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The digitalisation of banking and social media: Implications for deposit pricing*

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Abstract

This paper examines the implications of two coincident digital trends — the digitalisation of banking and the widespread adoption of social media — for the pricing of deposits in the United States. Using branch-level data, we analyse how both trends interact to influence the level of deposit rates as well as their adjustment to changes in the policy rate. Our analysis distinguishes between traditional banks with physical branch networks and digital banks. Using panel regression analysis and local projections, we find that digital banks' deposit rates are higher and more reactive to changes in policy rates, consistent with the view that their customers are more price sensitive. We further find that digital banks offer higher deposit rates and react more sharply to policy rate changes in counties with higher social media activity, as measured by Twitter usage, supporting the notion that high social media use further increases price sensitivity.

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1. Introduction

Over the past decade, two major digital trends have affected large parts of the population: the digitalisation of banking services, including the ability to manage deposit accounts remotely; and the spreading of social media as digital communication platforms where users can easily share information and other content. The proliferation of remote banking services and increased digitalisation have enabled depositors to react more rapidly to price differences in deposit markets and to changes in market conditions. Depositors now find it easier to compare interest rates across different banks or money market funds and to transfer funds to higher-yielding accounts. At the same time, the growing adoption of social media has been a contemporaneous development that has accelerated the diffusion of information.[1]

Both developments have likely affected the elasticity of deposit supply and deposit pricing. In particular, deposit rates offered by digital banks, i.e., banks operating primarily through online platforms, would be expected to be higher compared to traditional relationship banks with a physical branch network and to be more sensitive to changes in market conditions. Traditional banks typically incur higher costs, provide more banking and personalised services, and enjoy greater market power in their local environment. To compete, digital banks may have to offer higher deposit rates. Since customers of digital banks are typically more accustomed to online banking and less attached to their bank due to the absence of personal relationships, they may react more quickly and easily to changes in market conditions, thereby also forcing their online banks to react faster. These effects are expected to be particularly pronounced in markets with strong social media activity, which accelerates the speed and scope of information dissemination.

In this paper, we test these potential implications by comparing deposit pricing of digital banks, defined as centralised and virtually structured institutions, with that of traditional banks, defined as decentralised and physical branch-based institutions. First, we assess whether there are systematic differences in the level of deposit rates offered by digital versus traditional banks and whether these differences are in turn affected by the use of social media in local markets. Second, we investigate whether the pass-through of changes in the policy rate to deposit rates differs between digital and traditional banks and how it depends on the intensity of social media usage in local markets.

Our study extends the previous literature on deposit pricing (Drechsler et al., 2017; d'Avernas et al., 2023; Yankov, 2023) and its relationship with digitalisation (Jiang et al., 2023; Koont, 2023; Rose, 2023). Our contribution is a comprehensive analysis of the interaction of banking digitalisation and social media use in affecting deposit margins and policy rate transmission to deposit rates. We merge several datasets: the FFIEC Call Reports on the financial statements of banks, the FDIC's Summary of Deposits (SoD), the S&P RateWatch database on branch-level deposit rates, and geotagged Twitter (now X) data from the Twitter Streaming Application Programming Interface (API). Our empirical strategy follows a top-down approach. It begins at

[1] See BCBS (2024) and Cornelli et al. (2024) for further discussion of these trends and their implications.

an aggregated level to identify trends and stylized facts and concludes with a within-bank regression approach. The latter allows us to control for differences in banks' external environment using bank-time fixed effects, with a view to disentangling the differential responses of digital and traditional banks to changes in monetary policy, notably across markets with varying levels of social media activity.

The main results of our analysis are as follows.

First, digital banks tend to offer higher deposit rates than traditional, physical branch-based banks, particularly compared to larger banks. The differences in deposit rates are more pronounced in the higher-yielding savings deposit and small time deposit segments.

Second, digital banks offer significantly higher savings and small time deposit rates in states with high social media activity. This finding supports the notion that digital banks face greater competition when information can spread faster through social media.

Third, digital banks exhibit a higher pass-through of policy rate changes to deposit rates than traditional banks. The differential responses are more pronounced in the savings and small time deposit segments, and they vary over time. The higher responsiveness of deposit rates is consistent with the view that digital banks counter deposit outflows from more reactive customers by means of more attractive remuneration. We also find asymmetric adjustments, with deposit rates responding more strongly to monetary loosening than to tightening, consistent with previous studies (e.g. Hannan and Berger, 1991; Neumark and Sharpe, 1992; Driscoll and Judson, 2013). For the higher-yielding deposit products, this asymmetry is less pronounced for digital banks.

Fourth, high social media activity is associated with faster policy rate pass-through by digital banks. More specifically, when comparing branches of the same bank, digital banks' branches in counties with higher social media activity raise deposit rates more than their branches in counties with less social media activity. This type of differential response is not observed among branches of traditional banks.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 describes the data. Section 4 outlines the strategy to identify digital banks by means of a cluster analysis. In section 5, we analyse differences in the level of deposit rates offered by digital banks versus traditional banks. Section 6 presents the empirical analysis examining how digital and traditional banks adjust deposit rates to changes in policy rates. Section 7 analyses how social media activity affects the short-run sensitivity of deposit rates to changes in monetary policy rates. Section 8 concludes.

2. Related literature

This paper is connected to three main strands of literature.

The first strand examines the deposit pricing behaviour of banks. Previous studies have established a well-known stylized fact: the adjustment of deposit rates to changes in market rates is typically rigid, gradual, and asymmetric (Diebold and Sharpe, 1990; Hannan and Berger, 1991; Neumark and Sharpe, 1992; Hofmann and Mizen, 2004; Driscoll and Judson, 2013;

Gambacorta and Mistrulli, 2014; Drechsler et al., 2017). The slow adjustment of deposit rates to monetary policy conditions has been largely attributed to banks' market power. Yankov (2024) argues that imperfect information and search costs confer market power on banks, allowing them to avoid fully adjusting deposit remuneration in response to changes in market rates. The asymmetric response of deposit rates to monetary policy has been studied from two perspectives: differences in bank-specific characteristics (e.g. size, liquidity, and capitalization) and the sign of the policy change (tightening versus easing). Gambacorta (2008) finds that the adjustment of deposit rates is more gradual at large, well-capitalized, and highly liquid banks, as these institutions can more easily tap alternative funding sources when monetary conditions shift. Evidence also shows that deposit rates adjust more rapidly following monetary easing than tightening; in other words, they are downward flexible but upward sticky, reflecting banks' market power and the rigidity of deposit pricing (Gambacorta and Iannotti, 2007; Driscoll and Judson, 2013; Heider et al., 2019; Drechsler et al., 2021). We contribute to this literature by examining the interest-setting behaviour of digital versus traditional banks with different balance sheet characteristics and business models, and by distinguishing between monetary tightening and easing episodes.

The second strand of the literature examines how bank business models evolve in response to technological change. One aspect concerns the transformation of financial intermediation processes. Technology has reshaped how banks originate, price, and monitor loans, altering their cost structures and competitive positioning (Buchak et al., 2018; Fuster et al., 2019; Gopal and Schnabl, 2022). Another line of research highlights the growing competition and partnerships between banks, fintech, and big tech firms, emphasising strategic responses through collaboration, acquisitions, or platform integration (Parlour et al., 2022; Alfhaili et al., 2025; Serfes et al., 2025). A further dimension relates to the impact of digitalisation on the bank–client interface, as banks increasingly interact with customers through virtual channels rather than in-person relationships, which requires reconfiguring business models and client engagement strategies (Beck et al. 2022; Gambacorta et al., 2022). Koont et al. (2024) study the impact of digital banking on the value of the deposit franchise and the stability of the banking sector. They find that when the Fed funds rate increases, deposits flow out faster, and the cost of deposits increases more in banks that offer mobile apps and brokerage services. We contribute to this literature by moving beyond the deposit franchise value and by examining directly how digitalisation changes banks' interest-rate setting behaviour. In particular, we show that digital banks, which rely on virtual interactions instead of personal branch-based relationships, adjust deposit rates more in response to monetary policy changes, and that these effects are amplified in environments with greater social media activity.

The third strand of the literature studies how social media activity shapes financial decision-making. A growing body of work shows that online platforms influence investor attention, trading activity, and ultimately asset prices. For instance, Chen et al. (2014) document that stock opinions transmitted via social media help predicting trading volume and returns. Barber et al. (2022) show that digital attention tools can trigger retail trading surges and affect short-term returns. Cookson et al. (2024) analyse social media attention and sentiment across Twitter, StockTwits, and Seeking Alpha, showing that while attention is correlated across platforms, sentiment is largely idiosyncratic. More recently, Sui and Wang (2025) provide evidence of social transmission bias on investor platforms, showing that ideas and opinions are not transmitted neutrally but instead are selectively amplified depending on users' prior beliefs and the structure of the online network. Cookson et al. (2026) document that banks with high pre-existing Twitter exposure experienced larger declines in stock market value during the March 2023 SVB distress, particularly when tweets were widely retweeted. We contribute to this literature by shifting the focus from investment choices in financial markets to deposit pricing. Specifically, we analyse how social media activity affects the responsiveness of banks—particularly digital banks—in setting deposit rates in response to monetary policy changes. Anyfantaki et al. (2026) show that deposit rate shocks propagate across geographically distant markets through digital social connections, as social networks make rate changes salient to otherwise inattentive depositors, thereby increasing search activity and inducing banks to adjust their deposit pricing even in the absence of local shocks. While Anyfantaki et al. (2026) focus on cross-market spillovers driven by social networks, we examine how digitalisation and social media jointly affect within-bank deposit pricing and monetary policy rate pass-through, highlighting differences between digital and traditional banks.

3. Data

Our analysis covers the period 2002–23 and relies on branch-level data on bank deposit rates, bank-level data on financial control variables, county-level data on Twitter usage as well as aggregate macro data for the output gap, inflation and T-bill rates. We use both quarterly and annual data, reflecting a trade-off between granularity and model tractability. Specifically, we employ quarterly data when data granularity is critical, while we rely on annual data when parsimony and broader variable coverage are more important.

Branch-level deposit rate data

Data on deposit rates at the branch level, as well as information on which branches are rate setters versus rate takers, are sourced from S&P RateWatch. It covers all banks, thrifts, and credit unions with more than $1 billion in total assets, as well as 75% of all remaining institutions regardless of size. It tracks many banking products, including checking, savings and time deposit accounts.

Branch-level deposit data

We collect information on the location of deposits and branches from the Federal Deposit Insurance Corporation (FDIC) Summary of Deposits (SoD). This database provides a comprehensive annual snapshot of deposit data for all FDIC-insured institutions in the U.S. Using this data, we calculate branch-network metrics such as the average deposit volume per branch and the number of branches per county.

Bank-level financial data

We collect information on the financial statements of banks from the quarterly Federal Financial Institutions Examination Council (FFIEC) Call Reports. Specifically, our dataset includes information on both balance sheet and income statement indicators for each bank, such as total assets, cash, securities, loans, premises and fixed assets, deposits, total equity, tier 1 capital, interest income/expense, and non-interest income/expense.

