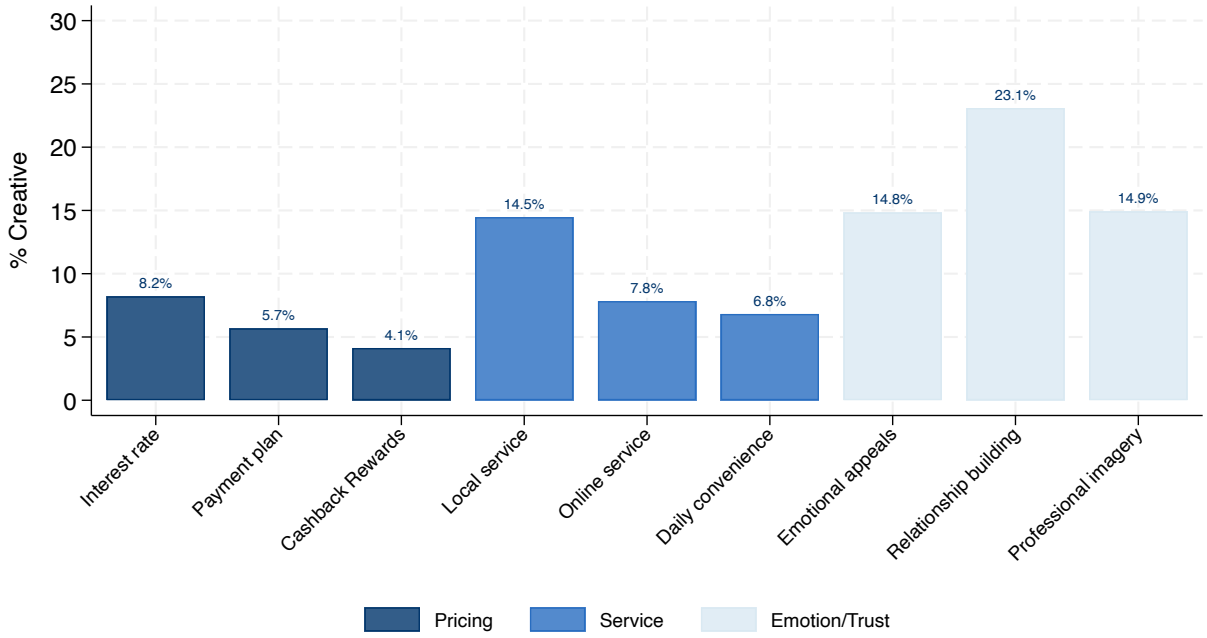
Notes. This figure shows the distribution of air months of financial advertising in Panel (a) and geographic coverage of financial advertising in Panel (b). In Panel (a), the tenure is measured in terms of the total number of months the advertising aired on television. In Panel (b), the dark blue line 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 Advertising Content



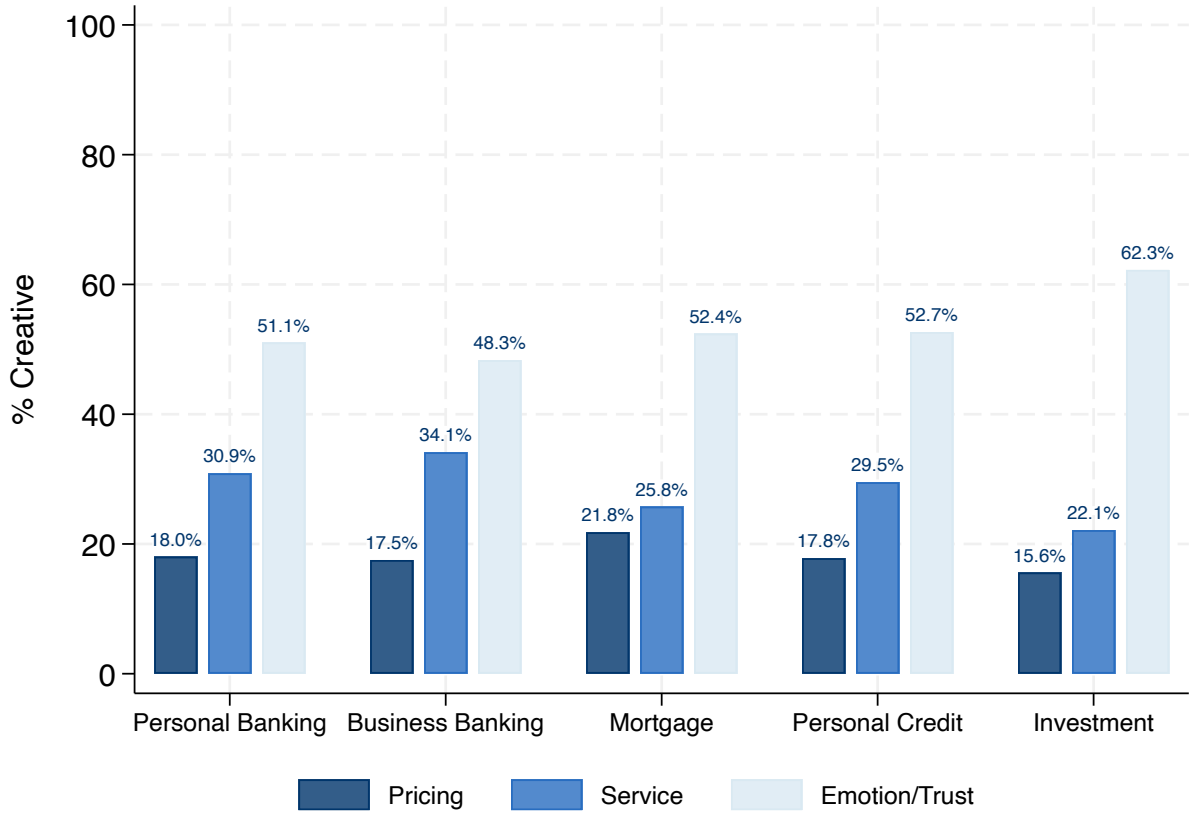
Notes. This figure shows the visualization of the 2-dimensional video embedding for detailed advertising content.

Figure A.3. Distribution of the Detailed Advertising Content



Notes. This figure shows the distribution of detailed advertising content for financial advertising. The list of financial advertising persuasive information can be found in Table 2. The financial information category contains detailed content 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.

