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# Digitalisation, social media and bank deposit dynamics: evidence from the recent euro area monetary tightening

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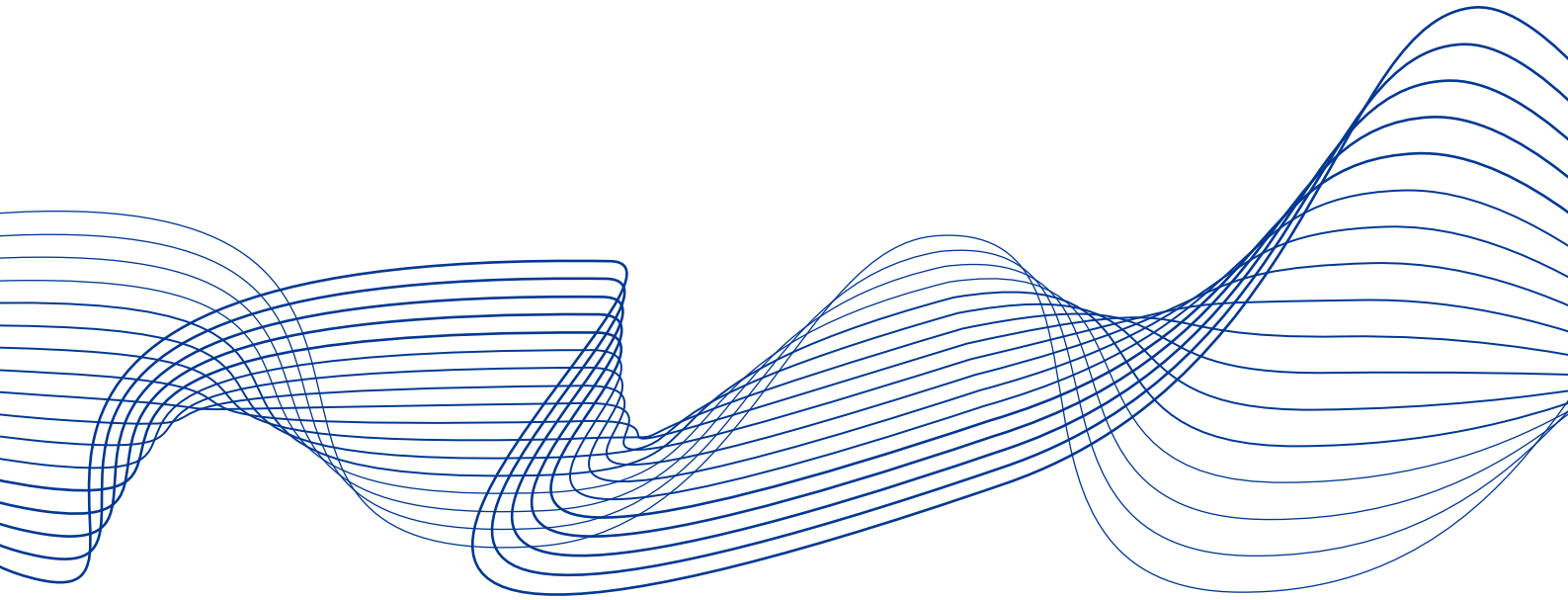

ESRB
European Systemic Risk Board
European System of Financial Supervision

**Abstract**

This study sheds light on the impact of digitalisation and social media on deposit flows and rates of euro area banks during the recent period of monetary tightening. Drawing on difference-in-differences analysis of confidential monthly data (12/2019 – 10/2023) of deposit flows and rates as well as measures of bank digitalisation and social media exposure through Twitter sentiment, the study offers two novel sets of findings. First, banks with a higher degree of digitalisation exhibit larger fluctuations in deposits, with higher inflows from mid-2020 to early 2022 but greater outflows in response to the tightening. Digitalisation is also correlated with higher sensitivity of banks' NFC deposit rates to policy rates. Second, a negative Twitter sentiment reduces deposit inflows, even after accounting for traditional news' sentiment and a comprehensive set of bank-specific factors, including asset prices and performance indicators.

*Keywords*: deposits; monetary tightening; digitalisation; social media; deposit franchise.
*JEL Classification*: G21.

# 1 Non-Technical Summary

**Research Question**. This study investigates how digitalisation and social media influence the behaviour of bank deposits in the euro area, with a particular focus on the deposits' sensitivity - in terms of volume and rates - to the recent interest rate hike. These questions are of growing importance, as digitalisation and social media are likely to play an increasingly dominant role in shaping the banking sector in the future.

**Analysis**. The analysis combines confidential monthly data of euro area banking groups with social media sentiment and web-scraped measures of bank digitalisation. The dataset covers the period from December 2019 to October 2023, encompassing both the pre-tightening phase and the subsequent period of rising interest rates. Digitalisation indicators are derived from information on the use and ratings of banks' mobile apps as well as the deposit-to-employee ratio. Sentiment data is measured using Twitter (also known as X) data, complemented by sentiment indicators from more traditional news sources. The study employs difference-in-differences estimation and entropy-balancing techniques (Hainmueller (2012)) to identify the effects of digitalisation and sentiment on deposit flows and deposit rates, controlling for bank time-varying characteristics (including stock performance and probability of default), macroeconomic conditions, and supervisory data on bank business models.

**Results**. While more digitalized banks recorded larger deposit inflows prior to early 2022, they also displayed greater volatility and a more pronounced response to monetary tightening than less digitalized peers. This pattern suggests that digitalisation may weaken the traditional deposit franchise. Digital banks face a slightly stronger pricing pressure on deposits. More digitalised banks offered higher deposit rates, particularly to non-financial corporations in response to the monetary tightening. This behaviour reflects efforts to counteract deposit outflows by adjusting remuneration more aggressively. Social media sentiment may amplify the sensitivity of deposit flows to interest rates. Banks subject to higher levels of negative Twitter sentiment experienced smaller deposit inflows, even after controlling for traditional news sentiment as well as stock returns, Google Trends and probability of default. The effect was particularly high in March 2023, during the sharp rise in concerns about US regional banks and Credit Suisse.

# 2 Introduction

*The combination of social media, a highly networked and concentrated depositor base, and technology may have fundamentally changed the speed of bank runs. Social media enabled depositors to instantly spread concerns about a bank run, and technology enabled immediate withdrawals of funding.* Michael Barr, Federal Reserve, April 2023 [1].

A number of studies highlight the various factors and heterogeneity in the pass-through of higher monetary policy to deposit rates due to frictions, including search costs (Duffie and Krishnamurthy (2016)), banks' market power (Scharfstein and Sunderam (2016)) and deposit concentration (Drechsler et al. (2017)). In light of the rapid evolution of digitalisation and the increasing influence of social media, there is a growing need among financial regulators and policymakers to better understand their potential impact on deposit dynamics, particularly during monetary tightening. Following the banking turmoil of 2023, the Basel Committee on Banking Supervision (2024) concluded that digitalisation and social media may significantly amplify the speed and reach of information flows, potentially accelerating bank runs and market stress.[2] Thus, supervisors are encouraged to adapt their monitoring tools as well as stress testing practices. The report to the G20 by the Financial Stability Board (2024) underscores the potential influence of innovative financial services and social media on aggregate bank deposit outflows. The ESRB Advisory Scientific Committee's Report, Beck et al. (2024), emphasises the importance of assessing the effects of digitalisation on bank funding to better understand the deposit dynamics during the 2022 banking turmoil.[3]

Despite remarkable academic and policy interest, the empirical investigation of this issue is still evolving. Our analysis contributes to this discussion by offering empirical evidence on two research questions in the euro area banking system. First, we analyse how bank-

[1] "Review of the Federal Reserve's Supervision and Regulation of Silicon Valley Bank"

[2] "Moreover, the "Report on the 2023 banking turmoil" by the Basel Committee on Banking Supervision highlighted that "the ongoing digitalisation of finance saw advances in faster payment / settlement services and on-demand access to banking services through mobile apps, thereby facilitating the ability of depositors to move their funds."