County-level social media activity data

We measure social media activity at the county level as the ratio of the number of Twitter users resident in a county relative to the total population in that county based on the estimates provided by Martin et al. (2021) for the period 2016–2019.[2] The data is based on more than one billion geotagged tweets from the Twitter Streaming API. The most repeated location among the tweets sent by each individual during a year is used to identify the residence of users, with non-resident users being those who tweeted outside of their residence county. Figures 1 and 2 provide an overview of the data.[3]

Macro variables

We collect data on inflation and the output gap from the Bureau of Labour Statistics and the Congressional Budget Office, respectively. The data on the 12-month T-bill rate are from the Federal Reserve Bank of St. Louis, while the Fed funds rate is obtained from Bloomberg.

Summary descriptive statistics

Table 1 provides summary statistics of the variables used in the analysis. Panel (A) of Table 1 reports the summary statistics of the annual variables used in the analysis, panel (B) shows the summary statistics of the quarterly data.

4. Identifying digital banks

4.1 Distinguishing digital from traditional banks

We identify digital banks through a cluster analysis. Our identification strategy is based on the premise that digital banks differ from traditional banks in terms of branch networks, investment profiles, and expenditure structures. More specifically, digital banks should operate through a more limited physical branch network, spend more on IT and advertising and less on fixed assets, rely more on virtual services with limited account options and investment services, and differ in the way they price their deposits across the country.

As a benchmark, we identify digital and online banks using consumer-rating platforms such as Forbes, FinTechlabs, Investopedia, Cent, and TopMobileBanks. These banks, listed in Table 2, serve as the basis for identifying distinguishing features to be used as input variables in the cluster analysis and for validating the clustering process. As shown in the table, the majority of these banks operate with fewer than 10 branches, not all report to S&P RateWatch, and they are heavily engaged in traditional lending and deposit-taking activities.

[2] The authors analysed spatial mobility patterns during the 2017 U.S. Solar Eclipse, which resulted in a significant movement of people towards counties in which the eclipse occurred.

[3] There is large variation in Twitter activity ranging from a median of less than 1% of the population, e.g. Nuckolls County, Nebraska, to more than 75%, such as in Richmond City, Virginia.

A comparison of digital and other banks, reported in Table 3, highlights several important distinguishing features.[4] In terms of assets and expenses, digital banks hold smaller securities portfolios, invest less in premises and fixed assets, and record higher non-interest expenses (e.g., salaries, IT, rental and equipment costs, and advertising). This is consistent with the view that digital banks are more focused on traditional lending activities but with limited physical presence. Higher non-interest expenses may reflect both higher average salaries and overhead costs – a dimension we investigate in greater detail below. By contrast, funding structures do not show significant differences. Digital banks are, however, clearly different in their branch network characteristics: they have fewer branches per county, larger branches in terms of deposits, and fewer rate-setting branches.[5] These features point to a more concentrated branch network structure under the digital banking model.

There are also noteworthy differences in the composition of deposits and in non-interest expenses (Table 4). Digital banks rely significantly less on non-interest bearing deposits, a pattern likely related to their limited physical presence and narrower range of banking services. To attract remote customers, they must offer remunerated deposits. On the expense side, digital banks spend more on advertising and on "other" non-interest items, including promotional, public relations, and business development costs, outsourced data-processing services, and internal software development. They also tend to pay higher average wages than the other banks, which may reflect a higher share of employees with both IT and financial advisory skills, as well as a lower employee-to-customer ratio.

4.2 Cluster analysis

The stylised facts presented in the previous section show that digital banks differ notably from the other banks in terms of branch networks, investment profiles, and expenditure structures. Specifically, digital banks tend to operate with a more limited physical branch presence, spend more on IT and advertising and less on fixed assets, rely heavily on virtual services with limited asset management options for clients, and adopt distinctive pricing strategies across the country.

These characteristics can be used as input variables in a formal cluster analysis to identify other digital banks in our sample.[6] The following variables are considered: (i) securities over total assets, (ii) premises and fixed assets over total assets, (iii) non-interest bearing deposits over total assets, (iv) other non-interest expenses over total assets, (v) wages and salaries per

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[4] Table 3 compares common balance sheet, risk and performance indicators, together with branch network characteristics, for our sample of 17 digital banks listed in Table 2 and for small, medium-sized and large banks.

[5] In the clustering exercise, we do not use information on deposit rates and related variables, as many of the benchmark digital banks in Table 2 are not covered by S&P RateWatch.

[6] In what follows, we exclude banks with less than 10 observations to reduce noise in the data, as well as very large banks — those with average total assets above $250 billion — because they are fundamentally different from the rest of the sample.

employee, (vi) advertising expenses over total assets, (vii) deposits per branch, and (viii) the number of branches per county.

We use median values of these indicators for each bank to remove the impact of outliers and short-term variation, which would complicate the detection of clusters. We also exclude variables that are highly correlated to avoid redundancies and standardise all input variables so that they have a mean of zero and a standard deviation of one. Standardisation is necessary because the clustering algorithm uses a distance metric to measure similarities when forming clusters. If we included input variables with large ranges, which occurs when variables have different units or scales (such as branch network and balance sheet indicators), some would have a disproportionate influence on the clustering and thus bias the results.

We base the cluster analysis on a measure of similarity used to classify banks into different groups or clusters. The similarity among banks should be high within groups and low across groups. Following the literature, we employ partition-clustering methods, in part because our sample is relatively large. More specifically, we use the K-median algorithm to partition banks into K clusters and minimise the squared error between the empirical median of a cluster and the observations in that cluster. The objective function is given by (Jain, 2010):

$$J(C) = \sum_{k=1}^{K} \sum_{x_i \in c_k} \|x_i - \mu_k\|^2$$

where K is the number of clusters c_k, x_i is a m-dimensional vector of indicators for bank i, and μ_k is a vector of cluster centroids (here medians). As similarity metric $\|\ \|$, we use the Euclidean distance.[7] The clustering results are sensitive to the choice of starting values for cluster initialisation and the pre-specified number of clusters.[8] We thus experiment with different initialisations and numbers of clusters, restricting the range to a minimum of three and a maximum of six clusters.[9]

The effectiveness and stability of the clustering procedure are assessed in several ways. First, we use the Calinski-Harabasz (1974) pseudo *F*-statistic, a goodness-of-fit measure for clustering outcomes, defined as the ratio of between-cluster variance to within-cluster variance normalised by their respective number of degrees of freedom. We compare the *F*-statistic across different initialisations, distance metrics, and numbers of clusters with the aim of identifying the allocation that consistently yields the highest *F*-statistic. Second, we check

7 We cross-check our results using alternative metrics for continuous variables such as the absolute value of the Minkowski distance and its square.

8 The minimisation is performed for a fixed number of clusters, since the objective function decreases as the number of clusters increases, approaching zero when the number of clusters equals the number of banks.

9 We do not use two clusters (digital versus non-digital banks), because the algorithm is prone to converge to local minima when clusters are not well separated (Meila, 2007), as is the case with two very broad groups of banks. For parsimony and ease of interpretability, we also limit the number of clusters to a maximum of six. For a given number of clusters, we experiment with different initialisations and distance metrics and retain the partition that consistently provides the best goodness-of-fit (highest F-statistic).

whether our partitioning successfully classifies the sample of 17 digital banks listed in Table 2 into the same cluster, i.e. the digital bank cluster. We also compare banks on an institution-by-institution basis for the allocations with the highest F-statistics. Finally, we compare the average characteristics of banks in the digital bank cluster with those in other clusters to assess whether the clustering effectively differentiates banks based on their most distinctive features, as reported in Table 6.

Depending on the configuration of the clustering algorithm, our identification strategy favours the use of three or four clusters. We report the resulting allocations in Table 5, which shows the number of banks belonging to each cluster across three groups: (i) digital banks listed in Table 2, (ii) small banks, and (iii) medium-sized banks. In what follows, we define digital banks as those in the intersection of clusters 3 under both the $K = 3$ and $K = 4$ specifications, while the remaining banks are considered as traditional banks.[10]

Overall, our strategy identifies 1,567 digital banks out of 7,190 banking institutions, which is somewhat higher than the 1,069 digital banks identified in Koont et al. (2023).[11] We cross-check our partition by comparing, in Table 6, the means and medians of the cluster input variables for digital banks (the intersection of cluster 3 under both specifications) and the remaining banks. As shown, digital banks hold significantly fewer securities, premises and fixed assets, operate with significantly fewer non-interest bearing deposits, and exhibit higher non-interest expenses and salaries per employee. In terms of branch networks, they hold significantly more deposits per branch and maintain a smaller branch presence compared to other banks.

Digital banks have also gained market share and provide higher deposit rates than other banks. In terms of market shares, digital banks increased their presence from 2.8% in 2002 to 13.1% in 2023, at the expense of both small and medium-sized banks (Figure 3).

5. Deposit rates at digital versus traditional banks

A comparison of deposit rate levels across digital and traditional banks supports the notion that the former offer higher deposit rates as a result of fiercer online competition. Figure 4 plots median values of annual deposit rates and deposit spreads over relevant reference rates over the past two decades for three types of banks: digital banks, medium-sized banks and small banks. Table 7 reports the median levels across the banks in each of the three groups for different sample periods. The chart and table reveal that digital banks tend to offer higher rates

[10] Three digital banks from Table 2 are not classified into cluster 3: Charles Schwab, SoFi Bank, and Salem Five Cents Savings Bank. Charles Schwab differs from the other digital banks due to its much smaller loan portfolio and greater reliance on deposit funding (Table 2). Salem Five Cents Savings Bank is characterized by a larger branch network, while SoFi Bank has a higher share of non-interest bearing deposits compared to the other banks.

[11] This discrepancy originates from the different approach that we use to identify digital banks. Koont et al. (2023) identify digital banks as those with at least 300 reviews for their mobile application on the Apple App or Google Play Store. Conversely, we use financial statement and branch network characteristics to identify digital banks.

than traditional banks, particularly in the higher-yielding savings and small time deposit segments. When considering different sub-periods across bank types and our three deposit products, the median remuneration offered by digital banks is almost in all cases significantly higher than that of the other banks (Table 7). The only exception in which differences of median rates are not statistically different are checking accounts of digital and small banks over the period 2008-09.

In some periods, the differences in the level of deposit rates are substantial. For instance, while the median rate of digital banks' savings deposits amounted to 1.44 percent per annum (p.a.) during 2002-07, it amounted to only 1.25 for small banks and 1.10 for large banks. In the wake of downward trending interest rates over the sample period, the differences became smaller over time in absolute terms, but not necessarily in relative terms. For instance, the median savings deposits rate of digital banks during the most recent period is 0.20 p.a. compared to 0.15 and 0.10 p.a. for small and large banks, respectively. Taken together these findings suggest that our categorisation of digital intermediaries captures variation not accounted for by intermediaries' size alone.

Twitter activity matters for deposit rate levels, too. As discussed before, high Twitter activity means that information may spread faster, adding to competition in deposit markets in particular for digital banks. In order to test this hypothesis, we split the counties into groups of high and low Twitter activity, with high Twitter activity counties identified as those with Twitter activity above the 90^{th} percentile of the distribution across all counties in the period 2016-2019.

A comparison of median deposit rates in high versus low Twitter activity counties suggests that digital banks offer significantly higher deposit rates when Twitter activity is high (Table 8), in line with the notion of heightened competition in such an environment. Specifically, we find that digital banks set significantly higher rates in the savings and small time deposit market segment, when their branches are located in counties with high Twitter activity, compared to branches located in counties with less Twitter activity.