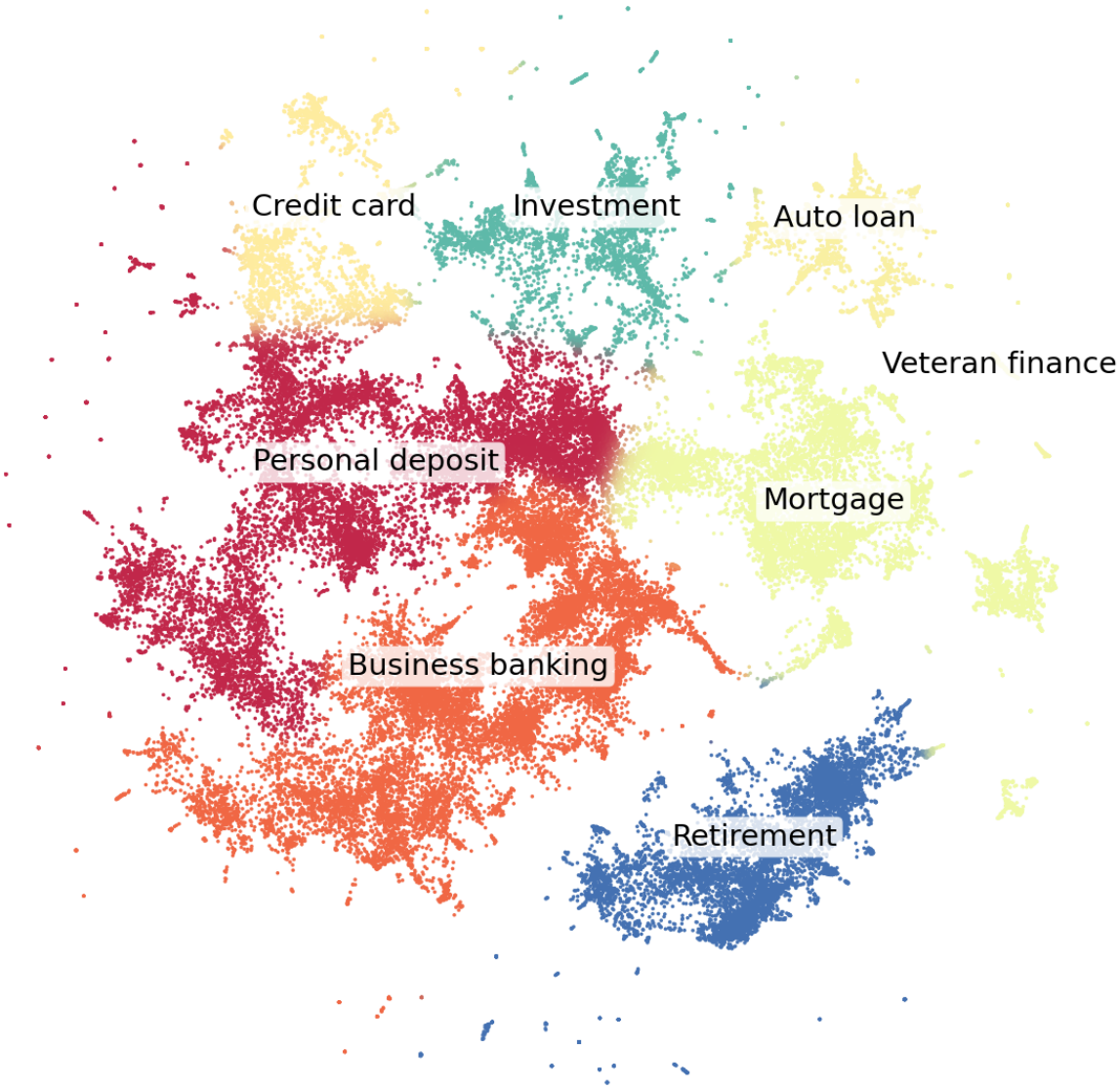
Figure A.4. Distribution of the Advertising Content by Product Categories



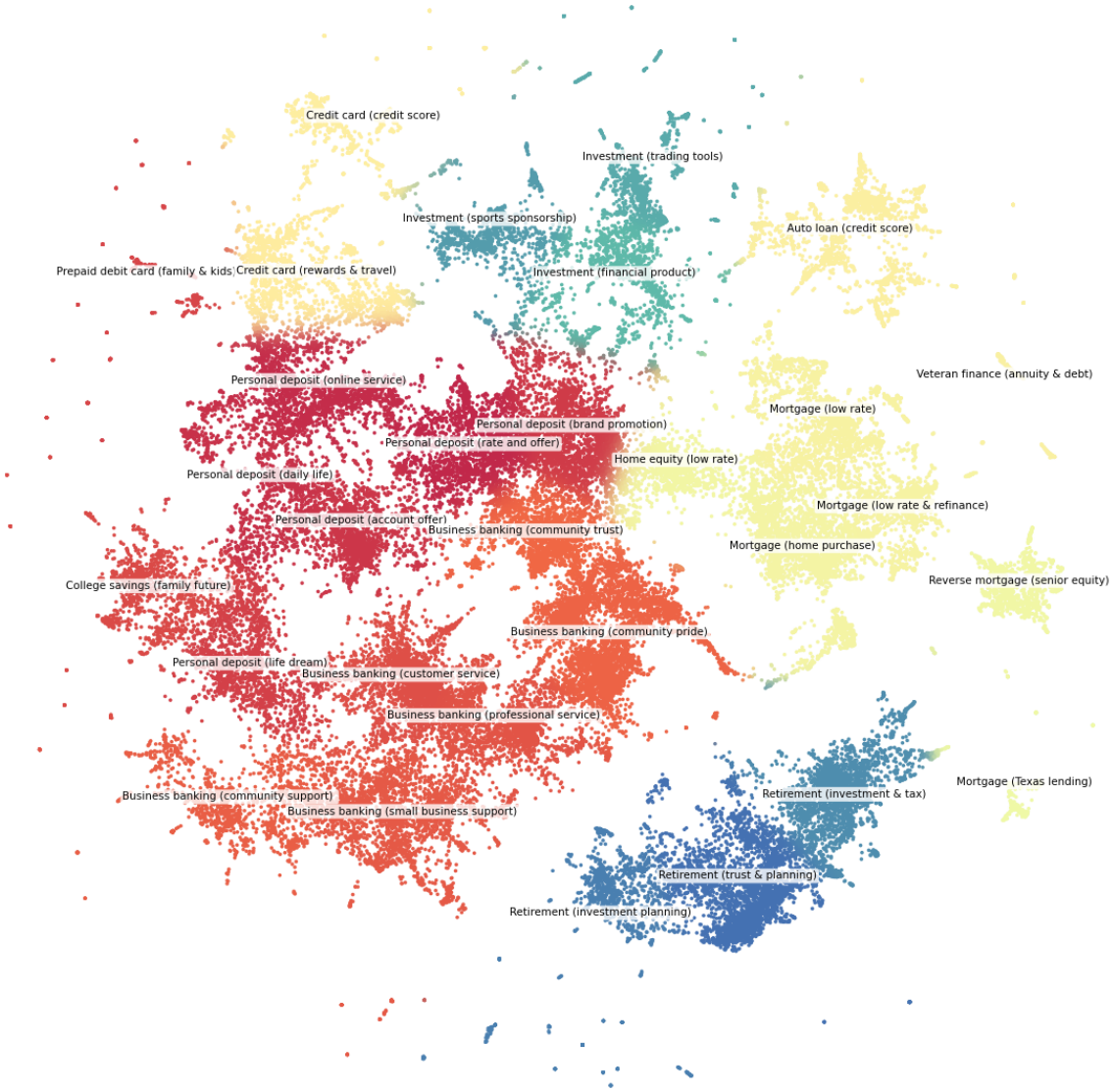
Notes. This figure shows the distribution of advertising content for different specific products. The list of financial advertising broad persuasive information can be found in Table 2.