[3] "Moreover, academic research emphasises the need for a potential review of bank liquidity regulation. Acharya and Vives (2024) suggest that the striking speed of the runs observed in March 2023 calls for an amendment of the way the risk of deposit outflows is considered in the computation of the LCR, especially for uninsured deposits.

level measures of digitalisation impact deposit volumes and pricing. Second, we examine the impact on deposit flows and rates resulting from banks' negative sentiment inferred from Twitter (also known as X).

Our empirical evidence suggests that more digitalised banks exhibit heightened deposit fluctuations. This is observed not only through a more pronounced deposit volatility but also through greater sensitivity of deposits to interest rate changes during recent monetary tightening. In fact, while the more digitalised banks experienced markedly stronger deposit inflows from mid-2020 to early 2022, the start of the monetary tightening brought a contraction to their deposit inflow volumes relative to other similar banks. Our empirical strategy controls for a comprehensive set of bank-specific factors, including supervisory classification of business model, profitability measured as return on equity, stock return, probability of default as well as deposit volatility beyond fixed effects. By controlling for these factors with several empirical approaches, we provide robust evidence that digital banks' deposits are more sensitive to monetary policy tightening. The monthly deposit growth for banks with digitalisation levels above median is approximately 1.3 percent smaller than otherwise similar banks. With alternative specifications using the entropy balancing method for causal effects by Hainmueller (2012), we find that the monthly change in deposit ratio for digital banks is approximately 2.45 percent smaller. This effect is equivalent to approximately 0.33 standard deviations (or 0.75 percentage points), compared to the monthly deposit growth of less digitalised banks. Moreover, banks with higher digitalisation levels tend to respond to such deposit outflow pressure by offering higher deposit rates. However, this finding is not robust across all model specifications and the effect does not appear economically significant, with digital banks increasing their NFC deposit rates by 0.01 percentage points (or 0.07 standard deviations) more than less digitalised banks.

Our analysis also reveals that banks affected by negative Twitter sentiment experience stronger negative pressure on deposit flows. Our empirical strategy accounts for potential confounding factors, such as traditional news sentiment, Google Trends, digitalisation, and bank performance metrics, such as stock return and probability of default. The monthly change in deposit ratio for banks with a share of negative Twitter sentiment above the country-level median is approximately 1.5 percent smaller relative to otherwise similar banks. This

difference equates to 0.16 standard deviations (or 0.32 percentage points) less deposit inflows than to those banks with better Twitter sentiment. Moreover, we show that the shock of negative Twitter sentiment in March 2023 was in part responsible for some of the deposit outflows from the euro area banking system.

# 3 Literature Review

The stability of banks can be critically compromised by abrupt deposit withdrawals, which may stem from either weak fundamentals, speculative behavior or an interaction between the two. Foundational studies have distinguished between fundamental runs, driven by concerns about a bank's solvency (Chari and Jagannathan (1988)), and speculative runs, which emerge from coordination failures among depositors (Diamond and Dybvig (1983)). Subsequent theoretical developments have sought to reconcile these mechanisms, demonstrating how imperfect information and correlated depositor signals can interact to produce collective withdrawal dynamics (Rochet and Vives (2004); Goldstein and Pauzner (2005); Matta and Perotti (2024)). This literature also highlights the critical role of continuous and close monitoring of deposit flows and its determinants, as delays in support for the financial system during periods of withdrawal pressure can amplify systemic losses (Cecchetti and Schoenholtz (2023)).

Banks' deposit flows have historically been underpinned by the presence of a deposit franchise—the structural capacity of banks to attract and retain deposit funding even when offering interest rates below those available to depositors on alternative financial instruments. The deposit franchise constitutes a critical source of profitability and funding stability for banks (Drechsler et al. (2021), Beck et al. (2024) and Rice and Guerrini (2025)). This mechanism is consistent with a well-established body of literature documenting that various frictions contribute to deposit stickiness by limiting the pass-through of market interest rate changes to deposit rates, including those directly influenced by monetary policy authorities (Hannan and Berger (1991), Neumark and Sharpe (1992), and Driscoll and Judson (2013)). Such frictions typically arise from factors such as imperfect competition within the banking sector. However, the abrupt deposit outflows observed during the 2023 banking turmoil, following global interest rate hikes, illustrate that the value of banks' deposit franchises is vulnerable to forces that can accelerate depositor withdrawals or compel banks to raise rates sharply in order to retain

funding (Beck et al. (2024)). Our study contributes to this literature by investigating how digitalisation and social media may erode traditional sources of deposit stickiness, thereby increasing the responsiveness of deposit flows and rates to monetary policy changes. This question is of growing importance, as digitalisation and online information channels not only characterise the current financial landscape but are likely to play an increasingly dominant role in shaping depositor behaviour and bank funding dynamics in the future.

There is an emerging and rapidly expanding body of literature exploring the effects of digitalisation on banking institutions. Jiang et al. (2022) investigate the impact of bank competition in the era of digital banking on financial inclusion. Haendler (2022) examines how mobile banking competition affects the business models of small community banks. Hong et al. (2025) illustrate that the digitalisation of asset management can result in highly synchronized investor behavior.

This study is most closely related to a growing literature examining the impact of digitalization on deposit dynamics. Two recent papers place strong emphasis on banks' responses to monetary tightening, albeit with analyses focused on the U.S. banking system. Koont et al. (2024) show that US banks with popular e-banking platforms experience deposit outflows in response to rising interest rates. Erel et al. (2023) suggest that online US banks attract more deposits by offering more attractive deposit rates when rates increase, where the definition of online banks appears to be more restrictive than the definition of digital banks in our analysis and in Koont et al. (2024). In the euro area, Fascione et al. (2025) examine the determinants of the tails of the distributions of deposit flows from 2016 to 2024. They show that banks with more popular e-banking platforms exhibit more severe extreme outflows, while their interest sensitivity is unaffected. Our empirical evidence is closer to the findings of Koont et al. (2024), as we show that the deposits of banks with higher levels of digitalisation exhibit statistically significant stronger responses to monetary tightening. Our analysis offers a complementary perspective in several respects. We examine shifts in the distribution of deposits investigating changes in the mean rather than in the tail, and considering both volume and pricing dimensions. With several empirical methods, our analysis delves into how digitalization influences the transmission of monetary policy within the euro area banking sector. Furthermore, our measures of digitalization capture - with several weighting matrices - both the popularity and

perceived quality of banks' mobile apps, as well as the deposit-to-employee ratio.

There is also a literature that emphasises the solid positive effects of digitalisation on banks, particularly in terms of profitability. For instance, Andersson et al. (2018) suggest that a reduction in physical branch networks in favour of digital banking can improve the profitability of banks in the euro area through a substantial cost-saving opportunity. Descriptive evidence in our paper suggests that digital banks exhibited better profitability, probability of default, as well as more pronounced deposit inflows from mid-2020 to early 2022.