6. Policy rate pass-through at digital versus traditional banks

We next examine how banks adjust their deposit rates in response to changes in monetary conditions, testing whether there are significant differences between digital and traditional banks. We use dynamic panel analysis, which allows us to estimate responses over time, conditional on control variables, and to distinguish between the reactions of different types of banks.

6.1 Annual analysis

We start with a simple specification at the annual frequency, allowing the model to differentiate the behaviour of digital and traditional banks, as well as to account for heterogeneity across monetary policy conditions (tightening versus easing episodes). This framework enables us to capture the effects of policy changes over a horizon of up to two years. In the second step, we investigate the dynamic pass-through at a quarterly frequency. This approach allows us to explore short-term adjustments (up to one year) in greater detail, capturing the gradual response of deposit rates to changes in monetary policy while increasing the number of observations and improving estimation precision. In the third step, we employ local projection methods to address some of the limitations of the panel approach, which does not allow for the inclusion of lagged dependent variables due to the Nickell bias (Nickell, 1981). This bias is particularly pronounced in our setting with a small time dimension relative to the number of cross-sections.

We use a simple empirical model to investigate how banks — digital versus traditional — adjust the deposit rates of their branches in response to changes to policy rates. Following the literature, we restrict the sample to active rate-setting branches and exclude those that do not actively set deposit rates (Drechsler et al., 2017; Doerr, 2024). This helps mitigate issues with double-counting and spurious correlation.[12]

Our first set of regressions examines the sensitivity of deposit rates to the policy rate on an annual basis. We distinguish between digital banks and other banks and allow for both contemporaneous and lagged pass-through after one year. The model can be summarized as follows:

$$\Delta y_{b,i,t} = \alpha_b + \sum_{j=0}^{1} \beta_j \times \Delta PR_{t-j} + \sum_{j=0}^{1} \beta_j^* \times \Delta PR_{t-j} \times Digital_i + \gamma X_{it} + \epsilon_{b,i,t} \qquad (1)$$

where b refers to rate-setting branches of bank i in year t. The dependent variable ($\Delta y_{b,i,t}$) is the annual change in a particular deposit rate.[13] We analyse three standard retail deposit products: (i) interest-bearing checking accounts with a minimum balance of $2,500 (checking deposits), (ii) money market deposit accounts with a minimum balance of $25,000 (savings deposits), and (iii) retail certificates of deposit with an account size of $10,000 and a tenor of 12 months (small time deposits). These products are the most commonly offered in their respective segments of deposits and provide the highest number of observations.

Branch fixed effects are denoted by α_b and the change in the policy rate by ΔPR. For small time deposit rates, we use the one-year T-bill rate as the reference policy rate, as it better matches the maturity of this type of deposit product, while for the others we use the federal funds rate. Digital banks are distinguished from other banks using an indicator variable, $Digital_i$, equal to one for digital banks identified through the cluster analysis and zero otherwise. We also include macroeconomic and bank-specific control variables in vector X_{it}. These include the output gap relative to potential GDP, the inflation rate, and lagged indicators of bank size, equity ratio and the return on assets (ROA).

The sensitivity of deposit rates to changes in the policy rate for branches of traditional banks is measured by the coefficients β_0 and β_1: the first captures the contemporaneous pass-through and the second the additional pass-through after one year, conditional on the response in the initial period. For branches of digital banks, sensitivity is measured by the sum of the coefficients $\beta_0 + \beta_0^*$ and $\beta_1 + \beta_1^*$. A higher coefficient indicates greater sensitivity of deposit rates to changes in the policy rate. Following the reasoning above, we expect deposit

[12] Close to 10% of the branches in S&P RateWatch are active rate setters, representing 7% of SoD branches as of 2012 (32% and 25% in terms of deposits, respectively).

[13] Using the deposit spread instead of the deposit rate, as in Drechsler et al. (2017), yields the same result because the sensitivity of the deposit spread to the federal funds rate is simply $1 - \beta$.

rates at digital banks to react more strongly to changes in the policy rate compared to other banks, i.e. $\beta_j^* > 0$, since they have stronger incentives to align deposit remuneration with market rates in order to limit potential deposit outflows from more rate-sensitive customers.

The results are presented in Table 9, using a triangular format as we gradually add more control variables. Focusing on the final specifications in columns (7) to (9), we find that on average all banks adjust deposit rates when policy rates change. For instance, following a 100 bp increase in the policy rate, non-digital banks increase on average the remuneration of savings deposits by 11.9 bp in the same year and, conditional on this, by an additional 8.2 bp one year later (column (8)). The pass-through is much lower for checking deposits and more than twice as high for small time deposits, which is consistent with Drechsler et al. (2017). For digital banks, we generally find a higher sensitivity of deposit rates compared to their traditional counterparts. For example, while the contemporaneous pass-through of small time deposit rates is 28.9 bp at non-digital banks, it is equal to 33.5 bp (28.9 + 4.6) at digital banks. The higher responsiveness tends to persist in the following year, with the exception of small time deposits for which the interaction term is insignificant.

Next, we estimate a model that distinguishes between periods of monetary tightening and loosening. The literature suggests that banks respond asymmetrically to changes in monetary conditions, with deposit rates being upward sticky and downward flexible when market rates move (Hannan and Berger, 1991; Neumark and Sharpe, 1992; Driscoll and Judson, 2013). The intuition is that, if deposit supply is not perfectly elastic, banks find it optimal to raise deposit rates partially when market rates increase, while decreasing them more readily when market rates decline. If this holds, one should observe a stronger pass-through of policy rate changes to deposit rates during monetary loosening and weaker pass-through during tightening. If digital banks face a more elastic deposit supply than traditional relationship banks, as argued before, such asymmetry could be weaker in their case compared to traditional banks.

To keep the model tractable and parsimonious, we focus only on the contemporaneous pass-through and exclude the one-year lag of the policy rate. Specifically, we estimate:

$$\Delta y_{b,i,t} = \alpha_b + \beta \times \Delta PR_t + \beta^T \times \Delta PR_t \times Tighten_t$$
$$+ \beta^* \times \Delta PR_t \times Digital_i + \beta^{*T} \times \Delta PR_t \times Digital_i \times Tighten_t + \gamma X_{it} + \epsilon_{b,i,t} \qquad (2)$$

where $Tighten_t$ is a dummy variable that equals one when the Federal funds rate increased (2004–06, 2015–19, and 2022–23) and zero otherwise. The sensitivity of deposit rates to policy rate changes is equal to β and $\beta + \beta^T$ for traditional banks during periods of monetary loosening and tightening, respectively, and equal to $\beta + \beta^*$ and $\beta + \beta^T + \beta^* + \beta^{*T}$ for digital banks. The estimation results suggest that there is indeed evidence of asymmetric pass-through for traditional banks, with stronger deposit rate adjustments during loosening than tightening. There is also some evidence that this asymmetry is less pronounced for digital banks at least for some deposit products. The estimation results are reported in Table 10. Focusing on the final specifications in columns (7) to (9), we find asymmetric responses of traditional banks to changes in the policy rate across all types of deposits. For example, in the case of savings deposits the contemporaneous pass-through is 15.9 bp during monetary loosening but only 12.6 bp (15.9-3.3) during monetary tightening. Deposit rates are thus more flexible when market rates fall. As before, we tend to find a stronger pass-through at digital banks. For small time deposits, there is evidence of weaker asymmetric pass-through for digital banks. While traditional banks raise small time deposit rates by 37.6 bp in response to a 100 bp policy rate cut, the response is 7.3 bp lower in response to a policy rate hike. By contrast, for digital banks the response is only about 2 bp lower in response to a rate hike compared to a rate cut (column 9). For savings deposits there is, by contrast, evidence of somewhat stronger asymmetry in the adjustment of digital banks over the rate cycle (column (8), while there are no significant differences in asymmetric adjustment for checking deposits (column (7)).[14]

Overall, the results from Table 10 confirm that digital banks respond more strongly to changes in the policy rate compared to their traditional counterparts. The effect is not homogeneous across deposit products and monetary policy stances. While deposit rates on checking accounts at digital banks respond more strongly than those at other banks, regardless of the monetary policy stance, deposit rates on small time deposits exhibit a differential effect only during periods of monetary tightening.

6.2 Quarterly analysis

The next set of regressions is estimated on a quarterly frequency. This allows us to dig deeper into short-term adjustments, capturing the gradual response of deposit rates to changes in monetary conditions while increasing the number of observations and improving estimation precision. Moreover, the quarterly specification enables us to trace the timing and persistence of banks' reactions more accurately than in the annual framework. We consider the contemporaneous effect and three additional quarters so that the model captures the effects for up to one year. As before, we distinguish between digital banks and traditional banks and allow for a sluggish responsiveness of deposit rates to changes in the policy rate.

The quarterly regression model for our pass-through analysis is specified as follows:

$$\Delta y_{b,i,c,t} = \alpha_b + \sum_{j=0}^{3} \beta_j \times \Delta PR_{t-j} + \sum_{j=0}^{3} \beta_j^* \times \Delta PR_{t-j} \times Digital_i + \gamma X_{it} + \epsilon_{b,i,t} \qquad (3)$$

where b refers to rate-setting branches of bank i in county c and quarter t. We estimate three specifications, gradually augmenting the set of control variables. In the most stringent specification, we include our macroeconomic control variables along with bank-year fixed effects, the latter capturing annual variations affecting each bank differently. The response coefficients are interpreted as before, except that they now represent quarterly instead of annual responses.

The estimates of the quarterly model are consistent with the previous results obtained from the annual model, indicating faster adjustment of deposit rates by digital banks (Table 11). In the final specification, which controls for quarterly macroeconomic and bank-specific variables

[14] In unreported regression results, we augment equation (2) by including separate interaction terms between the policy rate and indicator variables for the Global Financial Crisis (GFC, 2007–09) and the Covid-19 pandemic (2020–21) to control for potentially different dynamics during these episodes (Egan et al., 2017; Martin et al., 2018; Ahn and Brei, 2024). Overall, the results on the asymmetric pass-through and the differential effect for traditional versus digital banks are consistent with our baseline results, supporting their robustness.

along with bank-year fixed effects, we find that banks progressively adjust deposit rates in response to changes in the policy rate. For small time deposits, the strongest impact occurs contemporaneously (within the first quarter): banks increase deposit rates at their branches by 34.1 bp following a 100 bp increase in the policy rate (column 9). In the subsequent quarters, the pass-through continues but at a differential scale across traditional and digital banks. More specifically, the additional increase in small time deposit rates is 25.6 bp after one quarter, 10.1 bp after two quarters, and -5.6 bp after three quarters at non-digital banks. Over the first year, the cumulative pass-through in this market segment is thus equal to 64.2 bp at non-digital banks, conditional on the control variables. Digital banks react more strongly with a lag of one quarter with a cumulative pass-through of 72.1 bp for small time deposits. The implied pass-through is somewhat higher than what we obtained at the annual frequency, where the pass-through after one year was 28.9 bp for non-digital banks and 33.5 bp for digital banks. Similar results are also obtained when including further interactions, as in the tightening versus loosening specifications that are not reported for the sake of brevity.[15]

6.3 Local projection analysis

Our analysis so far relies on dynamic panel regressions in first differences and, to avoid the Nickell bias, we exclude lags of the dependent variable from the regressors. As a result, these models may not fully capture delayed adjustment dynamics in deposit rate responses. To address this limitation, in this section we instead employ local projection methods (Jordà, 2005, 2023). Local projections (LPs) allow us to infer impulse response functions that are not constrained in their shape and thus they are less sensitive to misspecification compared to vector autoregressions. Using a single regression equation, LPs allow us to model non-linearities and state dependency.