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

Panel (a): Broader Product Category



Panel (b): Detailed Product Category



Notes. This figure shows the visualization of the two-dimensional video embeddings 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)
$\text{Z-Score}_{b,t-1}$	-0.002			−0.002
	(0.002)			(0.002)
$\text{ROA}_{b,t-1}$	−0.059*			−0.020
	(0.032)			(0.024)
Tobin's $q_{b,t-1}$		−0.130*		−0.125*
		(0.073)		(0.074)
$\text{Deposit Spread}_{b,t-1}$		−0.039**		−0.026*
		(0.016)		(0.016)
$\text{Deposit Productivity}_{b,t-1}$		0.040**		0.007
		(0.019)		(0.068)
$\text{Asset Productivity}_{b,t-1}$		0.006		0.012
		(0.012)		(0.012)
$\text{Deposits HHI}_{b,t-1}$			−0.905***	−0.913***
			(0.313)	(0.309)
$\text{Mortgage HHI}_{b,t-1}$			−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 Advertising Content

Panel (a): For All Financial Advertising

	$\text{AdContent}_{b,t+1}$		
$\text{AdContent}_{b,t}$	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

	$\text{AdContent}_{b,t+1}$		
$\text{AdContent}_{b,t}$	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

	$\text{AdContent}_{b,t+1}$		
$\text{AdContent}_{b,t}$	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 advertising content over year. Panel (a) contains advertising content at the bank-year level using all the financial advertising. Panel (b) and Panel (c) contains advertising content 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 Advertising Content 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 (b) Product Category

	Advertising Content (Clustering)			
	Pricing	Service	Emotion	Trust
# Videos	10,535	16,585	8,512	21,948
Distribution of Advertising Content 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 Advertising Content 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 advertising content obtained specifically through the clustering method and LLM. Panel (a) and Panel (b) shows the distribution of product categories and advertising content, 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. Advertising Content by Service Quality Banks: Alternative Measure

	(1)	(2)	(3)
Measure of Service Quality	Branch Network		
Ad Category	Deposit		
% AdContent$_{b,c,t}$	Pricing	Service	Emotion/Trust
High Service 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 advertising content across banks with different levels of service quality in a bank(b)-county(c)-year(t) panel. The analysis considers the deposit business. % AdContent$_{b,c,t}$ is the share of advertising content used by bank b in county c in year t. High Service 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.

Table A.5. Advertising Content by High Versus Low 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		
% AdContent$_{b,c,t}$	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust	Pricing	Service	Emotion/Trust
Large (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 advertising content 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). % AdContent$_{b,c,t}$ is the share of advertising content for that specific product used by bank b in county c in year t. Large (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 A.6. Advertising Spending and Bank Value

	(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

Notes. This table examines the relationship between bank advertising spending 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. $\text{Ad}_{b,t-1}$ is Compustat advertising expense scaled by Call Reports total non-interest expense for bank b in quarter $t-1$. 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 A.7. Advertising Spending and Monetary Policy Transmission

	(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

Notes. This table examines the relationship between advertising spending and the transmission of monetary policy in a bank(b)-county(c)-year(t) panel. $\ln(\text{Ad})_{b,c,t-1}$ is the lagged log advertising spending for bank b in county$c$ in year $t-1$. 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.

Table A.8. Advertising Spending and Financial Product Demand: Border Discontinuity Design

	(1)	(2)	(3)	(4)
Ad Category	Deposit		Mortgage	Loan
$Y_{b,c,t}$	$\Delta \ln$(Deposits)	Δ(Deposit Spread)	ln(Mortgage)	ln(Small Business Loan)
$\ln(\text{Ad})_{b,c,t}$	0.0009**	0.0017***	0.010**	0.007***
	(0.0004)	(0.0006)	(0.004)	(0.001)
Observations	48,709	48,709	335,171	401,296
R-squared	0.284	0.954	0.680	0.784
No. of Institutions	352	352	930	418
Mean of Y	0.0375	−0.0072	11.64	12.35
Bank-County FE	Y	Y	Y	Y
Bank-Border-Year FE	Y	Y	Y	Y

Notes. This table examines the relationship between advertising spending and demand for financial products using a border discontinuity design in a bank(b)-county(c)-border($d(c)$)-year(t) panel. The outcome variables, $Y_{b,c,t}$, include the changes in the log of deposits $\Delta \ln$(Deposits) in Column (1), changes in the deposit spread Δ(Deposit Spread) in Column (2), the log amount of new mortgage origination ln(Mortgage) in Column (3), and the log amount of new small business loan origination ln(Small Business Loan) from CRA in Column (4). $\ln(\text{Ad})_{b,c,t}$ is the log amount of advertising spending for bank b in county c in year t. We use product-specific advertising measures, namely deposits in Column (1)-(2), mortgages in Column (3), and business loans in Column (4). 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 A.9. Advertising Content After Economic Shocks: Financial Crisis