In relation to the role of social media as catalyst for the banking crisis, Cookson et al. (2023) document the role of Twitter in precipitating the stock rates of US banks during the failure of Silicon Valley Bank. Cera et al. (2023) explore the performance of large listed euro area banks during the March 2023 banking turmoil, and find that the negative Twitter sentiment appears to be negatively correlated with stock returns and uncorrelated with deposit growth. Fascione et al. (2025) find no significant effects of social media on extreme tails of deposit flows. Our paper contributes to this strand of the literature in several ways. Regarding the dependent variables, we investigate the effect of Twitter sentiment on deposit in terms of both volumes and rates. Regarding the independent variables we examine the impact of Twitter sentiment controlling in different ways for traditional news sentiment as well as relatively high-frequency performance metrics. Moreover, methodologically, we apply a range of econometric approaches to quantify the potential shifts in the distributions of deposits examining their means rather than extreme values.

# 4 Data

## 4.1 Data on digitalisation

The measurement of the degree of digitalisation of bank services is a complex and multifaceted issue, without yet well-established measures. Earlier papers have typically relied their analysis on a single indicator to assess the level of digitalisation. For instance, Koont et al. (2024) considered the absolute number of Google Reviews, defining digital banks as those with more than a set number of Google Reviews. Instead, Zhang et al. (2024) used the ratio of deposits to the number of bank branches to measure the level of digitalisation.

Our paper uses measures that leverage on the diverse information contained in three baseline bank-level indicators. The three baseline indicators are related to the effectiveness of the mobile banking app as well as the ability of the bank to serve customers with a relatively smaller number of employees. They are as follows: (i) the reviews for the banking app, defined as the number of Google Reviews scaled by the amount of deposits [4]; (ii) the satisfaction of the banking app users, defined as the average vote expressed by the users of Google Reviews, ranging from 1 to 5, where 5 represents the best vote; (iii) the deposit-to-employee ratio, determined by dividing the total deposits by the number of employees.[5] [6] Each of the three baseline indicators is converted into a binary variable, which is assigned a value of one if the indicator is above the country-level median, and zero otherwise.[7] We use a country-level median as the threshold because of the following two reasons: first, the use of Google Reviews can have prominent country-level specificities; second, competition for bank deposits typically is particularly intense among banks within the same country, largely due to the still-incomplete implementation of the Banking Union. [8] [9] Next, we calculate a bank-level proxy for the degree of digitalisation defined as the average of the three dummy variables. The empirical models use a dummy variable separating "digital" banks from "traditional" ones, which takes the value of one when the degree of digitalisation is above the median level and zero otherwise.[10] The terminology distinguishing digital banks from traditional banks

[4]Some banks do not have a mobile banking app, at least in part of the time series. We assign the value of zero to such observations.

[5]The results are also robust when we use the assets-to-employee ratio.

[6]We do not have access to the supervisory bank-level time series of the number of physical branches. However, the results on the impact on the deposit ratio growth are robust when we use a significantly reduced sample using Bloomberg's information on the number of physical branches. Moreover, the number of employees is strongly correlated with the number of branches. Our data show a high correlation with the number of branches (i.e., 0.45) as well as a strongly significant positive linear relationship between employees and branches, with a 85 percent R-square.

[7]The number of listed banking groups in four countries (i.e., HR, LT, PT and SI) does not allow for a meaningful calculation of the medians conditional on each single country. Thus, the main results calculate the median conditional on the sample of banks in the aforementioned four countries. The results are robust to the relaxation of this assumption.

[8]Buch (2024) explains that the "banking union's third pillar, a European Deposit Insurance Scheme (EDIS), [...] would ensure a more comparable level of protection of depositors, thus potentially stimulating cross-border demand for deposits" (Speech: Financial integration in Europe: where do we stand after the banking union's first decade?).

[9]The main results are robust when the relevant threshold is the unconditional median, that is a median defined at euro area level rather than country-level.

[10]As shown later, the results are generally robust when different unbalanced weightings are applied on the three dummy variables.

closely aligns with the lexicon used by Koont et al. (2024), who classify digital banks as those with a high number of Google reviews in their banking app.

Interestingly, the average level of digitalisation of the euro area banks has increased remarkably over the past years. This can be seen from Figure 1, which shows the evolution of the average euro area digitalisation measure calculated using the bank-level information as described above, and compares it with the country-level annual digitalisation measure published by the Eurostat. The figure highlights two main developments. First, the average degree of digitalisation of euro area banks in our sample has expanded from 38 percent in December 2019 to 51 percent in October 2023. Second, this increase of 13 percentage points is generally consistent with the 10 percentage points increase inferred from the Eurostat's indicator that is based on an annual country-level survey on the use of bank digital services.

## 4.2 Data on Twitter and news sentiment

Quantifying banks' exposure to social media sentiment is inherently complex and lacks standardized metrics. Focusing on the impact on the stock price of listed US banks, Cookson et al. (2023) compile a high-frequency dataset of tweets and retweets [11] In the ECB's Financial Stability Review, Cera et al. (2023) employ the daily Twitter sentiment calculated by Bloomberg, which is the same source utilized in this paper. A key open question in analysing the impact of social media dynamics on financial variables is whether the Twitter sentiment represents a relevant factor for deposit flows when controlling for traditional information sources about bank performance, such as the sentiment inferred from the traditional news rather than social media. In this paper, we utilise the sentiment analysis by Bloomberg because, inter alia, it assesses the sentiment from both Twitter and traditional news applying a single standardised learning algorithm for both sources. Bloomberg's supervised learning algorithm classifies tweets and news articles referring to individual banking groups as "negative" (or "positive") depending on whether the wording in the posts predicts future negative (or positive) daily stock returns.[12] We construct a monthly bank-level negative tweet ratio, defined as the share

[11]The dataset used by Cookson et al. (2023) requires the access to a specific license for researchers that has to be granted by X.

[12]The observations in which a bank exhibits missing information on Twitter or news sentiment are treated as neutral given that Twitter does not receive enough signals to classify the sentiment as positive or negative. Therefore, we assign the value of zero to such observations.

of negative tweets over the sum of positive and negative tweets. Figure 2 compares the aggregate time series of the negative Twitter sentiment ratio with the negative news sentiment ratio. Figure 2 shows that the negative Twitter sentiment ratio tends to exhibit positive and negative deviations around an unconditional average of 51 percent. It also highlights notable spikes in negative Twitter sentiment for the euro area banks in our sample in March 2023 due to the US and Swiss banking turmoil as well as in March 2020 (COVID-19) and December 2022 (energy crisis in Europe). The negative news sentiment appears to be correlated with the Twitter sentiment, although the magnitude of the shock of the Twitter sentiment ratio is more pronounced during the 2023 banking turmoil.

## 4.3 Overview of data sources and construction of the dataset

We construct the monthly dataset at banking group level, combining information from Bloomberg, ECB's Individual Balance Sheet Items (IBSI)[13], ECB's Individual MFI Interest Rate statistics (IMIR)[14], web-scraped data from Google Reviews, supervisory classification of business models, as well as hand-collected data of Google Trends. The data on banks' balance sheet items, profitability (return on equity), stock price, 1-year probability of default, as well as Twitter and news sentiment are collected from Bloomberg. ECB's IBSI data is used to construct the deposit flows, while the ECB's IMIR data provides information of the deposit interest rates. As described earlier, Google Reviews data is used to construct the measure for digitalisation. Google Reviews' data is also necessary to retrieve the bank-level monthly total number of users' reviews, along with the respective vote from 1 to 5 stars (where 1 indicates the worst score). Finally, Google Trends' data is necessary to gather information on the Google searches of the specific banks, which is automatically normalized at bank level.

The measure for total deposits at the banking group level includes all terms of deposits (i.e., overnight, agreed maturity and redeemable at notice) and all counterparties, with the exception of central bank, intra-group and non-euro deposits[15]. The bank-level deposit data is merged with the other bank data provided by Bloomberg.