Our benchmark specification in first differences $\Delta y_{b,i,t+h}$ for different horizons ($h = 0, \dots, 8$ quarters) is as follows:

$$\Delta y_{b,i,t+h} = \alpha_b + \beta_h \Delta PR_t + \beta_h^* \Delta PR_t \times Digital_i + \gamma_h X_{it} + \epsilon_{b,i,c,t} \qquad (4)$$

where β_h and β_h^* are the impulse response coefficients of deposit rates to the change in the policy rate h quarters ahead — the former for non-digital banks and the sum of the two coefficients for digital banks. At each horizon, the coefficients correspond to the impact of the policy rate change in t on the change in deposit rates contemporaneously and in subsequent quarters. Because our cross-section is large and the time dimension is relatively small, we cluster standard errors at the branch level to account for serial correlation in the error term. As before, the vector X_{it} includes our macroeconomic and bank-specific controls. In addition, we include three lags of the dependent variable and the policy rate.

We will also estimate LPs for the cumulative impact. In this case, the specification is as follows:

$$y_{b,i,t+h} - y_{b,i,t-1} = \alpha_b + \beta_h \Delta PR_t + \beta_h^* \Delta PR_t \times Digital_i + \gamma_h X_{it} + \epsilon_{b,i,c,t} \qquad (5)$$

where now the impact coefficients measure how much the level of deposit rates at $t + h$ has changed relative to the level of deposit rates prior to the change in the monetary policy stance.

15 For an analysis of the monetary policy pass-through over time, see Appendix A.

The impulse response analysis confirms that the pass-through is faster in digital banks' deposit rates. The estimation results are presented in Figure 5 for the first differences (LHS) and the cumulative differences (RHS), respectively. In line with the previous results, we observe the lowest pass-through of changes in policy rates on the rates of checking accounts. At both types of banks, the instantaneous impact of a 100 bp increase in the policy rate is roughly 3 bp, increasing to an additional 4 bp in the next quarter in the case of digital banks, before falling again (LHS, upper panel). While in first differences the initial impact is not statistically different across the two types of banks, it is significantly different in quarters 2 and 3. In cumulative terms the difference in the pass-through is significant from the second until the seventh quarter (RHS, upper panel). At traditional banks, the peak of 10 bp is reached at h=7, while at digital banks it is slightly above 12 bp at h=6.

For small time deposits, the impact is much more pronounced (lower panel). Both types of banks increase deposit rates instantaneously and in the subsequent quarters, lasting until a horizon of 6 quarters. We observe a stronger pass-through of policy rate changes to deposit rates at digital banks. The peak response of the change in deposit rates occurs in the initial quarter at h=0 for both types of banks with an increase in the remuneration of small time deposits of 28 bp at this horizon. Over the next four quarters, the pass-through is 1-2 bp lower at non-digital banks. The differential impact on first differences accumulates over time with a peak at h=6 quarters. While a 100 bp increase in the policy rate translates into an 89 bp pass-through at traditional banks, the corresponding effect at digital banks reaches 96 bp. This implies that digital banks nearly fully compensate their customers in this deposit market segment after a year and a half. In all cases, deposit rate sensitivity is significantly higher at digital banks compared to their traditional counterparts.

7. Policy rate pass-through and social media activity

So far, we have established a stronger deposit rate sensitivity at digital banks. But how does this sensitivity change during periods of heightened social media activity, or in counties in which bank customers are more inclined to use social media?

To answer this question, we re-estimate our regressions at the quarterly frequency, focusing on a short time window based on the view that social media effects are not long-lasting. In particular, we estimate a model that includes only contemporaneous effects — therefore capturing responses within a three-month horizon — and interaction terms with our county-level measure of social media activity, $Twitter_{ct}$, derived from Martin et al. (2021) for the period 2016–19. More specifically, we use the percentage of Twitter users resident in a given county relative to the total population in that county, as shown in Figure 2. The regression model can be summarised as follows:

$$\Delta y_{b,i,c,t} = \alpha_b + \beta \times \Delta PR + \beta_T \times \Delta PR_t \times Twitter_{ct} +$$

$$+\beta^* \times \Delta PR_t \times Digital_i + \beta_T^* \times \Delta PR_t \times Digital_i \times Twitter_{ct} + \gamma X_{it} + \epsilon_{b,i,c,t} \qquad (6)$$

where b refers to rate-setting branches of bank i in county c and quarter t. The deposit rate sensitivity to changes in the policy rate is now given by:

$$\frac{\partial \Delta y_{b,i,c,t}}{\partial \Delta PR_t} = \beta + \beta_T \times Twitter_{ct} + \beta^* \times Digital_i + \beta_T^* \times Digital_i \times Twitter_{ct}$$

The key coefficients of interest are those associated with the interaction terms, β_T and β_T^*. If we find that these are significant, banks set deposit rates at branches conditional on the Twitter activity in the county in which the branches are located. For instance, if we find that $\beta_T^* > 0$, then the deposit rate sensitivity at branches of digital banks increases in counties with higher Twitter activity compared to that at non-digital banks.

We estimate three specifications in which we gradually expand the set of control variables. In the last set of regressions, we follow Drechsler et al. (2017) and include bank-quarter fixed effects, which absorb any time-varying differences across banks. This specification allows us to control for bank-specific lending opportunities and to compare changes in deposit rates across branches of the same bank located in areas with different Twitter activities. In other words, we eliminate the possibility that differences in bank-specific lending opportunities drive the results by comparing deposit spreads across different branches of the same bank in different market environments. The identifying assumption here is that banks can raise deposits at one branch and lend them at another.

The results suggest that higher social media activity is indeed associated with a greater sensitivity of digital banks' deposit rates to changes in policy rates (Table 12). In specifications (4)–(6), which control for quarterly bank-specific characteristics, we find that during 2016-19 banks increase deposit rates in response to contemporaneous changes in the policy rate. For small time deposits and no Twitter activity, $Twitter_{ct} = 0$, traditional banks increase their remuneration by 7.9 bp within the same quarter for each 100 bp increase in the policy rate (column 6). For digital banks the pass-through is stronger and equal to 10.7 bp (7.9+2.8). While branches of non-digital banks in counties with higher Twitter activity do not respond differently, at digital banks, we observe some variation in the savings and small time deposit segments. For instance, they tend to increase the remuneration of small time deposits when their branches are located in counties with higher Twitter activity. A one-standard-deviation increase in Twitter activity (16.35 percentage points) raises the pass-through by 3.9 bp (0.0024 × 16.35).

When considering the final specifications that include bank-quarter fixed effects, all explanatory variables that are common to banks are wiped out, including the policy rate (columns 7-9).[16] The only terms that remain are the interactions with the branch- and county-specific Twitter activity. This specification is equivalent to equation (16) in Drechsler et al. (2017) where they include an interaction of the change in the Federal funds rate with a county-specific Herfindahl-Hirschman index. We observe one significant result. As can be seen in column (9), in the small time deposit market segment — which generally is the most sensitive to changes in monetary policy — digital banks increase the remuneration at branches located in counties

[16] One should note that this specification can only be estimated for banks with branches in at least two counties because the coefficient of interest, β_T^*, is not identified for single-county banks when bank-quarter fixed effects are included. Therefore, the number of observations decreases from roughly 80,000 to 20,000 (of which 1,500 observations are on digital banks).

with higher Twitter activity relative to the other banks. The key coefficient of interest, β_T^*, is equal to 0.0018, which means that digital banks' deposit rate sensitivity is by 2.9 bp higher in counties with a one-standard-deviation higher Twitter activity compared to counties with no Twitter activity and to all traditional banks, whose deposit rate sensitivity does not vary across counties with different levels of Twitter activity.

8. Conclusions

This paper provides new evidence on how digital transformation has altered banks' deposit pricing behaviour. Using detailed branch-level data for U.S. banks over two decades, we show that digital banks exhibit a significantly stronger and faster pass-through of monetary policy changes to deposit rates compared with traditional branch-based institutions. The difference is most pronounced in the small time deposit segment, consistent with higher deposit elasticity and lower switching costs in digital environments. We also uncover an asymmetric response to monetary policy: deposit rates adjust more rapidly during easing cycles than during tightening, reflecting competitive pressures and balance sheet constraints.

We further find that the responsiveness of digital banks is amplified in counties with higher social media activity, suggesting that digital information channels heighten depositors' awareness of rate differentials and accelerate competitive adjustments. These results highlight how technology and social connectivity jointly shape the transmission of monetary policy through the banking sector.

Overall, our findings indicate that digitalisation increases deposit rate sensitivity and may weaken banks' market power in retail funding markets. For policymakers, this implies that the pass-through of policy rates could become faster but also more volatile as digitalisation and social media adoption continue to expand.

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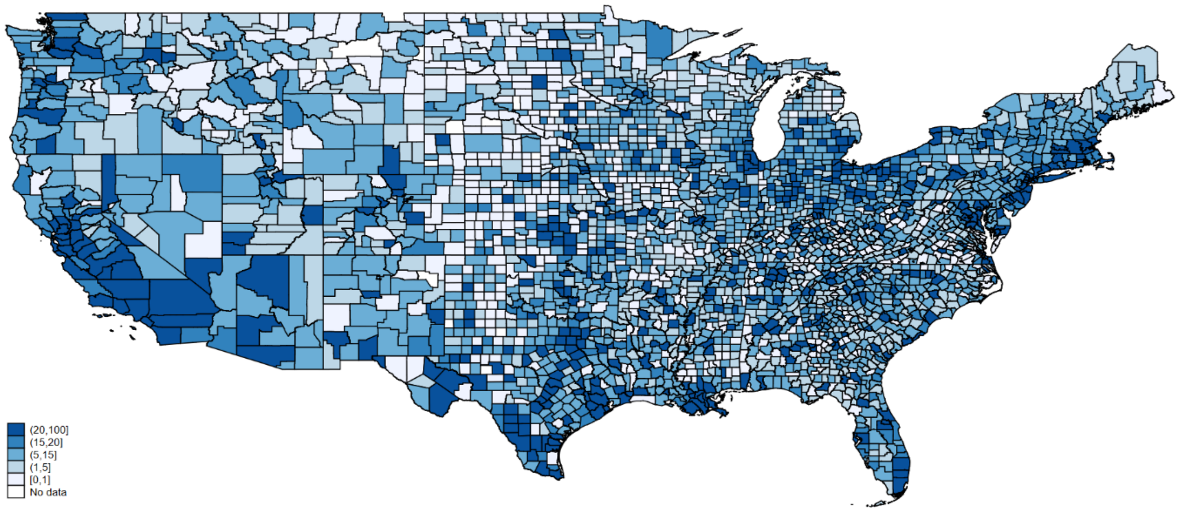
Figures and Tables