	(1)	(2)	(3)
Ad Category	All		
% $\text{AdContent}_{b,c,t}$	Pricing	Service	Emotion/Trust
Post(GFC)_t	1.680***	−5.236***	3.556***
$\times 1(\text{Lehman Cosyndication})_b$	(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 advertising content changes after financial crisis, using a bank(b)-county(c)-year(t) panel. Post(GFC)_t is a dummy variable for whether year t falls in the range of 2007 to 2011. $1(\text{Lehman Cosyndication})_b$ 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 A.10. Balance Test: Border Discontinuity Design

	(1) ln(Ad)	(2) Pricing	(3) Service	(4) Emotion/Trust
ln(Income)	0.0116	0.0009	−0.0024	0.0015
	(0.0585)	(0.0021)	(0.0035)	(0.0029)
ln(Population)	−0.0380	−0.0059*	0.0031	0.0027
	(0.1073)	(0.0034)	(0.0059)	(0.0046)
Female (%)	0.0024	0.0001	−0.0004	0.0002
	(0.0073)	(0.0003)	(0.0004)	(0.0003)
Minority (%)	−0.0026	0.0001	−0.0003	0.0001
	(0.0037)	(0.0001)	(0.0002)	(0.0002)
Age<20 (%)	−0.0043	−0.0000	0.0003	−0.0003
	(0.0053)	(0.0002)	(0.0003)	(0.0002)
20<=Age<35 (%)	−0.0029	−0.0001	0.0002	−0.0001
	(0.0060)	(0.0002)	(0.0004)	(0.0003)
35<=Age<60 (%)	−0.0036	0.0000	0.0001	−0.0002
	(0.0051)	(0.0002)	(0.0003)	(0.0002)
Less than High School (%)	0.0403	0.0086	−0.0304	0.0218
	(0.3222)	(0.0143)	(0.0219)	(0.0159)
High School (%)	0.1464	0.0025	−0.0134	0.0110
	(0.2480)	(0.0112)	(0.0172)	(0.0126)
College (%)	−0.0298	0.0015	−0.0136	0.0121
	(0.2613)	(0.0117)	(0.0182)	(0.0134)
Observations	2,814,698	2,814,698	2,814,698	2,814,698
R-squared	0.636	0.269	0.279	0.262
No. of Institutions	2,361	2,361	2,361	2,361
Mean of Y	4.642	0.140	0.366	0.494
Bank-Border-Year FE	Y	Y	Y	Y
Bank-County FE	Y	Y	Y	Y

Notes. This table examines the balance test across the borders using a border discontinuity design in a bank(b)-county(c)-border($d(c)$)-year(t) panel. The outcome variables include the log amount of advertising spending and the three categories of advertising content. 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.

A.3. Technical Details for the Conceptual Framework

A.3.1. More Details on Rate Sensitivity

The framework uses two equivalent representations of $\bar{\alpha}_j$:

- *Attention representation:* $\bar{\alpha}_j = \lambda_j \alpha$, where λ_j is the wakeup rate—the probability that a depositor is awake to rates when evaluating bank j—and α is the common rate sensitivity of awake depositors. This makes the micro-foundation transparent: $\bar{\alpha}_j$ is high when the bank's advertising wakes many depositors up.

- *Content representation:* $\bar{\alpha}_j = (\alpha_0 + \alpha_1) - (\alpha_1 + \alpha_2 \tilde{q}_j) s_j - (\alpha_1 + \alpha_3)\tau_j$. This makes comparative statics transparent: each unit of service content reduces effective rate sensitivity by $(\alpha_1 + \alpha_2 \tilde{q}_j)$; each unit of trust content reduces it by $(\alpha_1 + \alpha_3)$.

The two representations are linked by $\alpha_k = \lambda_k \alpha$ for $k \in \{0, 1, 2, 3\}$: the content parameters in the second representation are the attention parameters times the common rate sensitivity. The bank-specific wakeup rate is endogenous, determined by the content allocation: $\lambda_j = \bar{\alpha}_j / \alpha$, which is decreasing in own non-price content. Higher $(s_j + \tau_j)$ puts more depositors to sleep, reducing effective rate sensitivity.

The central mechanism is linked through the wakeup rate λ_j in (2) in the main text, which is motivated by models of depositor inattention in Egan et al. (2025) and Lu and Wu (2026). We formalize the connection here.

Depositors evaluate banks under limited rate attention (Egan et al., 2025; Lu and Wu, 2026). When considering bank j, a depositor is *awake* to rates with probability λ_j and *asleep* to rates with probability $1 - \lambda_j$. An awake depositor perceives the full utility $\alpha(r_j - r_M) + s_j q_j + \tau_j \xi$. An asleep depositor perceives only the non-rate components $s_j q_j + \tau_j \xi$—she still values quality and trust, but does not register the rate gap. The expected deterministic utility is:

$$V_j = \lambda_j [\alpha(r_j - r_M) + s_j q_j + \tau_j \xi] + (1 - \lambda_j)[s_j q_j + \tau_j \xi] = \lambda_j \alpha (r_j - r_M) + s_j q_j + \tau_j \xi \quad \text{(A5)}$$

Defining $\bar{\alpha}_j \equiv \lambda_j \alpha$, this becomes $V_j = \bar{\alpha}_j (r_j - r_M) + s_j q_j + \tau_j \xi$.

This formulation is grounded in two recent empirical contributions. Egan et al. (2025) document that depositors infrequently shop for deposits, with 5–15% opening a new account each year, and model depositors as alternating between "awake" and "asleep" states following Beggs and Klemperer (1992) and Brown et al. (2023). They estimate that depositor sleepiness accounts for 58% of the average bank's deposit franchise value. Lu and Wu (2026) use transaction-level data on millions of U.S. depositors to show that inattention varies widely: unscheduled income remains in low-rate accounts much longer than scheduled income, and banks serving more inattentive depositors set lower rates and have weaker pass-through.