The sample of banking groups is selected using the following steps. First, our initial

[13]see more information at https://data.ecb.europa.eu/data/datasets/BSI/data-information
[14]see more information at https://data.ecb.europa.eu/data/datasets/MIR/data-information
[15]Non-euro denominated deposits are necessarily excluded because they are excluded by IBSI

sample includes 88 banking groups with publicly listed stocks, which are domiciled in the euro area and classified under GICS 4010 (i.e., banks). [16] Second, due to missing information regarding the number of employees, it is necessary to exclude 24 banking groups, leaving 64 banking groups to the sample domiciled in the following 16 euro area countries: AT, BE, CY, DE, EE, ES, FI, FR, GR, IE, IT, LT, MT, NL, PT and SI. Overall, the sample includes 2591 bank-month observations from December 2019 to October 2023 [17]. Third, the respective Bloomberg tickers are subsequently linked to the Legal Entity Identifier (LEI) code of the respective ultimate parent companies, which are associated with the RIAD code[18] that identifies the banking group in the IBSI data. Fourth, we manually associate each bank with the bank-level Google Reviews. We also show that results are robust when we exclude banks without any Google Review or Bloomberg-classified tweets. Through the Legal Entity Identifier, we also merge the above dataset with the SSM's supervisory classification of bank business model. This step allows us to define the banks in our sample as asset manager, corporate/wholesale lender, diversified lender, G-SIB, G-SIB universal, retail lender, small market lender and universal bank.

Furthermore, we link the dataset with country-level information from EPFR on net flows into less risky fund categories including MMF, investment grade bond funds and government bond funds. The inclusion of these control variables is warranted by the fact that depositors in some countries may exhibit a more pronounced tendency to transfer their bank deposits to non-bank sectors, which may confound the effect of digitalisation. All variables are winsorized at the o.1 percent level to remove data-quality related outliers.

Finally, several empirical models in our paper also utilize ECB's IMIR information on monthly bank-level deposit interest rates. These specifications use a reduced sample including 43 banking groups domiciled in the aforementioned 16 euro area countries.

[16]The cut-off date for this sample is June 2023. To avoid double counting issues, in this initial sample we also exclude the entities that consolidate in a parent banking group that is included in our sample. For instance, we have to exclude the several French caisses regionales that consolidate in Credit Agricole.

[17]The coverage of small banks in IBSI before December 2019 is significantly smaller.

[18]see more information at https://www.ecb.europa.eu/stats/financial-corporations/list-of-financial-institutions/html/mfi-userguide.en.html

# 5 Descriptive analysis

## 5.1 Relationship between deposit flows and the digitalisation proxy

Figure 3 shows the monthly deposit growth of the two cohorts of banks, defined with digitalisation data as of December 2019. Digital banks exhibit better deposit inflows up to Q2-2022, probably supported - inter alia - by better digital services such as online customer authentications, which was crucial during the pandemic due to the diminished in-person services. This finding is in line with the evidence presented by Erel et al. (2023) that US online banks experienced a significantly greater inflow during the pandemic in 2020 and 2021. After Q2-2022, the euro area's digital banks experienced an overall decline in deposits, which is consistent - even in chronological terms - with the higher deposit growth rates of US digital banks highlighted by Koont et al. (2024), and may apparently be inconsistent with Erel et al. (2023) who show that US online banks experienced a significantly greater inflow in 2022. The latter inconsistency may be motivated by the fact that the cohort of online banks in Erel et al. (2023) is more restrictive than the definitions in our paper and Koont et al. (2024) as they include only banks with a very limited number of physical branches, i.e., one branch for the vast majority of digital banks.

Figure 3 suggests that digital banks exhibit heightened deposit outflows in response to increases in ECB policy rates. This phenomenon can be attributed to two primary channels. First, digital banks reduce the opportunity costs associated with moving deposits, thereby making it easier and more cost-effective for depositors to transfer their funds in search of higher returns or perceived safety. This increased ease of transfer can lead to a deposit base that reacts more swiftly to changes in interest rates or other market conditions. Second, digital banks tend to attract depositors who inherently have a higher propensity for mobility. These depositors, who are more likely to utilize digital banking platforms, may exhibit greater readiness to move their funds even independently of policy rate dynamics. Both of these channels have critical implications for financial stability, as they can exacerbate liquidity risks and increase the susceptibility of banks to sudden deposit outflows. We investigate whether the heightened deposit outflows of digital banks are merely motivated by the fact that they attract a clientele that is predisposed to such behavior. Understanding this distinction

is key to formulating regulatory and risk management strategies that can mitigate the potential destabilizing effects of digital banking. Figure 4 documents the extent to which digital banks exhibit more pronounced deposit instability, which is the case since it shows that their quarterly standard deviation deposit flows at any point during the time series of this paper, except for three quarters. The examination of the influence of digitalisation on bank deposit flows requires an appropriate descriptive analysis to recognize differences between digital and traditional banks along key structural and non-structural bank characteristics. Table 1 shows that banks with a higher degree of digitalisation exhibit an unconditionally lower probability of default, higher capitalization and profitability, but are also more exposed to negative sentiment and with a larger variability in deposit growth rates.

### 5.2 Relationship between deposit flows and the bank sentiment

Figure 5 shows the monthly deposit flows of two groups of banks, defined dynamically in each month based on their share of negative sentiment tweets. Somewhat unsurprisingly, banks affected by a larger share of negative tweets tend to experience a more subdued deposit growth compared to others.

## 6 Empirical Strategy

### 6.1 Influence of digitalisation on deposit flows during the monetary tightening

The difference-in-difference approach in this section formalizes and builds on the descriptive analysis of the previous sections, which found a stronger impact of monetary tightening on deposit flows among banks with a stronger profile in terms of digital services. The baseline empirical specification to explore this relationship is depicted in the month-bank level panel regression described by Model (1):

$$\begin{aligned} Y_{i,t} = \alpha + \beta(\text{MonTight}_t \times \text{Digit}_{i,t-1}) + \gamma(\text{Digit}_{i,t-1}) \\ + \text{bankFE}_i + (\text{monthFE}_t \times \text{BusinessModelFE}_i) + \epsilon \end{aligned} \tag{1}$$

Y is a vector of four bank-level monthly dependent variables including: (a) the growth rate of the deposit-to-assets ratio; (b) the growth rate of deposits; (c) the change in net NFC deposit rate, defined as the monthly change in the NFC deposit interest rate net of the monthly change in ECB rates; (d) the monthly change in net household deposit rate. Digit is the treatment dummy separating digital banks from traditional ones. MonTight is the time dummy identifying the monetary tightening period, which takes the value of one in the post-June-2022 period [19] [20]. Model (1) also includes fixed effects at bank- and month-and-business-model- levels.

In line with Koont et al. (2024), we hypothesise that digital banks experience more pronounced outflows in response to hikes in policy rates. Regarding the interpretation of regression coefficients, this hypothesis would be corroborated by a negative coefficient for the interaction between the digitalisation and the monetary tightening when the dependent variable is the growth rate of deposits or deposit ratio. We also test a second type of hypotheses, namely that digital banks attempt to mitigate their weaker deposit flows by offering higher rates to their depositors compared to traditional banks. This hypothesis would be consistent with a positive coefficient for the interaction between digitalisation and the monetary tightening when the dependent variable is the net change in NFC or HH deposit rates.