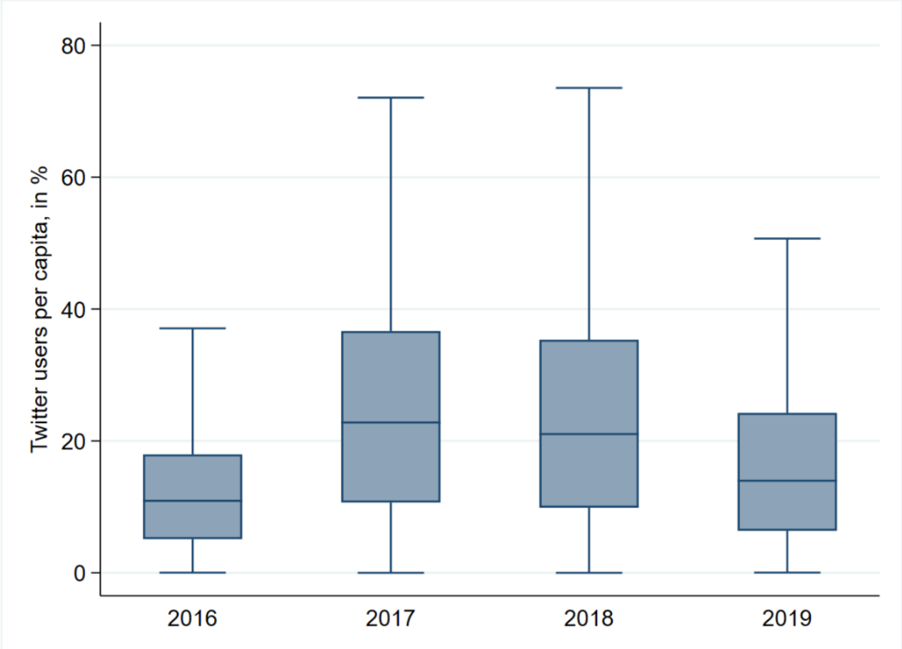
Figure 1: Twitter users per county

Resident Twitter users



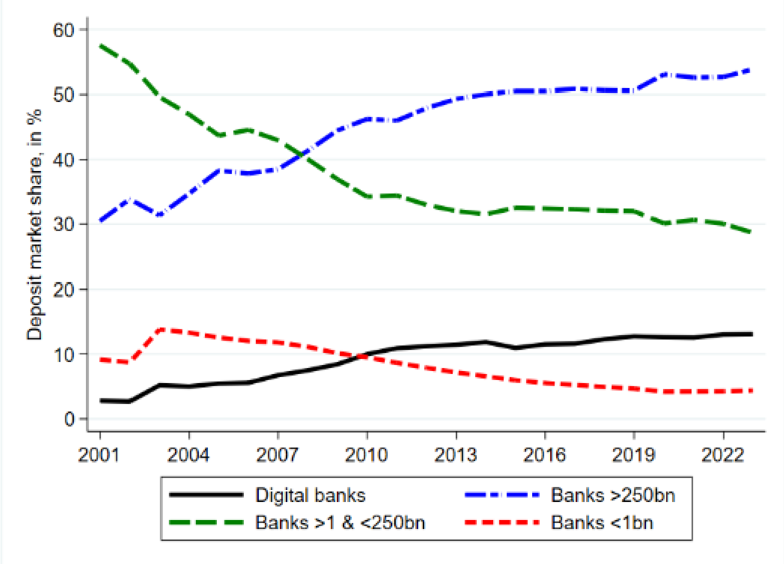
Note: The figures show median values of Twitter users per capita by county over the period 2016-2019. The colouring of the shaded areas indicates the intensity of Twitter activity based on the ratio of Twitter users in percentage of the total population of a given county (darker areas indicate more Twitter activity). "Resident Twitter users" are defined based on the most repeated location among the tweets sent by each individual in a given year.
Sources: Martin et al. (2021); U.S. Census Bureau. Authors' calculations.

Figure 2: Twitter users over time



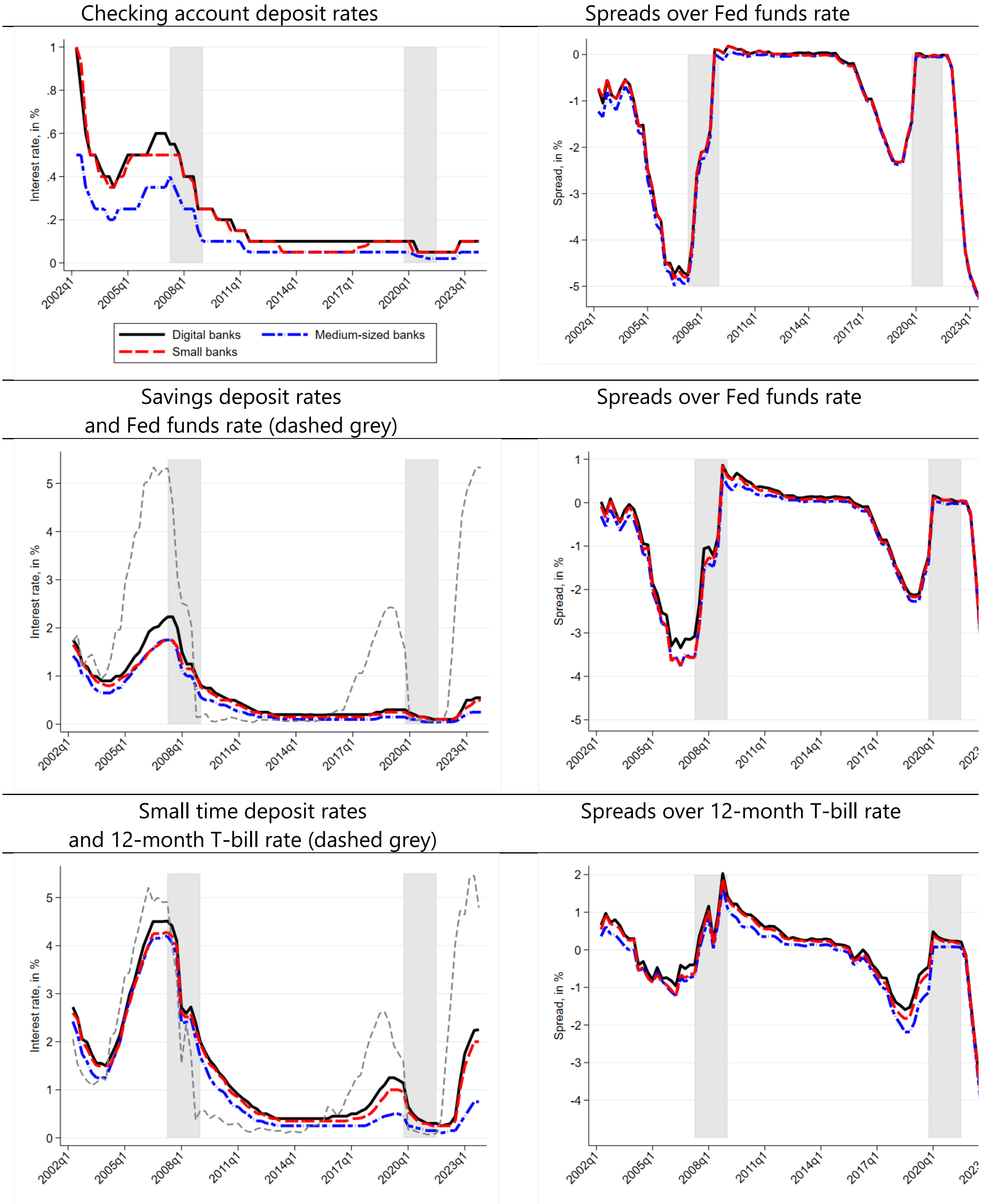
Note: The figure shows annual boxplots for the ratio of resident Twitter users in percentage of the total population of a given county, in percentages.
Sources: Martin et al. (2021); U.S. Census Bureau. Authors' calculations.

Figure 3: Deposit market shares



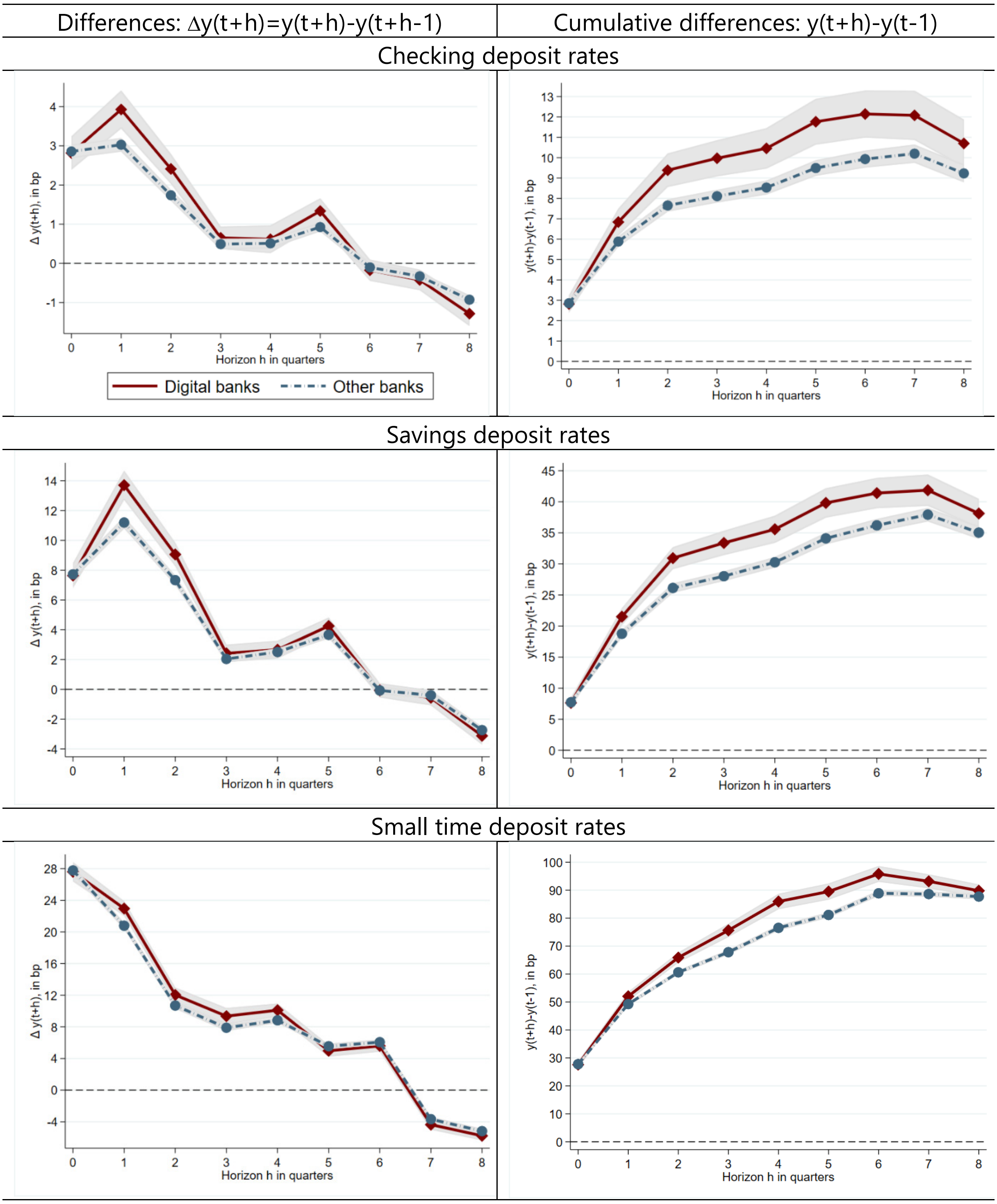
Note: The figure shows market shares for deposits of (i) digital banks (identified using cluster analysis, see Table 5), (ii) banks with median assets above $250 billion, (iii) banks with median assets between $1 billion and $250 billion, and (iv) banks with median assets below $1 billion.
Sources: RateWatch, Call reports, SoD. Authors' calculations.