Our contribution is to endogenize the wakeup rate λ_j through advertising content. In Egan et al. (2025), the wakeup rate is an exogenous depositor characteristic. In our framework, λ_j is bank-specific and determined by bank j's advertising mix via (2) in the main text: pricing content wakes depositors up; service and trust content keep them asleep with respect to rates. The linear specification for λ_j in advertising content is a first-order approximation valid for interior content allocations. The empirical advertising distribution (18%/29%/53% across pricing/service/trust) suggests most banks are interior. Substituting the budget constraint $p_j = 1 - s_j - \tau_j$ and defining $\alpha_k \equiv \lambda_k \alpha$ yields the main-text representation (3).

A.3.2. Proof of Proposition 1

Bank j chooses content (s_j, τ_j) and deposit rate r_j to maximize:

$$\Pi_j = (r_M - r_j) \cdot D_j - \frac{\gamma_s}{2} s_j^2 - \frac{\gamma_\tau}{2} \tau_j^2 \tag{A6}$$

where logit demand is $D_j = \exp(V_j)/[\exp(V_H)+\exp(V_L)+1]$ with $V_j = \bar{\alpha}_j(r_j - r_M) + s_j q_j + \tau_j \xi$ and the outside option normalized to $V_0 = 0$.

First-order condition for deposit rate. The standard logit demand gives $\partial D_j / \partial \mu_j = D_j(1 - D_j)(-\bar{\alpha}_j)$. Differentiating $\Pi_j = \mu_j D_j - C_j$ with respect to μ_j gives $\partial \Pi_j / \partial \mu_j = D_j - \mu_j \bar{\alpha}_j D_j (1 - D_j) = 0$. This yields the standard logit markup:

$$\mu_j^* = \frac{1}{\bar{\alpha}_j (1 - D_j)}. \tag{A7}$$

First-order condition for content. Using the budget constraint $p_j = 1 - s_j - \tau_j$, Bank j chooses (s_j, τ_j). By the envelope theorem at $\mu_j = \mu_j^*$, the FOC with respect to s_j (holding τ_j fixed, so $dp_j = -ds_j$) gives:

$$\frac{\partial \Pi_j^*}{\partial s_j} = \mu_j^* \frac{\partial D_j}{\partial s_j} - \gamma_s s_j = 0 \tag{A8}$$

The total effect of increasing s_j (at the expense of p_j) on demand operates through two channels: (i) the direct utility effect of substituting service for pricing content, and (ii) the indirect effect through reduced rate sensitivity (more depositors put to sleep):

$$\frac{\partial D_j}{\partial s_j} = D_j(1 - D_j)\left[q_j + (\alpha_1 + \alpha_2 \tilde{q}_j)(r_M - r_j)\right] \tag{A9}$$

The first term, q_j, is the direct gain from revealing service quality. The second term, $(\alpha_1 + \alpha_2 \tilde{q}_j)\mu_j$, captures the attention-reduction channel: shifting content from pricing to service puts more depositors to sleep with respect to rates (lowers $\bar{\alpha}_j$ by $\alpha_1 + \alpha_2 \tilde{q}_j$), which increases demand by making depositors less sensitive to the rate gap. Both terms are strictly positive whenever $\mu_j > 0$. Thus, the FOC becomes:

$$\mu_j^* D_j(1 - D_j)\left[q_j + (\alpha_1 + \alpha_2 \tilde{q}_j)\mu_j^*\right] = \gamma_s s_j \tag{A10}$$

The bounded LHS and linearly growing RHS guarantee an interior solution.

The FOC with respect to τ_j is analogous, with $(\alpha_1 + \alpha_3)$ replacing $(\alpha_1 + \alpha_2 \tilde{q}_j)$ in the rate-sensitivity term, and ξ replacing q_j in the direct effect:

$$\mu_j^* D_j(1 - D_j)\left[\xi + (\alpha_1 + \alpha_3)\mu_j^*\right] = \gamma_\tau \tau_j \tag{A11}$$

Part (i): Existence and uniqueness of equilibrium. We divide the bank's problem into two stages: the rate-setting subgame and the content-choice game.

In stage 1, the rate-setting subgame, the bank chooses the deposit rate r_j to maximize its profit given the content choice of the other bank. For any fixed content pair, the rate-setting game is a standard logit pricing game with an outside option. Each bank's profit $\Pi_j = (r_M - r_j)D_j - C_j$ is strictly concave in r_j (since $\partial^2 \Pi_j / \partial r_j^2 = -\bar{\alpha}_j D_j(1 - D_j)[2 - \mu_j \bar{\alpha}_j(1 - 2D_j)] < 0$

when $D_j < 1/2$), so best responses $r_j^*(r_{-j})$ are well-defined. The best-response mapping is a contraction under the standard condition $|\partial^2\Pi_j/\partial r_j \partial r_{-j}| < |\partial^2\Pi_j/\partial r_j^2|$, which holds under sufficient quality differentiation. By the contraction mapping theorem, there exists a unique Nash equilibrium in rates for each content profile.

In stage 2, the content-choice game, the bank chooses the content (s_j, τ_j) to maximize its profit. Each bank's reduced-form profit $\Pi_j^*(s_j, \tau_j; s_{-j}, \tau_{-j})$ is continuous on the compact simplex. With convex content costs ($\gamma_s, \gamma_\tau > 0$), the own-content Hessian is dominated by the cost terms for sufficiently large γ_s, γ_τ, ensuring strict concavity. Existence follows from the Debreu–Fan–Glicksberg theorem.

Under logit demand with sufficient quality differentiation ($q_H - q_L$ large), content choices approach dominant strategies: Bank H suppresses pricing ($p_H^* \approx 0$) regardless of p_L, and Bank L emphasizes pricing ($p_L^* \approx 1$) regardless of p_H. For smaller quality gaps, content choices exhibit weak strategic substitutability ($dp_H^*/dp_L < 0$): if Bank L increases pricing content, Bank H has slightly more incentive to differentiate via non-price content. This downward-sloping best-response structure stabilizes the differentiated equilibrium.

A sufficient condition for a unique pure-strategy Nash equilibrium with $p_H^* < p_L^*$ is $(q_H - q_L)\alpha_2/\bar{q} > (\alpha_1 + \alpha_3) \cdot |dp_H^*/dp_L|_{\max}$. Intuitively, uniqueness obtains when quality differentiation is large enough that the comparative advantage in content choice dominates any strategic complementarity. Under the illustrative parameter values in Appendix A.3.4, this condition holds comfortably; we cannot rule out multiple equilibria for arbitrary parameter configurations, but the empirical content distributions are consistent with the unique equilibrium the model predicts.