This paper presents a wide set of empirical findings on the influence of digitalisation that are robust after controlling in several ways for a number of bank-specific and macro characteristics – both observable and unobservable. This aspect is important because the selection in control and treatment groups is not random as it can be related to banks' characteristics which can influence their deposit flows during the tightening. We address this concern in several ways. First, we control for heterogeneity across banks in the treatment and control groups by including a wide range of bank characteristics (in Model (2)) as well as interactions between these time-varying characteristics and the monetary tightening (in Model (3)) . Thus, we control for business model, size [21] , stock return, capitalization, profitability, probability of default, Google Trends, deposit interest rates, together with various types of

[19]The results are robust when we use two alternative definition of monetary tightening: ECB's Main Refinancing Operations Interest Rate (MRR) and the change in ECB MRR.

[20]The ECB announcement of higher marginal refinancing rates occurred on June 9th 2022.

[21]Controlling for bank size is important since evidence indicates that when depositors start a run, they reallocate their funds towards larger, thus seeking shelter in the banks that enjoy (higher) explicit or implicit government guarantees (Iyer et al. (2019); Acharya et al. (2022))

bank and time fixed effects. This wide range of controls allows us to take into account characteristics that could drive both digitalisation and deposit flows and rates. Importantly, we also directly address the issue of non-random treatment assignment by employing the entropy balance re-weighting algorithm in Hainmueller (2012). This method ensures the comparability of the treatment and control groups by ensuring - through a re-weighting procedure - that the former is indistinguishable from the latter in terms of observable characteristics at both micro and macro levels. By applying this algorithm, we confirm the robustness of our results, thereby mitigating concerns regarding potential biases due to non-random treatment selection. Therefore, we estimate Model (2), which is a month-bank level panel regression of the form:

$$\begin{aligned} Y_{i,t} = \alpha + \beta(\text{MonTight}_t \times \text{Digit}_{i,t-1}) + \gamma(\text{Digit}_{i,t-1}) + \theta(\text{X}_{i,t-1}) \\ + \text{bankFE}_i + (\text{monthFE}_t \times \text{BusinessModelFE}_i) + \epsilon \end{aligned} \tag{2}$$

As in Model (1), Y is a vector of four bank-level monthly dependent variables describing the deposit growth and pricing. Through the vector X, Model (2) controls for many bank-specific potential confounding factors: monthly stock returns, ROE, CET1 ratio, 1-year probability of default, (logarithm of) total assets, Google Trends, bank deposit interest rates and bank FE. The specification also controls for a large set of macroeconomic trends through its month and month-business-models fixed effects, as well as flows into MMFs, sovereign and investment grade funds. While Model (2) addresses the potential confounding factors at both micro and macro levels in several ways, we also propose a further specification, Model (3), which controls for the set of explanatory variables in Model (2) not only linearly but also by interacting each one of them with the monetary tightening. Thus, this specification includes the control variables in exactly the same way as digitalisation, which allows for a strong test of whether the effect of digitalisation is a mere reflection of a bank's business model, size, stock return, capitalization, profitability, probability of default, Google Trends, deposit instability and deposit interest rates. Model (3) is described by the following equation:

$$\begin{aligned} Y_{i,t} = \alpha + \beta(\text{MonTight}_t \times \text{Digit}_{i,t-1}) + \gamma(\text{Digit}_{i,t-1}) + \theta(\text{X}_{i,t-1}) + \rho(\text{MonTight}_t \times \text{X}_{i,t-1}) \\ + \text{bankFE}_i + (\text{monthFE}_t \times \text{BusinessModelFE}_i) + \epsilon \end{aligned} \tag{3}$$

As in Model (1), Y is a vector of four bank-level monthly dependent variables describing

the deposit growth and the respective pricing. The fact that coefficients are not substantially influenced by the inclusion of this restrictive set of controls would further ensure that the digitalisation interaction variable identifies dynamics that are not correlated with bank-level characteristics.

## 6.2 Influence of the Twitter sentiment on deposit flows and rates

The empirical analysis in this section enhances the descriptive evidence suggesting a correlation between the Twitter negative sentiment and weaker deposit growth. We estimate a month-bank level panel regression (Model (4)):

$$\begin{aligned} Y_{i,t} = \alpha + \beta(\text{UnfavourableTwitter}_{i,t-1}) + \gamma(\text{UnfavourableNews}_{i,t-1}) + \theta(\text{X}_{i,t-1}) \\ + \text{bankFE}_i + (\text{monthFE}_t \times \text{BusinessModelFE}_i) + \epsilon \end{aligned} \tag{4}$$

Similar to previous specifications, Y is a vector of bank-level monthly dependent variables describing the deposit growth and the respective pricing. The variable of interest is the dummy for unfavourable Twitter sentiment, which takes the value of 1 if the monthly bank-level ratio of negative tweets is greater than the median calculated at country level, but the results are robust when we use the unconditional ratio of negative tweets. This model includes the dummy for bank digitalisation as well as the same set of controls and fixed effects included in Model (2). This section also separately examine whether the supposed negative impact of the negative Twitter sentiment becomes more intense during monetary tightening. Therefore, Model (5) includes a new variable of interest, namely the interaction between Twitter sentiment and monetary tightening.

$$\begin{aligned} Y_{i,t} = \alpha + \beta_1(\text{MonTight}_t \times \text{UnfavourableTwitter}_{i,t-1}) + \beta_2(\text{UnfavourableTwitter}_{i,t-1}) \\ + \gamma_1(\text{MonTight}_t \times \text{UnfavourableNews}_{i,t-1}) + \gamma_2(\text{UnfavourableNews}_{i,t-1}) \\ + \theta_1(\text{MonTight}_t \times \text{X}_{i,t-1}) + \theta_2(\text{X}_{i,t-1}) \\ + \text{bankFE}_i + (\text{monthFE}_t \times \text{BusinessModelFE}_i) + \epsilon \end{aligned} \tag{5}$$

Model (5) uses the same dependent variables as Model (4) and controls for the same vector of control variables. Moreover, Model (5) includes the control variables not only linearly (with

respect to time), but also by interacting them with the monetary tightening. With Model (6) we also propose an alternative approach to investigate whether the correlation between Twitter sentiment and deposit flows becomes more intense in response to monetary tightening or banking turmoil, which saw the peak in the intensity of negative tweets (as described in Figure 2). This model addresses the issues related to the non-randomness of the negative-sentiment treatment by employing the entropy balance re-weighting algorithm in Hainmueller (2012), which enables us to statistically compare the treatment group to a control sample that is indistinguishable in terms of any observable characteristics, both at micro and macro levels. The regression specification for Model (6) is as follows:

$$\begin{aligned} Y_{i,t} = \alpha + \beta(\text{Post}_t \times \text{UnfavourableTwitter}_{i,t-1}) + \gamma(\text{UnfavourableTwitter}_{i,t-1}) \\ + \theta(\text{X}_{i,t-1}) + \text{bankFE}_i + (\text{monthFE}_t \times \text{BusinessModelFE}_i) + \epsilon \end{aligned} \tag{6}$$

Model (6) includes regressions examining the response to the monetary tightening as well as the 2023 banking turmoil. In fact, we present separate sets of results using either June 2022 or March 2023 as the key events.