Figure 4: Deposit rates and spreads across banks



Note: The figures present quarterly median values of annual deposit rates and spreads, i.e. the difference between the deposit rate and the respective policy rate, for (i) digital banks (identified using cluster analysis, see Table 5), (ii) banks with median assets above $1 and below $250 bn, and (iii) banks with median assets below $1 bn. Saving deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest-bearing checking accounts with a minimum balance of $2,500. The shaded areas correspond to the period 2007Q2-2009Q1 and 2019Q4-2021Q3.
Sources: RateWatch, Call reports, SoD. Authors' calculations.

Figure 5: Branch-level responses of deposit rates to changes in the Fed funds rate



Note: The estimated responses at the branch-level are based on equations (4) and (5) and measured in basis points (bp). The figures show the local projection (LP) responses of deposit rates to a 100 bp increase in the federal funds rate (for checking and savings deposits) and a 100 bp increase in the 12-month T-bill rate (for small time deposits). Saving deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest-bearing checking accounts with a minimum balance of $2500. The shaded area indicates 99% confidence intervals based on standard errors clustered at the branch level.
Sources: RateWatch, Call reports, SoD. Authors' calculations.

Table 1: Summary statistics of the regression variables at the branch-level

	Obs.	Mean	Std. dev.	Min	Max
Panel A: Annual regression variables					
Checking deposit rate	118679	0.24	0.31	0.00	4.90
Savings deposit rate	118099	0.60	0.70	0.00	5.13
Small time deposit rate	123410	1.32	1.28	0.00	5.75
Fed funds rate	123410	1.35	1.67	0.04	5.33
One-year T-bill rate	123410	1.54	1.63	0.10	4.99
Δ Checking deposit rate	118025	-0.04	0.20	-3.57	4.41
Δ Savings deposit rate	117463	-0.06	0.45	-4.35	4.44
Δ Small time deposit rate	123410	-0.07	0.76	-4.72	5.15
Δ Fed funds rate	123410	0.10	1.32	-2.92	4.26
Δ One-year T-bill rate	123410	0.05	1.28	-2.97	4.34
Dummy, Digital banks	123410	0.15	0.36	0	1
Size (t-1)	123410	12.82	1.99	8.31	19.16
Equity ratio (t-1)	123410	10.78	3.40	-5.19	91.70
ROA (t-1)	123410	0.18	0.51	-26.82	87.00
Output gap	123410	-1.12	1.65	-4.12	1.49
Inflation	123410	2.38	1.56	-0.34	8.01
Panel B: Quarterly regression variables					
Checking deposit rate	449878	0.26	0.33	0.00	6.08
Savings deposit rate	448042	0.65	0.72	0.00	5.84
Small time deposit rate	470445	1.38	1.29	0.00	5.90
Fed funds rate	470445	1.45	1.72	0.04	5.34
One-year T-bill rate	470445	1.57	1.63	0.07	5.46
Δ Checking deposit rate	448690	-0.01	0.10	-4.00	5.58
Δ Savings deposit rate	447035	-0.02	0.21	-4.25	4.35
Δ Small time deposit rate	470445	-0.02	0.32	-4.61	4.97
Δ Fed funds rate	470445	0.01	0.44	-1.89	1.50
Δ One-year T-bill rate	470445	0.00	0.46	-1.79	1.25
Dummy, Digital banks	470445	0.15	0.36	0.00	1.00
Size (t-1)	470445	12.86	2.00	8.30	19.27
Equity ratio (t-1)	470445	10.83	3.55	-12.37	96.19
ROA (t-1)	470445	0.23	0.35	-34.58	30.43
Output gap	470445	-1.10	1.85	-9.55	2.03
Inflation	470445	2.37	1.64	-1.58	8.62
Twitter users (2016-2019)	79493	16.68	16.35	0.00	99.63

Note: The table shows summary statistics of the regression variables.

Table 2: Digital and online banks identified by consumer-rating platforms

	Branches	Assets	Time	Savings	Checking	Loans	Loans net	Deposits			Interest exp.
				Deposit rates				total	non-interest	interest	
	No.	bn $	in percentage points			in percentage of total assets					
Charles Schwab Bank	12	348.7				22.9	13.3	91.9	0.2	91.6	0.11
Ally Bank	2	181.9				72.3	72.3	63.1	1.7	61.4	0.44
Discover Bank	3	129.4	1.8	1.4	0.9	88.0	82.6	63.8	1.2	62.6	0.57
Synchrony Bank	8	96.3					81.1	73.6	0.5	73.2	0.33
CIBC Bank USA	40	50.9	1.1	0.4	0.2	72.4	70.0	81.0	16.7	64.3	0.34
Tiaa FSB	18	39.4					83.2	69.8	5.2	64.6	0.26
Axos Bank	3	17.9					86.1	81.5	12.0	69.5	0.25
Sofi Bank	8	9.1				73.0	72.3	89.4	33.9	55.5	0.17
Flushing Bank	33	8.4	1.1	0.8	0.2		49.7	72.2	4.5	67.8	0.24
Lendingclub Bank	6	7.6					76.0	80.5	7.9	72.6	0.19
Salem Five Cents sav	53	6.6	1.0	0.6	0.2	62.1	67.1	71.8	9.2	62.5	0.42
First Internet B. of Ind.	3	4.5				63.5	68.3	79.9	2.5	77.4	0.50
Tab Bank	2	1.2	1.8	0.5	0.2	63.1	70.0	82.7	1.2	81.5	0.48
NBKC Bank	9	1.1	1.4	1.1	0.4	56.2	54.7	64.8	9.5	55.3	0.49
M1 Bank	3	0.8	0.9	0.5	0.2	72.6	66.2	91.2	13.8	77.4	0.35
Quontic Bank	6	0.6					83.9	77.1	5.9	71.2	0.28
Varo Bank	1	0.5						48.3	20.9	27.4	
Average	**12.4**	**53.2**	**1.3**	**0.8**	**0.3**	**64.6**	**68.5**	**75.5**	**8.6**	**66.8**	**0.3**

Note: "Average" refers to unweighted averages over banks. "Assets" refers to the balance sheet situation at the end of 2022. Deposit rates and balance sheet indicators are calculated as simple averages over the period 2002–2022. Saving deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest checking accounts with a minimum balance of $2500. Total deposits are decomposed into interest-bearing ("interest") and non-interest bearing ("non-interest"). "Interest exp." are interest expenses. Sources: Forbes, FinTechlabs, Investopedia, Cent, TopMobileBanks, RateWatch, Call reports, SoD. Authors' calculations.

Table 3: Average bank characteristics

	Digital banks	Banks, <1bn	Banks, >1bn and <250bn	Banks, >250bn	Digital banks	Banks, <1bn	Banks, >1bn and <250bn	Banks, >250bn
	Median				Mean			
Number of banks	17	8729	1739	15	17	8729	1739	15
Total assets (in $million)	2996	119	1085	257576	28272	172	4942	554389
Assets								
Cash/TA	6.4	5.1	3.7**	8.0	12.3	8.3	6.3***	12.3
Securities/TA	**10.7**	18.4**	16.8**	21.3***	**14.7**	21.5*	19.5	21.8
Fed funds sold/TA	0.0	0.7***	0.0***	1.5***	2.0	3.7*	2.1	3.3***
Loans net/TA	**74.2**	64.8***	69.0	53.7***	64.8	61.0	65.6	47.0**
Trading assets/TA	0.0	0.0***	0.0	**2.5*****	0.0	0.0	0.1	**5.4*****
Premises and fixed assets/TA	**0.2**	1.5***	1.4***	0.8**	**0.6**	1.9***	1.5***	0.8
Other assets/TA	5.2	3.2***	4.6	9.2***	5.8	4.2	5.5	9.4***
Liabilities and equity								
Deposits/TA	79.5	85.1***	81.0	67.5***	75.9	81.3	77.1	60.1***
Fed funds purchased/TA	0.0	0.0	0.6***	1.5***	1.0	1.1	3.0	3.7*
Trading liabilities/TA	0.0	0.0***	0.0	**1.9*****	0.0	0.0	0.0	**2.7*****
Other borrowed money/TA	6.0	0.9*	3.9	5.9	8.8	3.6**	6.5	6.4
Oher liabilities/TA	1.2	0.5***	0.8*	10.8***	2.5	1.2	2.5	16.5***
Total equity/TA	10.0	10.1	10.0	9.7	11.8	12.9	11.4	10.4
Tier 1 capital/TA	9.5	9.5	8.8**	7.2***	12.2	12.3	10.3	7.6**
Total capital/TA	10.2	10.3	9.7**	9.5**	11.5	12.9	11.2	9.5
Income statement and risk indicators								
Interest income/TA	1.1	1.2	1.1	0.9*	1.3	1.4	1.2	0.9**
Interest expense/TA	0.3	0.3	0.2	0.2**	0.4	0.4	0.3	0.3
Non-interest income/TA	0.3	0.1*	0.2	0.4**	0.8	1.0	0.3	0.5
Non-interest expense/TA	0.8	0.8	0.7	0.7	**1.7**	1.6	0.8***	0.7
Net income/TA	0.2	0.2	0.2	0.2	-0.2	0.2	0.1***	0.2
Risk-weighted assets/TA	69.0	68.1	72.8	72.9	70.8	66.2	71.3	71.0
Loan-loss provisions/TA	0.1	0.0**	0.0	0.1	0.3	0.1***	0.1	0.1
Branch network								
Deposits (in $mln) per branch	**8415**	383***	704***	2495	**81778**	525***	6816***	45425
Branches per county	**1.4**	2.0	3.1***	7.8***	**2.1**	2.2	4.0**	7.6***
Rate setters share	**0.0**	50.0***	40.0*	23.6	**20.4**	55.5***	39.4***	26.0
Rate on 12m 10k CD accounts	0.60	1.04	0.55	0.19*	0.71	**1.32***	0.85	0.66
Rate on 25k money market	0.25	0.40	0.20	0.15	0.36	0.64	0.38	0.22
Rate on 2-5k checking accounts	0.10	**0.15***	0.08	0.01	0.22	0.28	0.13	0.06

Note: Median and simple averages are reported for the period 2002-2023. Most indicators are expressed in percentage of total assets (TA). Digital banks are those listed in Table 2. Asterisks indicate the significance of differences between digital banks (reference group) and other banks in terms of medians (nonparametric K-sample test on the equality of medians) and means (two-sided t tests on the equality of means). (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 4: Distinguishing features of digital banks

	Digital banks	Banks, <1bn	Banks, >1bn and <250bn	Banks, >250bn	Digital banks	Banks, <1bn	Banks, >1bn and <250bn	Banks, >250bn
			Median				**Mean**	
Number of banks	17	8729	1739	15	17	8729	1739	15
Securities/TA	**10.7**	18.4**	16.8**	21.3***	**14.4**	21.0*	18.7***	21.9
Premises and fixed assets/TA	**0.2**	1.5***	1.4***	0.8**	**0.5**	1.8***	1.5**	0.8
Non-interest bearing deposits/TA	**6.5**	13.0**	12.9**	17.9**	**8.7**	13.8***	13.8***	15.9***
Other non-interest expenses/TA	**0.4**	0.2	0.2	0.3	**0.7**	0.5	0.3***	0.3
Salaries/employees	**28.5**	15.1***	17.8***	23.4	**27.7**	16.5***	19.4	25.0
Advertisements/TA	**0.021**	0.009***	0.013**	0.012*	**0.035**	0.017	0.023	0.012*
Deposits (in mil.)/branch	**8.4**	0.4***	0.7***	2.5	**81.8**	0.5***	6.8***	45.4
Branches/county	**2.0**	3.0	3.8***	7.9***	**3.0**	3.5	5.2**	7.7
Rate setters/branch	**0.0**	50.0***	40.0	23.6	**20.4**	55.6***	39.4***	26.0

Note: Median and simple averages are reported for the period 2002-2023. Most indicators are expressed in percentage of total assets (TA). Digital banks are those listed in Table 2. Variable definitions are reported in Appendix B. Asterisks indicate the significance of differences between digital banks (reference group) and other banks in medians (using nonparametric K-sample test on the equality of medians) and means (two-sided t tests on the equality of means). (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 5: Partitioning results and classification of bank types

	Digital banks	Small banks	Medium-sized banks	Total
		K=3 clusters		
Cluster 1	2	2680	763	3445
Cluster 2	1	1749	172	1922
Cluster 3	***13***	***1331***	***404***	***1748***
		K=4 clusters		
Cluster 1	1	1899	300	2200
Cluster 2	1	1632	117	1750
Cluster 3	***13***	***1350***	***322***	***1685***
Cluster 4	1	879	600	1480
Total	16	5760	1339	7115

Note: The table shows the number of banks classified into three and four clusters, respectively. Digital banks are those listed in Table 2, small banks have median assets of less than $1 billion and medium-sized banks are those with median assets between $1 billion and $250 billion.