Part (i): Bank H chooses more non-price content. From (A10), the marginal benefit of service content is $\mu_j^* D_j(1 - D_j)[q_j + (\alpha_1 + \alpha_2\tilde{q}_j)\mu_j^*]$. Since $q_H > q_L$ and $\tilde{q}_H > \tilde{q}_L$, Bank H has a strictly larger marginal benefit at any given (s_j, μ_j^*) pair. With the same marginal cost $\gamma_s s_j$, Bank H optimally chooses more service content: $s_H^* > s_L^*$. The trust FOC (A11) gives a similar comparison, $\tau_H^* > \tau_L^*$. Putting these together, we get $s_H^* + \tau_H^* > s_L^* + \tau_L^*$.

Part (ii): Bank H's depositors are sleepier. From (3): $\bar{\alpha}_H - \bar{\alpha}_L = -(\alpha_1 + \alpha_2\tilde{q}_H)(s_H^* - s_L^*) - (\alpha_1 + \alpha_3)(\tau_H^* - \tau_L^*) - \alpha_2(\tilde{q}_H - \tilde{q}_L)s_L^*$. All three terms are negative using Part (i) and $\tilde{q}_H > \tilde{q}_L$. Hence $\bar{\alpha}_H < \bar{\alpha}_L$: Bank H's depositors are more asleep to rates.

Part (iii): Service share increasing in quality. Dividing (A10) by (A11), the $\mu_j^* D_j(1 - D_j)$ terms cancel:

$$\frac{s_j^*}{\tau_j^*} = \frac{\gamma_\tau}{\gamma_s} \cdot \frac{q_j + (\alpha_1 + \alpha_2\tilde{q}_j)\mu_j^*}{\xi + (\alpha_1 + \alpha_3)\mu_j^*} \tag{A12}$$

The numerator is increasing in q_j (both directly and through $\tilde{q}_j$); the denominator is independent of q_j directly. Hence s_j^*/τ_j^* is increasing in bank quality: high-quality banks tilt non-price content toward service because quality-revealing advertising is more effective at absorbing depositor attention.

Part (iv): $\mu_H^* > \mu_L^*$. From the markup $\mu_j^* = 1/[\bar{\alpha}_j(1 - D_j)]$, we need $\bar{\alpha}_H(1 - D_H) < \bar{\alpha}_L(1 - D_L)$. Part (ii) gives $\bar{\alpha}_H < \bar{\alpha}_L$. For the demand side: Bank H's higher non-rate utility $Q_H = s_H q_H + \tau_H \xi$ makes $V_H > V_L$ for sufficiently large quality differentiation (the Q difference dominates the $\bar{\alpha}\mu$ difference), so $D_H > D_L$ and $1 - D_H < 1 - D_L$. Both channels push $\mu_H^* > \mu_L^*$.

More formally: as $q_H/q_L \to \infty$, $Q_H \to \infty$ while $\bar{\alpha}_H \to 0$ (all content goes to non-price). Then $V_H \to \infty$, $D_H \to 1$, $\bar{\alpha}_H(1 - D_H) \to 0$, and $\mu_H^* \to \infty$. By continuity (via the implicit function theorem on the FOC system), $\mu_H^* > \mu_L^*$ holds for $q_H/q_L > \theta^*$. □

A.3.3. Proof of Proposition 2

In the logit demand model with outside option ($V_0 = 0$), deposit demand for bank j is:

$$D_j = \frac{\exp(V_j)}{\exp(V_H) + \exp(V_L) + 1}$$

where $V_j = \bar{\alpha}_j(r_j - r_M) + s_j q_j + \tau_j \xi$. The rate FOC $\partial \Pi_j / \partial r_j = 0$ yields the standard logit markup $\mu_j^* = 1/[\bar{\alpha}_j(1 - D_j)]$, where $1 - D_j$ includes both the rival bank's share and the outside option share.

Service content effect. First, we consider the service content effect. From Proposition 2, we know that $\mu_j^* = 1/[\bar{\alpha}_j(1-D_j)]$. Differentiating properly:

$$\frac{\partial \mu_j^*}{\partial s_j} = -\big[\bar{\alpha}_j(1-D_j)\big]^{-2} \cdot \frac{\partial\big[\bar{\alpha}_j(1-D_j)\big]}{\partial s_j} \tag{A13}$$

$$= -\big[\bar{\alpha}_j(1-D_j)\big]^{-2} \cdot \left(\frac{\partial \bar{\alpha}_j}{\partial s_j}(1-D_j) + \bar{\alpha}_j\Big(-\frac{\partial D_j}{\partial s_j}\Big)\right) \tag{A14}$$

$$= -\big[\bar{\alpha}_j(1-D_j)\big]^{-2} \cdot \Big\{-(1-D_j)\big[(\alpha_1+\alpha_2\tilde{q}_j) + \bar{\alpha}_j D_j(q_j + (\alpha_1+\alpha_2\tilde{q}_j)\mu_j)\big]\Big\} \tag{A15}$$

$$= \frac{\big[(\alpha_1+\alpha_2\tilde{q}_j) + \bar{\alpha}_j D_j(q_j + (\alpha_1+\alpha_2\tilde{q}_j)\mu_j)\big]}{\bar{\alpha}_j^2(1-D_j)} > 0, \tag{A16}$$

where the third equality follows from the fact that $\frac{\partial \bar{\alpha}_j}{\partial s_j} = -(\alpha_1+\alpha_2\tilde{q}_j)$ and $\frac{\partial D_j}{\partial s_j} = D_j(1-D_j)\big[q_j + (\alpha_1+\alpha_2\tilde{q}_j)\mu_j\big]$.

The effect of service content on the spread is increasing in $\tilde{q}_j$: high-quality banks get a larger spread increase per unit of service content. The mechanism: service content puts more depositors to sleep ($\bar{\alpha}_j$ falls by $\alpha_1+\alpha_2\tilde{q}_j$), widening the optimal markup.