# 7 Empirical results

## 7.1 Amplification effect of the digitalisation proxy on deposit flows and rates in response to the monetary tightening

### 7.1.1 Impact of the digitalisation proxy before and after the monetary tightening

Table 2 presents the output of the baseline Model (1). In line with the descriptive evidence, the significantly negative coefficients in columns 1 and 2 for the interaction between the digitalisation proxy and the monetary tightening suggest that the deposit growth of digital banks is weaker than others from June 2022. The significantly positive coefficient in column 3 for the interaction variable may indicate that digital banks tend to compensate the weaker deposit flows with higher NFC deposit rates, compared to banks with more traditional services. The insignificant coefficient in column 4 suggests that the adjustment of household deposit rates of digital banks in response to the monetary tightening is not statistically different from other

banks. Unlike columns from 1 to 4, the analysis presented in columns 5 to 7 aims at describing the *levels* of the sensitivity to digitalisation rather than the comparison between the pre- and post-onset of the monetary tightening. Columns 5 to 7 suggest that the monetary tightening period after June 2022 is characterised by negative correlation between the deposit ratio growth and the digitalisation dummy, and a positive sensitivity of NFC deposit rates to the digitalisation dummy, controlling for bank and month-business-model fixed effects. Columns 8 to 10 focus on the pre-tightening period. With insignificant results, columns 8 and 9 suggest that the sensitivities to digitalisation of the deposit ratio growth and deposit rates are, respectively, more positive and more negative than the tightening period. This comparison is broadly consistent with the message in columns 1 through 4, that is, digital banks exhibit a more sensitive deposit growth and pricing in response to the monetary tightening.

### 7.1.2 Amplification effect of the digitalisation proxy using the full set of controls

Table 3 presents the output of the Model (2) and the interaction coefficients in columns 1 and 2 indicate that the impact of digitalisation on the growth of deposit and deposit ratio during the tightening is significantly greater than in other months. Column 3 indicates that the net NFC deposit rate is positively related to the digitalisation proxy. In line with Table 2, column 4 confirms that the coefficient for the impact of the interaction variable on the net household deposit rate is strongly insignificant. Columns 5 to 7 do not include the deposit rates in the set of independent variables, which makes the number of observations in column 5 significantly greater. Columns 5 and 6 corroborate the direction and significance levels of the impacts on the deposit ratio growth and net NFC rate changes presented in Table 2, since they use the same sample. The specifications in columns 8 to 11 are similar to the ones in columns 1 to 4 except for the exclusion of the control for deposit instability. The results corroborate sign, significance and magnitude of columns from 1 to 4. The specifications in columns from 12 to 14 show that the results are generally robust when we use three significantly different proxies of digitalisation, which assign three different weighting matrices to the baseline indicators (i.e., number of reviews, vote in the reviews and deposit-to-employee ratio), instead of the equally weighted mean of the baseline indicators. [22]

[22] (Specifically, each alternative digitalisation measure - i.e., Digit1, Digit2 and Digit3 - assigns an unbalanced weight of 50 percent to one baseline indicator and 25 percent to the other two indicators.

### 7.1.3 Amplification effect of the digitalisation proxy using the full set of controls, Hainmueller (2012) and interacted controls

Table 4 presents the output of the Model (2) with the entropy balance re-weighting algorithm of Hainmueller (2012). Columns 1 to 3 use the same sample and controls as columns 1 to 4 of Table 3 and generally corroborate the findings in terms of sign, magnitude and - in part - significance. Columns 4 to 6 use the same set of controls as columns 5 to 7 in Table 3 and confirm the output in terms of sign, magnitude and significance. The results are further corroborated in columns 7 to 9, which exclude the deposit instability from the list of controls. Table 5 presents the output of Model (3), which offers an alternative approach to control for confounding factors by including all the control variables in exactly the same way as digitalisation. This approach allows for a stringent test of whether the effect of digitalisation is a mere reflection of a bank's size, stock return, deposit rates, deposit instability, capitalization, profitability, probability of default, Google Trends and business model. The results confirm the statistically significant negative impact of digitalisation on the monthly growth of the deposit ratio. However, we also note that the positive impact of digitalisation on NFC deposit rates during tightening is not significant in this specification. Columns 6 and 7 show that the sign on the deposit ratio growth is robust when we use two different definitions of monetary tightening.

## 7.2 Impact of bank sentiment on deposit flows and rates

### 7.2.1 Impact of the Twitter sentiment ratio independently from the monetary tightening

Table 6 presents the output of Model (4), which aims to examine the impact of the negative Twitter sentiment on deposit flows and rates, controlling for several potential confounding factors, such as the news sentiment and the same set of controls used in previous models, including stock returns and probability of default. The specifications in columns 1 to 3 include the entire set of control variables, including news sentiment, deposit instability, and deposit rates of NFCs and HHs. They show that the negative Twitter sentiment is correlated with lower deposit ratio growth but uncorrelated with deposit rates, arguably due to the overall

temporary nature of the negative sentiment. The specification in column 4 confirms the negative and statistically significant impact on the deposit ratio growth using a specification that does not control for deposit rates and deposit instability, and uses the unconditional sentiment ratio instead of the dummy variables calculated at country level utilized in all other specifications. Column 5 confirms the negative impact of the Twitter sentiment controlling also for the bank-level digitalisation measure. Columns 6 to 8 present the output of the Model (4) with the entropy balance re-weighting algorithm of Hainmueller (2012). They corroborate the results in columns from 1 to 3, with an amplification of deposit outflows due to the Twitter negative sentiment on the deposit ratio growth.

### 7.2.2 Amplification effect of the Twitter sentiment ratio in response to the monetary tightening and the banking turmoil

Table 7 examines whether the sensitivity of deposit flows and rates to monetary tightening is influenced by the Twitter sentiment. The insignificant coefficients in columns from 1 to 3 for the interaction between negative Twitter sentiment and monetary tightening suggest that the Twitter sentiment does not significantly amplify the effects of policy rates. This insignificant additive impact is corroborated by the insignificant results in columns from 4 to 6, which examine the same hypotheses of the previous columns in Table 7 applying the entropy balance re-weighting algorithm of Hainmueller (2012). It is also relevant to examine whether a separate prominent event, i.e., the March 2023 bank turmoil, amplified the effects of the Twitter sentiment. The relevance of this analysis is based on the fact that the 2023 bank turmoil represented a sharp shock on the perceptions of liquidity and solvency risk for banks. Columns 7 and 10 suggest that in March and April 2023 the negative impact of Twitter sentiment on deposit flows was significantly greater than in the two months before the turmoil. Moreover, column 9 indicates a weakly significant amplification effect of the Twitter sentiment on the household deposit rates.

# 8 Conclusions

The rapid evolution of digitalisation and the increasing influence of social media have raised concerns among financial regulators and policymakers about their potential impact on deposit dynamics, particularly at the times of financial stress as e.g. observed during the 2023 banking turmoil. Our analysis contributes to this important policy issue with two novel empirical findings using monthly data on euro area bank deposit flows and rates as well as measures of bank digitalisation and social media exposure through Twitter sentiment. First, banks with a higher degree of digitalisation exhibit larger fluctuations in deposits, with higher inflows from mid-2020 to early 2022 but greater outflows in response to the monetary tightening. By controlling for bank-specific factors, we provide robust evidence that digital banks' deposits are more sensitive to monetary policy changes. Second, our analysis reveals that banks affected by negative Twitter sentiment experience weaker deposit inflows. Controlling for traditional news sentiment, digitalisation levels, Google Trends, and bank performance metrics, we show that the negative Twitter sentiment in March 2023 contributed to deposit outflows from the euro area banking system. In summary, our findings underscore the significant influence of digitalisation and social media on bank deposit dynamics and the broader implications for financial stability. As the financial landscape continues to evolve, it is important for regulators and policymakers to consider these factors in their assessments and revisions of liquidity rules and stability frameworks. Further research aimed at developing more comprehensive measures of the multifaceted dimensions of digitalization and information sharing in social media is essential for advancing our understanding of their economic and financial implications. Capturing the various technological, organizational, and behavioral aspects of digital transformation would allow for a more accurate assessment of how digitalization shapes bank performance, risk dynamics, and the transmission of monetary policy.