Table 6: Distinguishing features of digital banks identified by cluster analysis

	Digital banks	Other banks	Digital banks	Other banks
	Median		Mean	
Number of banks	1567	5548	1567	5548
Securities/TA	10.57***	21.81	11.31***	23.89
Premises and fixed assets/TA	0.77***	1.80	0.85***	1.94
Non-interest bearing deposits/TA	11.72***	14.65	12.02***	15.63
Other non-interest expenses/TA	0.22***	0.23	0.34	0.29
Salaries/employees	20.82***	15.24	22.79***	15.97
Advertisements/TA	0.007***	0.011	0.013	0.015
Deposits (in mil.)/branch	0.71***	0.54	6.17***	1.06
Branches/county	1.33***	2.00	1.57***	2.74

Note: Digital banks are those belonging to clusters 3 in Table 5, while other banks comprise the remaining institutions. Asterisks indicate statistically significant differences in medians (nonparametric K-sample tests on the equality of medians) and means (two-sided t-tests on the equality of means). (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 7: Deposit rate levels across bank types and time

	Checking deposits	Savings deposits	Small time deposits
		Full sample: 2002-2023	
Digital banks	0.15	0.40	1.00
Small banks	0.15***	0.40*	1.00***
Medium and large banks	0.10***	0.25***	0.80***
		2002-2007	
Digital banks	0.50	1.44	2.85
Small banks	0.50***	1.25***	2.70***
Medium and large banks	0.35***	1.10***	2.50***
		2008-2009	
Digital banks	0.25	1.00	2.05
Small banks	0.25	0.90***	2.00***
Medium and large banks	0.15***	0.75***	1.84***
		2010-2015	
Digital banks	0.10	0.25	0.55
Small banks	0.10***	0.20***	0.50***
Medium and large banks	0.05***	0.15***	0.35***
		2016-2019	
Digital banks	0.10	0.25	0.65
Small banks	0.10***	0.20***	0.50***
Medium and large banks	0.05***	0.10***	0.30***
		2020-2023	
Digital banks	0.07	0.20	0.45
Small banks	0.05***	0.15***	0.40***
Medium and large banks	0.03***	0.08***	0.18***

Note: The table reports median deposit rates of rate setting branches in percentages. Asterisks indicate statistically significant differences in medians relative to digital banks, as determined by a nonparametric K-sample test of median equality. (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 8: Deposit rate levels for digital banks for low and high Twitter activity

	Checking deposits	Savings deposits	Small time deposits
		2016-2019	
Digital banks, low Twitter activity	0.10	0.22	0.65
Digital banks, high Twitter activity	0.10	0.25***	0.75***

Note: The table reports median deposit rates of rate setting branches in percentages. "High (low) Twitter activity" refers to counties in which the Twitter activity indicator is above (below) the 90th percentile of its distribution. Asterisks indicate statistically significant differences in medians across high versus low Twitter activity counties, as determined by a nonparametric K-sample test of median equality. (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 9: Baseline results on annual deposit rate sensitivities of bank branches

y = Δ deposit rate	(1) Checking deposits	(2) Savings deposits	(3) Small time deposits	(4) Checking deposits	(5) Savings deposits	(6) Small time deposits	(7) Checking deposits	(8) Savings deposits	(9) Small time deposits
Δ PR (t)	**0.030*** **	**0.116*** **	**0.280*** **	**0.028*** **	**0.117*** **	**0.284*** **	**0.029*** **	**0.119*** **	**0.289*** **
	(0.001)	**(0.002)**	**(0.003)**	**(0.001)**	**(0.002)**	**(0.003)**	**(0.001)**	**(0.002)**	**(0.003)**
Δ PR (t-1)	**0.037*** **	**0.100*** **	**0.247*** **	**0.039*** **	**0.079*** **	**0.180*** **	**0.039*** **	**0.082*** **	**0.190*** **
	(0.001)	**(0.001)**	**(0.002)**	**(0.001)**	**(0.001)**	**(0.002)**	**(0.001)**	**(0.001)**	**(0.002)**
Δ PR (t)*Digital banks	**0.012*** **	**0.030*** **	**0.052*** **	**0.011*** **	**0.030*** **	**0.052*** **	**0.012*** **	**0.031*** **	**0.046*** **
	(0.002)	**(0.005)**	**(0.007)**	**(0.002)**	**(0.005)**	**(0.007)**	**(0.002)**	**(0.006)**	**(0.007)**
Δ PR (t-1)*Digital banks	**0.006*** **	**0.013*** **	**0.001**	**0.006*** **	**0.013*** **	**0.001**	**0.007*** **	**0.013*** **	0.004
	(0.002)	**(0.003)**	**(0.005)**	**(0.002)**	**(0.003)**	**(0.005)**	**(0.002)**	**(0.003)**	(0.005)
Output gap (t)				-0.005***	0.035***	0.104***	-0.004***	0.032***	0.097***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Inflation rate (t)				0.005***	-0.015***	-0.041***	0.005***	-0.013***	-0.029***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Size (t-1)							0.023***	0.003	-0.096***
							(0.001)	(0.002)	(0.004)
Equity ratio (t-1)							0.003***	0.005***	0.002*
							(0.001)	(0.001)	(0.001)
ROA (t-1)							-0.000	0.011***	0.040***
							(0.001)	(0.003)	(0.010)
Observations	120606	120258	125949	120606	120258	125949	118256	117765	123410
R^2	0.212	0.365	0.610	0.213	0.371	0.629	0.219	0.372	0.644
R^2 within	0.16	0.34	0.59	0.17	0.34	0.61	0.17	0.34	0.63
Branch fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: The regressions are based on equation (1) and cover the period 2002-2023. Savings deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest checking accounts with a minimum balance of $2500. The policy rate (PR) is the federal funds rate for checking and savings deposits, and the 12-month T-bill rate for small time deposit rates. Standard errors are clustered at the county-level and reported in brackets. (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 10: Annual deposit rate sensitivities of bank branches depending on the monetary policy stance

y =Δ deposit rate	(1) Checking deposits	(2) Savings deposits	(3) Small time deposits	(4) Checking deposits	(5) Savings deposits	(6) Small time deposits	(7) Checking deposits	(8) Savings deposits	(9) Small time deposits
Δ PR (t)	**0.046*** **	**0.172*** **	**0.435*** **	**0.042*** **	**0.159*** **	**0.375*** **	**0.042*** **	**0.159*** **	**0.376*** **
	(0.001)	**(0.003)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.003)**	**(0.001)**	**(0.003)**	**(0.003)**
Δ PR (t)*tightening	**-0.004*** **	**-0.034*** **	**-0.146*** **	**-0.005*** **	**-0.035*** **	**-0.082*** **	**-0.004*** **	**-0.033*** **	**-0.073*** **
	(0.001)	**(0.003)**	**(0.004)**	**(0.001)**	**(0.003)**	**(0.004)**	**(0.001)**	**(0.003)**	**(0.004)**
Δ PR (t)*Digital banks	**0.017*** **	**0.050*** **	**0.024*** **	**0.017*** **	**0.049*** **	**0.020*** **	**0.017*** **	**0.048*** **	**0.020*** **
	(0.004)	**(0.008)**	**(0.006)**	**(0.004)**	**(0.008)**	**(0.006)**	**(0.004)**	**(0.008)**	**(0.006)**
Δ PR (t)*tightening*Digital banks	**-0.007***	**-0.028*** **	**0.046*** **	-0.006	**-0.022*** **	**0.058*** **	-0.004	**-0.022*** **	**0.052*** **
	(0.004)	**(0.009)**	**(0.010)**	(0.004)	**(0.008)**	**(0.010)**	(0.004)	**(0.008)**	**(0.010)**
Observations	120606	120258	125949	120606	120258	125949	118256	117765	123410
R^2	0.143	0.259	0.427	0.169	0.336	0.575	0.177	0.336	0.585
R^2 within	0.091	0.23	0.40	0.12	0.31	0.56	0.13	0.31	0.57
Branch fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank-specific controls	No	No	No	No	No	No	Yes	Yes	Yes

Note: The regressions are based on equation (2) and cover the period 2002-2023. Monetary tightening took place in 2005-06, 2016-19 and 2022-23. Saving deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest checking accounts with a minimum balance of $2500. The policy rate (PR) is the federal funds rate for checking and savings deposits, and the 12-month T-bill rate for small time deposit rates. Macroeconomic controls include the output gap and inflation rate. Bank-specific controls include lagged bank size, equity ratio and ROA. Standard errors are clustered at the county-level and reported in brackets. (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 11: Baseline results on quarterly deposit rate sensitivities of bank branches