Trust content effect. Similarly, we can show that the trust content effect is:

$$\frac{\partial \mu_j^*}{\partial \tau_j} = -\big[\bar{\alpha}_j(1-D_j)\big]^{-2} \cdot \frac{\partial\big[\bar{\alpha}_j(1-D_j)\big]}{\partial \tau_j} \tag{A17}$$

$$= -\big[\bar{\alpha}_j(1-D_j)\big]^{-2} \cdot \left(\frac{\partial \bar{\alpha}_j}{\partial \tau_j}(1-D_j) + \bar{\alpha}_j\Big(-\frac{\partial D_j}{\partial \tau_j}\Big)\right) \tag{A18}$$

$$= -\big[\bar{\alpha}_j(1-D_j)\big]^{-2} \cdot \Big\{-(1-D_j)\big[(\alpha_1+\alpha_3) + \bar{\alpha}_j D_j(\xi + (\alpha_1+\alpha_3)\mu_j)\big]\Big\} \tag{A19}$$

$$= \frac{\big[(\alpha_1+\alpha_3) + \bar{\alpha}_j D_j(\xi + (\alpha_1+\alpha_3)\mu_j)\big]}{\bar{\alpha}_j^2(1-D_j)} > 0, \tag{A20}$$

where the third equality follows from the fact that $\frac{\partial \bar{\alpha}_j}{\partial \tau_j} = -(\alpha_1+\alpha_3)$ and $\frac{\partial D_j}{\partial \tau_j} = D_j(1-D_j)\big[\xi + (\alpha_1+\alpha_3)\mu_j\big]$.

The effect of trust content on the spread is independent of $\tilde{q}_j$. Moreover, for Bank H with $\tilde{q}_H > 1$, $\partial\mu_H^*/\partial s_H > \partial\mu_H^*/\partial\tau_H$, when (1) $q_j \geq \xi$, i.e., service quality is at least as valued as trust, and (2) $\alpha_2\tilde{q}_H > \alpha_3$, i.e., quality is high enough that service content is more effective at putting depositors to sleep than trust content.

A.3.4. Deposit Beta Derivation

Period-2 setup. In Period 2, the policy rate rises to $r'_M = r_M + \Delta r$ and bank j re-optimizes its deposit rate given the depositor base inherited from Period 1. The bank's advertising content is fixed (campaigns are pre-committed). The wakeup rate λ_j from Period 1 continues to govern which depositors are awake.

Of bank j's Period-1 depositors (mass $D_j^{(1)}$): (i) fraction λ_j are *awake*—they observe the new rate environment and re-optimize between the bank and the outside option via a binary logit with rate sensitivity α; (ii) fraction $1 - \lambda_j$ are *asleep*—they do not observe the rate change and remain at bank j regardless. Total Period-2 deposits are:

$$D_j^{(2)}(r_j) = \underbrace{(1-\lambda_j)D_j^{(1)}}_{\text{asleep: stay}} + \underbrace{\lambda_j D_j^{(1)} \cdot \sigma_j(r_j - r'_M)}_{\text{awake: re-optimize}}$$

where $\sigma_j(x) = e^{\alpha x}/(1+e^{\alpha x})$ is the logit retention probability: the probability that an awake depositor stays at bank j given rate gap $x = r_j - r'_M$.

First-order condition. The bank maximizes $\Pi_j^{(2)} = (r'_M - r_j) \cdot D_j^{(2)}$. Using $\partial\sigma_j/\partial r_j = \alpha\sigma_j(1-\sigma_j)$, the FOC $\partial\Pi_j^{(2)}/\partial r_j = 0$ yields:

$$D_j^{(2)} = \mu_j \cdot \alpha\sigma_j(1-\sigma_j)\lambda_j D_j^{(1)} \tag{A21}$$

where $\mu_j \equiv r'_M - r_j$ is the deposit spread.

Why logit alone yields $\beta = 1$. Because σ_j depends only on the rate gap $x \equiv r_j - r'_M$, the profit function $\Pi_j^{(2)} = (-x) \cdot [(1-\lambda_j)D_j^{(1)} + \lambda_j D_j^{(1)}\sigma_j(x)]$ depends on r'_M only through x. The FOC $\partial\Pi/\partial x = 0$ therefore pins down a constant optimal gap x^*, independent of the level of r'_M, implying $dr_j^*/dr'_M = 1$—full pass-through regardless of the wakeup rate λ_j. This translation invariance is a standard property of logit demand: the constant semi-elasticity $\partial\sigma/\partial x = \alpha\sigma(1-\sigma)$ ensures the optimal markup does not depend on rate levels. A lower wakeup rate λ_j (more asleep depositors) widens the *level* of the spread—the bank earns rents on its captive asleep base—but does not change the *response* to rate shifts.

Sources of incomplete pass-through ($\beta < 1$). Empirical deposit betas are well below unity (Drechsler et al., 2017), reflecting frictions that break translation invariance: (a) *imperfect outside-option pass-through*—money market fund yields do not track the policy rate one-for-one, so the effective outside option available to depositors rises by less than Δr; (b) *search and adjustment frictions*—even awake depositors face information costs and inertia that dampen rate responsiveness; (c) *deposit insurance*—FDIC coverage reduces the marginal attractiveness of outside options at high rate levels. Each friction means that a one-unit increase in r_M translates to a less-than-one-unit increase in the competitive pressure the bank faces, generating $\beta < 1$.

Reduced-form deposit beta. To formalize the intuition that the deposit beta is increasing in $\bar{\alpha}_j$, we adopt a tractable parametrization: it maps $\bar{\alpha}_j \in (0, \infty)$ to $\beta \in (0, 1)$, is monotonically increasing in $\bar{\alpha}_j$, and approaches the frictionless limit ($\beta \to 1$ as $\bar{\alpha}_j \to \infty$) and the fully captive limit ($\beta \to 0$ as $\bar{\alpha}_j \to 0$):

$$\beta_j^{\text{dep}} \approx \frac{\bar{\alpha}_j}{\bar{\alpha}_j + \phi} = \frac{\lambda_j \alpha}{\lambda_j \alpha + \phi} \tag{A22}$$

where $\bar{\alpha}_j = \lambda_j \alpha$ is the effective rate sensitivity and $\phi > 0$ is a single parameter capturing the aggregate friction wedge, treated as exogenous to the bank's content choice (it reflects market-level frictions such as deposit insurance and search costs). The numerator captures the bank's marginal cost of lagging (losing awake depositors who notice the rate gap); the denominator adds the friction-induced benefit of retaining captive rents on asleep depositors at below-market rates. We do not derive ϕ from the logit structure (which yields $\beta = 1$ as shown above), but instead treat it as encoding the frictions that generate incomplete pass-through empirically.