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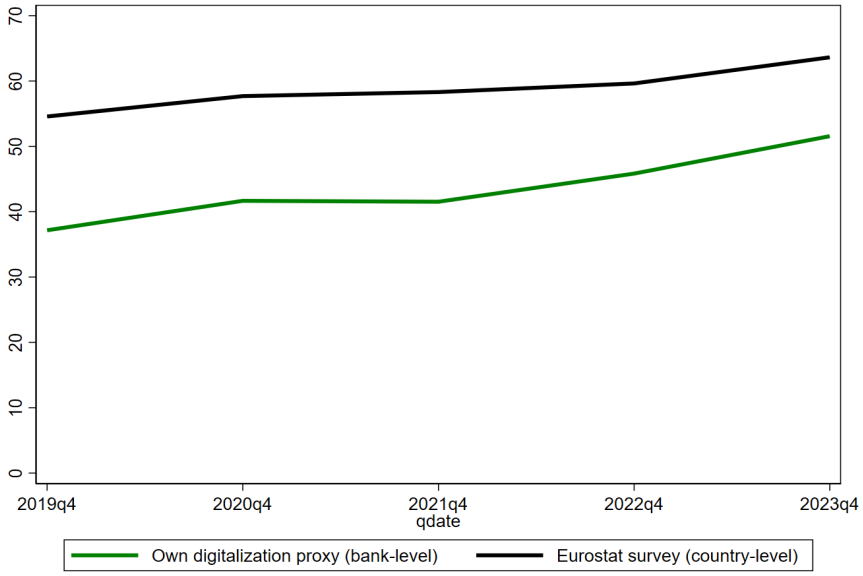
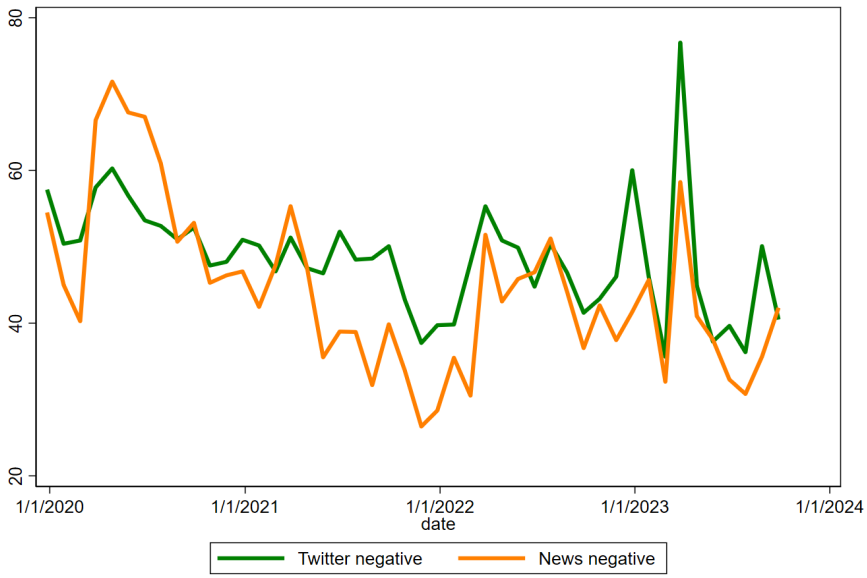
# 9 Figures

Figure 1: **Digitalisation measures for euro area banks**



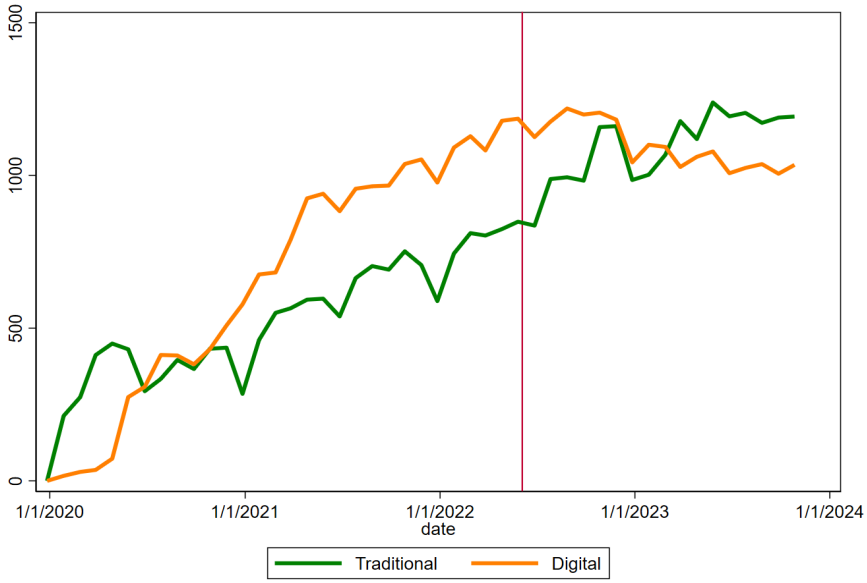

**Source:** Google Reviews, Bloomberg, Eurostat, and authors' calculations.
**Notes:** The Eurostat measure gauges the percent of surveyed euro area population using internet banking at least once in 3 months. Our bank-level measure is the average of three indicators: deposits to number of employees, count of reviews in Google Reviews, and score in Google Reviews. Both variables in this chart range from 0 to 100 percent.

Figure 2: **Average negative Twitter and news sentiment ratios for selected euro area banks**



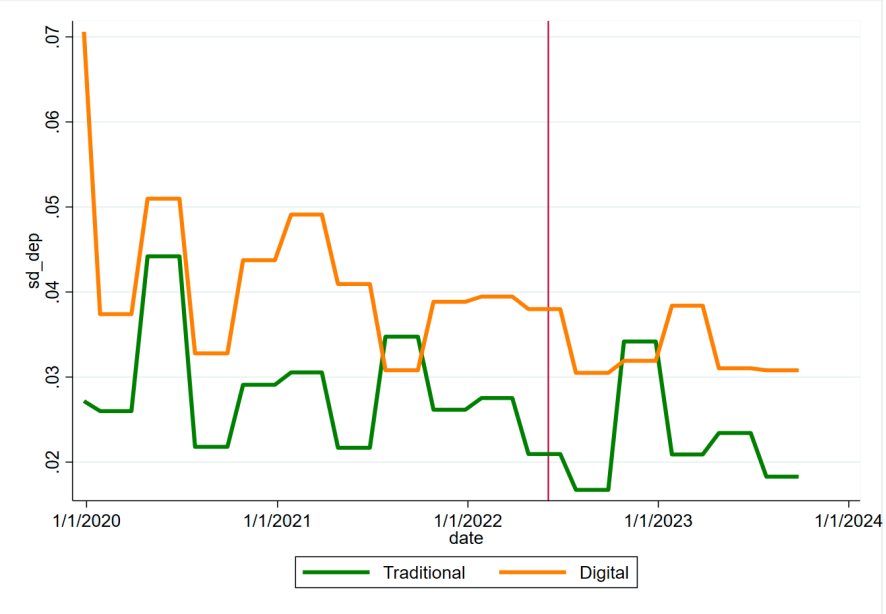

**Source:** Bloomberg and authors' calculations.
**Notes:** Ratio of negative sentiment tweets (or news) divided by sum of positive and negative tweets (or news). The average ratios are calculated for the euro area banks in the sample. Both variables in this chart range from 0 to 1.