y =Δ deposit rate	(1) Checking deposits	(2) Savings deposits	(3) Small time deposits	(4) Checking deposits	(5) Savings deposits	(6) Small time deposits	(7) Checking deposits	(8) Savings deposits	(9) Small time deposits
Δ PR(t)	**0.026*** **	**0.070*** **	**0.219*** **	**0.028*** **	**0.076*** **	**0.240*** **	**0.019*** **	**0.046*** **	**0.341*** **
	(0.001)	**(0.001)**	**(0.002)**	**(0.001)**	**(0.001)**	**(0.002)**	**(0.001)**	**(0.002)**	**(0.003)**
Δ PR(t-1)	**0.023*** **	**0.092*** **	**0.201*** **	**0.022*** **	**0.090*** **	**0.202*** **	**0.018*** **	**0.079*** **	**0.256*** **
	(0.001)	**(0.002)**	**(0.002)**	**(0.001)**	**(0.002)**	**(0.002)**	**(0.001)**	**(0.002)**	**(0.003)**
Δ PR(t-2)	**0.006*** **	**0.036*** **	**0.113*** **	**0.006*** **	**0.037*** **	**0.105*** **	**-0.006*** **	-0.000	**0.101*** **
	(0.001)	**(0.001)**	**(0.002)**	**(0.001)**	**(0.001)**	**(0.002)**	**(0.001)**	(0.001)	**(0.003)**
Δ PR(t-3)	**0.002*** **	**0.007*** **	**0.012*** **	-0.000	**0.003*** **	0.002	**-0.022*** **	**-0.053*** **	**-0.056*** **
	(0.000)	**(0.001)**	**(0.001)**	(0.001)	**(0.001)**	(0.002)	**(0.001)**	**(0.002)**	**(0.002)**
Δ PR(t)*Digital banks	0.001	0.002	-0.009	0.001	0.003	-0.009	-0.000	0.000	0.001
	(0.002)	(0.004)	(0.006)	(0.002)	(0.004)	(0.006)	(0.002)	(0.005)	(0.008)
Δ PR(t-1)*Digital banks	**0.010*** **	**0.025*** **	**0.016*** **	**0.009*** **	**0.025*** **	**0.014*** **	**0.009*** **	**0.026*** **	**0.030*** **
	(0.002)	**(0.004)**	**(0.004)**	**(0.002)**	**(0.004)**	**(0.004)**	**(0.002)**	**(0.005)**	**(0.006)**
Δ PR(t-2)*Digital banks	**0.005*** **	**0.010*** **	**0.016*** **	**0.005*** **	**0.009*** **	**0.018*** **	**0.004** **	**0.007** **	**0.027*** **
	(0.002)	**(0.003)**	**(0.004)**	**(0.002)**	**(0.003)**	**(0.004)**	**(0.002)**	**(0.003)**	**(0.006)**
Δ PR(t-3)*Digital banks	-0.001	-0.003	**0.012*** **	-0.002	-0.003	**0.012*** **	-0.002	-0.005	**0.022*** **
	(0.001)	(0.002)	**(0.004)**	(0.001)	(0.002)	**(0.004)**	(0.002)	(0.004)	**(0.007)**
Observations	463556	462566	484920	451727	450421	472309	449664	448465	470445
R^2	0.059	0.135	0.304	0.064	0.139	0.324	0.262	0.334	0.489
R^2 within	0.041	0.12	0.29	0.047	0.13	0.31	0.022	0.053	0.21
Branch fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-specific controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Macroeconomic controls	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Bank-year fixed effects	No	No	No	No	No	No	Yes	Yes	Yes

Note: The regressions are based on equation (3) and cover the period 2002q1- 2023q4. Saving deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest checking accounts with a minimum balance of $2500. The policy rate (PR) is the federal funds rate for checking and savings deposits, and the 12-month T-bill rate for small time deposit rates. Macroeconomic controls include the output gap and inflation rate. Bank-specific controls include lagged bank size, equity ratio and ROA. Standard errors are clustered at the county-level and reported in brackets. (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Table 12: Quarterly deposit rate sensitivities of bank branches and Twitter activity

y =Δ deposit rate	(1) Checking deposits	(2) Savings deposits	(3) Small time deposits	(4) Checking deposits	(5) Savings deposits	(6) Small time deposits	(7) Checking deposits	(8) Savings deposits	(9) Small time deposits
Δ PR(t)	**0.016*** **	**0.047*** **	**0.077*** **	**0.017*** **	**0.052*** **	**0.079*** **			
	(0.001)	**(0.003)**	**(0.004)**	**(0.001)**	**(0.003)**	**(0.004)**			
Δ PR(t)*Twitter users	-0.000	0.000	0.000	-0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Δ PR(t)*Digital banks	0.004	0.000	**0.025** **	0.004	0.001	**0.028*** **			
	(0.004)	(0.008)	**(0.010)**	(0.004)	(0.008)	**(0.010)**			
Δ PR(t)*Digital banks*Twitter users	0.000	**0.001** **	**0.002*** **	0.000	**0.001** **	**0.002*** **	-0.000	0.000	**0.002** **
	(0.000)	**(0.000)**	**(0.000)**	(0.000)	**(0.000)**	**(0.000)**	(0.000)	(0.000)	**(0.001)**
Observations	76056	77721	82102	73652	75236	79493	20181	21142	22077
R^2	0.094	0.072	0.059	0.082	0.075	0.059	0.608	0.707	0.726
R^2 within	0.009	0.024	0.019	0.010	0.027	0.019	0.0003	0.0001	0.0004
Branch fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank-specific controls	No	No	No	Yes	Yes	Yes	No	No	No
Bank-quarter fixed effects	No	No	No	No	No	No	Yes	Yes	Yes

Note: The regressions are based on equation (6) and cover the period 2016q1-2019q4. Twitter users is measured as resident Twitter users in percent of the total population in a given county. Saving deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest checking accounts with a minimum balance of $2500. The policy rate (PR) is the federal funds rate for checking and savings deposits, and the 12-month T-bill rate for small time deposit rates. Bank-specific controls include lagged bank size, equity ratio and ROA. Standard errors are clustered at the county-level and reported in brackets. (***, **, *) indicate significance at the 1%, 5% and 10% levels, respectively.

Appendix A: Monetary policy pass-through over time

In this section, we estimate average annual deposit rate sensitivities at the branch-level using quarterly data. For this purpose, we regress the change in the quarterly deposit rate on the contemporaneous change in the policy rate and its three lags over two-year non-overlapping rolling windows. More specifically, we estimate the following regressions:

$$\Delta y_{b,i,c,t} = \alpha_b + \sum_{j=0}^{3} \beta_j \times \Delta PR_{t-j} + \gamma X_{it} + \epsilon_{b,i,t} \quad \text{for t=2002q1-03q4, ..., 2022q1-23q4}$$

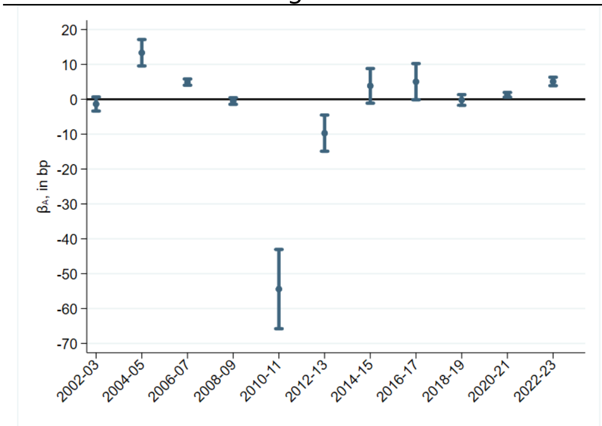
where b refers to rate-setting branches of bank i in county c and quarter t. The average annual deposit rate sensitivity is then defined by the sum of the four response coefficients:

$$\hat{\beta}_A = \sum_{j=0}^{3} \widehat{\beta_j}$$

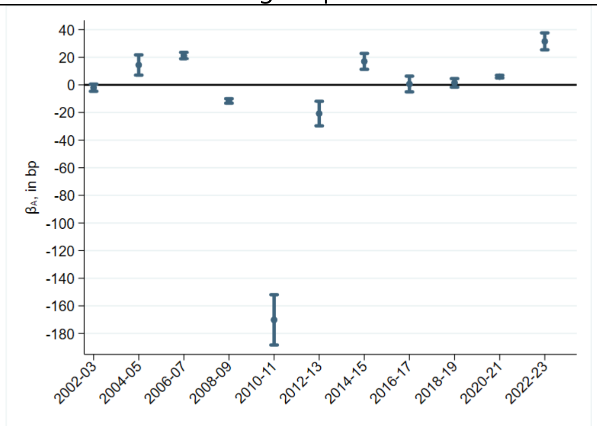
The results are shown in Figure A1. Focusing on small time deposit rates, we observe a negative pass-through during in the GFC indicating that, when the Federal Reserve Bank lowered its policy rate, banks did not follow but instead increased rates on small time deposits — a sign of heightened competition on this market segment.

Figure A1: Annual deposit rate sensitivities to changes in the policy rate

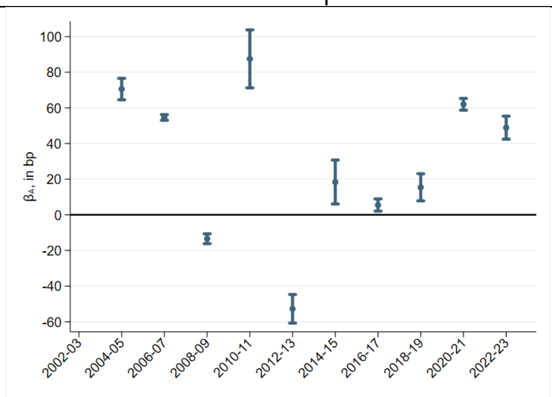
Checking accounts



Savings deposits



Small time deposits



Note: Saving deposits are money market deposit accounts with an account size of $25,000; small time deposits are 12-month certificates of deposit with an account size of $10,000; and checking deposits are interest checking accounts with a minimum balance of $2500. The policy rate (PR) is the federal funds rate for checking and savings deposits, and the 12-month T-bill rate for small time deposit rates. The figure shows annual deposit rate sensitivities to policy rate changes in basis points. Confidence levels of 95 percent are shown along with the point estimates.

Appendix B: Variable definitions

Table B1: Variable definitions of the most distinguishing features of digital banks

Variable name	Variable definition	Source
Non-interest bearing deposits	All non-interest bearing deposits	Call Report code rconB913
Total securities	Includes the sum of Held-To-Maturity Securities and Available-For-Sale Securities.	
Premises and fixed assets	Includes the book value (net of accumulated depreciation or amortization) of all premises, equipment, furniture, and fixtures purchased directly or acquired by means of a capital lease. Includes bank premises owned and occupied (fully or partially) by the bank.	Call Report code rcfd2145
Other non-interest expense	Includes all operating expenses not otherwise reported. Among others: advertising, promotional, public relations, and business development expenses; outsourced data processing services; research and development costs; internally developed software; office supplies, printing, postage; directors' fees for board or committee meetings.	Call Report code riad4092
Salaries and employee benefits/employees	Includes total salaries and benefits of all officers and employees (including maintenance and security staff) divided by the number of full-time equivalent employees.	Call Report codes riad4135/ riad4150
Computer software	Subcomponent for computer software expenses included in other assets (reported if amounts exceed $100,000 and 25% of this item). Schedule RC-F - Other Assets.	Call Report code rcfdft33
Advertising and marketing expenses	Includes advertising, production, agency fees, and direct mail; marketing research (including consultants); public relations (consultants, seminars, or customer magazines); sales training by consultants.	Call Report code riad0497
Branches per county	Number of branches divided by the number of counties in which a bank operates.	SoD
Rate setter share	Percentage of branches that actively set deposit rates, calculated as (number of rate-setting branches / total number of branches) × 100.	S&P RateWatch and SoD
Deposits per branch	Total deposits (in thousands of USD) divided by the number of branches	SoD
Fees and commissions from securities brokerage	Income earned from brokerage-related fees and commissions.	Call Report code riadC886
Investment banking, advisory, and underwriting commissions	Income from investment banking, advisory, underwriting, and related commission activities.	Call Report code riadC888
Fees and commissions from annuity sales	Income from the sale of annuities and related commissions.	Call Report code riadC386
Income from other insurance activities	Earnings from insurance-related activities not included elsewhere.	Call Report code riadC387
Income from fiduciary activities	Income from fiduciary and trust services.	Call Report code riad4070