Comparative statics. Recall from Equation (3) that $\bar{\alpha}_j = (\alpha_0 + \alpha_1) - (\alpha_1 + \alpha_2 \tilde{q}_j) s_j - (\alpha_1 + \alpha_3)\tau_j$. Since $\alpha_1, \alpha_2, \alpha_3 > 0$, both service and trust content reduce $\bar{\alpha}_j$ (put more depositors to sleep): $\partial \bar{\alpha}_j / \partial s_j = -(\alpha_1 + \alpha_2 \tilde{q}_j) < 0$ and $\partial \bar{\alpha}_j / \partial \tau_j = -(\alpha_1 + \alpha_3) < 0$. Applying the chain

rule to (A22):

$$\frac{\partial \beta_j^{\text{dep}}}{\partial s_j} = \underbrace{\frac{\phi}{[\bar{\alpha}_j + \phi]^2}}_{>0} \cdot \underbrace{\frac{\partial \bar{\alpha}_j}{\partial s_j}}_{<0} = \frac{-(\alpha_1 + \alpha_2 \tilde{q}_j)\phi}{[\bar{\alpha}_j + \phi]^2} < 0$$

$$\frac{\partial \beta_j^{\text{dep}}}{\partial \tau_j} = \frac{\phi}{[\bar{\alpha}_j + \phi]^2} \cdot \frac{\partial \bar{\alpha}_j}{\partial \tau_j} = \frac{-(\alpha_1 + \alpha_3)\phi}{[\bar{\alpha}_j + \phi]^2} < 0$$

Non-price advertising reduces the deposit beta by putting more depositors to sleep: service and trust content lower the wakeup rate λ_j, reducing the effective rate sensitivity $\bar{\alpha}_j = \lambda_j \alpha$ and hence the competitive pressure to match rate increases. Note that the *sign* of these comparative statics does not depend on the specific functional form $\bar{\alpha}/(\bar{\alpha} + \phi)$: for *any* $\beta = f(\bar{\alpha}_j)$ with $f' > 0$, the chain rule delivers the same sign because $\partial \bar{\alpha}_j / \partial s_j < 0$ and $\partial \bar{\alpha}_j / \partial \tau_j < 0$. The magnitudes, of course, depend on the parametrization.

Illustrative parametrization. To illustrate magnitudes (these values are chosen for exposition, not estimated), consider $\alpha = 1.0$, $\phi = 0.15$:

- Service-focused banks ($s_j + \tau_j = 0.90$, $\lambda_j \approx 0.10$, $\bar{\alpha}_j \approx 0.10$): $\beta \approx 0.10/(0.10 + 0.15) = 0.40$
- Pricing-focused banks ($p_j = 0.90$, $\lambda_j \approx 0.70$, $\bar{\alpha}_j \approx 0.70$): $\beta \approx 0.70/(0.70 + 0.15) = 0.82$

These are in the range documented by Drechsler et al. (2017): deposit betas of 0.30–0.40 for sticky banks and 0.60–0.80 for competitive banks. The wakeup rates ($\lambda_j \approx 0.10$ for service-focused, $\lambda_j \approx 0.70$ for pricing-focused) are broadly consistent with the shopping rates documented by Egan et al. (2025).

A.3.5. Service Bank Paradox (Prediction for Future Research)

We develop a prediction about nonlinear deposit dynamics that we flag for future empirical work. Service-focused banks (high $s_j + \tau_j$, low λ_j) should experience *accelerating* deposit outflows during large monetary shocks, while pricing-focused banks experience approximately linear outflows. The mechanism follows from the deposit beta result: service banks' low

wakeup rates mean that most depositors are asleep and do not notice gradual rate gaps. For small shocks, asleep depositors tolerate the widening gap. But when shocks are large enough, the accumulated rate gap becomes salient even to normally inattentive depositors—they "wake up" and defect rapidly. This nonlinearity is consistent with the evidence in Lu and Wu (2026) that depositor attention increases when rate gaps are large. Pricing-focused banks, whose depositors are already awake, adjust rates continuously and avoid this nonlinearity.

A.3.6. Welfare Analysis

Non-price advertising increases bank profits (Proposition 2) while having ambiguous effects on depositor surplus. A shift from pricing to non-price content puts more depositors to sleep with respect to rates, reducing aggregate depositor surplus if the rate cost to existing depositors exceeds the quality gain from better matching:

$$\underbrace{\frac{\partial \mu_j^*}{\partial s_j} \cdot D_j}_{\text{rate cost (wider spreads)}} > \underbrace{q_j \cdot \frac{\partial D_j}{\partial s_j}}_{\text{quality gain (better matching)}}$$

This condition is more likely to hold for *trust* content (which puts depositors to sleep without providing quality information) than for *service* content (which conveys genuine quality even as it reduces rate attention). The welfare ambiguity highlights a tension between informative and persuasive advertising in banking markets.

A.3.7. Model Limitations and Extensions

Limitation 1: Boundary conditions. The accommodation equilibrium of Proposition 1 requires that the profit from serving asleep depositors at wide spreads exceeds the profit from waking everyone up and competing on rates for the full market. This can fail under sufficiently small quality differentiation, highly attentive depositor markets, or merger-induced repositioning.

Limitation 2: Binary attention model. The awake/asleep representation follows Egan et al. (2025). Extensions to a continuous attention distribution (Lu and Wu, 2026) would enrich

the model but do not overturn core predictions, as long as non-price content shifts the attention distribution toward less rate-sensitive states.

Limitation 3: Linear content effects. The linear $\bar{\alpha}_j$ specification is a first-order approximation valid for interior allocations. The empirical distribution (18%/29%/53%) suggests most banks are interior.

Limitation 4: Exogenous bank quality. Quality q_j is treated as exogenous. Endogenizing quality investment would reinforce the core message: high-quality banks invest in quality *and* in non-price advertising that puts depositors to sleep, creating complementarity between quality and market power.

Limitation 5: Two-bank duopoly. Multibank oligopoly extensions are qualitatively robust under sufficient quality differentiation. The two-bank setup is standard in the deposits channel literature.