Figure 3: **Cumulative changes in deposits for digital and traditional banks**



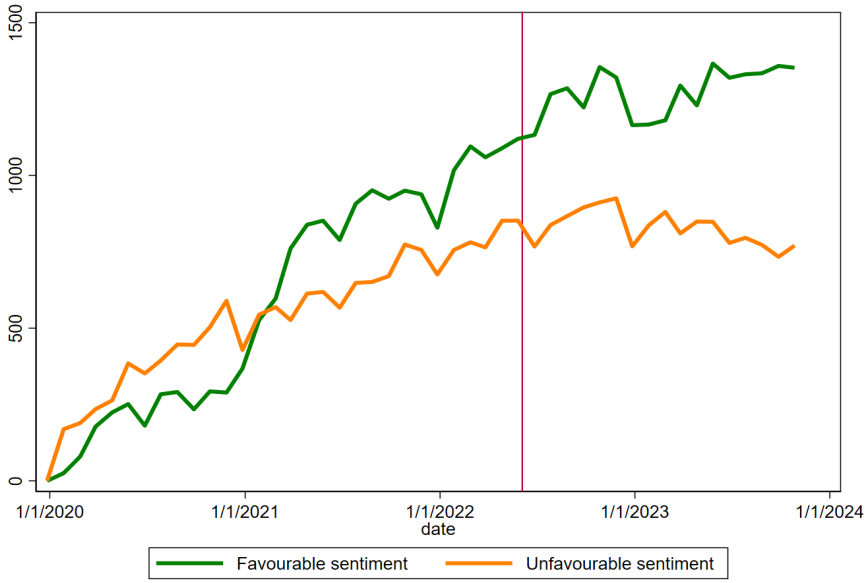

**Source:** IBSI, Google, Bloomberg.
**Notes:** Deposits on the y-axis are defined as the monthly cumulative change in euro billion, equalised to 0 at the end of December 2019.

Figure 4: **Variability of deposit rates for digital and traditional banks**




**Source:** IBSI, Google, Bloomberg.
**Notes:** Quarterly standard deviation of deposit growth rate.

Figure 5: **Cumulative changes in deposits for banks with different levels of twitter sentiment ratios**




**Source:** IBSI, Google, Bloomberg.
**Notes:** Deposits on the y-axis are defined as the cumulative monthly change in euro billion, equalised to 0 at the end of December 2019.

# 10 Tables

Table 1: **Descriptive statistics**

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Digital banks | | Traditional banks | | Digital vs. traditional | |
| | Mean | Std. | Mean | Std. | Difference in mean | N |
| **PD** | 0.18 | 0.43 | 0.40 | 1.21 | -0.23*** | 2591 |
| **Asset (EUR mil)** | 303,638 | 469,728 | 290,491 | 608,250 | 13,147.28 | 2591 |
| **ln TA** | 11.18 | 1.94 | 10.23 | 2.38 | 0.95*** | 2591 |
| **Stock Return** | 1.61 | 16.41 | 1.23 | 18.14 | 0.38 | 2591 |
| **CET1** | 16.76 | 3.58 | 15.44 | 3.61 | 1.32*** | 2591 |
| **ROE** | 7.32 | 9.26 | 4.95 | 13.23 | 2.37*** | 2591 |
| **GovFundInflow** | 0.08 | 2.17 | 0.25 | 3.68 | -0.17 | 2591 |
| **IGFundInflow** | 0.05 | 2.58 | 0.05 | 2.40 | 0.00 | 2591 |
| **MMFInflow** | 0.79 | 7.15 | 0.71 | 15.13 | 0.07 | 2591 |
| **Tweet neg.sent.ratio** | 0.36 | 0.35 | 0.26 | 0.33 | 0.10*** | 2591 |
| **News neg.sent.ratio** | 0.27 | 0.37 | 0.21 | 0.34 | 0.05*** | 2591 |
| **St.Dev. deposit** | 3.33 | 3.56 | 2.66 | 3.67 | 0.67*** | 2591 |
| **GoogleTrends** | 48.92 | 23.56 | 51.45 | 22.35 | -2.53*** | 2591 |

**Source:** IBSI, Google, Bloomberg.

**Notes:** PD is the monthly average of the daily 1-year probability of default, calculated by Bloomberg's machine learning model. ln TA is the natural logarithm of total assets. Stock return is the monthly stock return. GovFundInflow, IGFundInflow, and MMFInflow are the monthly country-level flows into government/IG bond funds and MMF. Tweet neg.sent.ratio is the ratio of negative sentiment tweets (or news) divided by the sum of positive and negative tweets (or news). News neg.sent.ratio is the ratio of negative sentiment news divided by the sum of positive and negative news. St.Dev. deposit is the quarterly standard deviation of monthly deposit growth rates.

Table 2: **Impact of digitalisation on deposit flows and rates during the monetary tightening, with fixed effects**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Dep Growth | DepRatio Growth | NFCRate Delta | HHRate Delta | DepRatio Growth | NFCRate Delta | HHRate Delta | DepRatio Growth | NFCRate Delta | HHRate Delta | Dep Growth | DepRatio Growth | NFCRate Delta | HHRate Delta |
| Digit x MonTight | -0.882*** | -1.495*** | 0.017* | 0.000 | | | | | | | -0.890*** | -1.379*** | 0.011 | -0.006 |
| | (0.283) | (0.444) | (0.008) | (0.005) | | | | | | | (0.255) | (0.401) | (0.010) | (0.007) |
| Digit | 0.084 | 0.528 | -0.006 | -0.006* | -1.399*** | 0.015* | -0.006 | 0.612 | -0.001 | -0.002 | 0.168 | 0.463 | -0.002 | -0.003 |
| | (0.227) | (0.387) | (0.004) | (0.003) | (0.387) | (0.008) | (0.004) | (0.452) | (0.001) | (0.002) | (0.219) | (0.374) | (0.004) | (0.003) |
| Bank FE | x | x | x | x | x | x | x | x | x | x | x | x | x | x |
| Business model FE | | | | | | | | | | | x | x | x | x |
| Month FE | | | | | | | | | | | x | x | x | x |
| Month × Business model FE | x | x | x | x | x | x | x | x | x | x | | | | |
| N | 2591 | 2591 | 1589 | 1589 | 1064 | 667 | 667 | 1527 | 922 | 922 | 2591 | 2591 | 1589 | 1589 |
| R-sq | 0.16 | 0.16 | 0.44 | 0.51 | 0.04 | 0.24 | 0.30 | 0.16 | 0.26 | 0.29 | 0.04 | 0.03 | 0.25 | 0.19 |

**Source:** IBSI, IMIR, Google, Bloomberg.

**Notes:** Four bank-level monthly dependent variables including: (a) the growth rate of the deposit-to-assets ratio; (b) the growth rate of deposits; (c) the change in net NFC deposit rate, defined as the monthly change in the NFC deposit interest rate net of the monthly change in ECB rates; (d) the monthly net household deposit rate change. Digit is the treatment dummy separating digital banks from traditional ones. MonTight is the time dummy identifying the monetary tightening period, which takes the value of one in the post-June-2022 period.

$$\mathrm{Y}_{i,t} = \alpha + \beta(\mathrm{MonTight}_t \times \mathrm{Digit}_{i,t-1}) + \gamma(\mathrm{Digit}_{i,t-1}) + \mathrm{bankFE}_i + (\mathrm{monthFE}_t \times \mathrm{BusinessModelFE}_i) + \epsilon$$

Table 3: **Impact of digitalisation on deposit flows and rates during the monetary tightening, with fixed effects and control variables**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Dep Growth | DepRatio Growth | NFCRate Delta | HHRate Delta | DepRatio Growth | NFCRate Delta | HHRate Delta | Dep Growth | DepRatio Growth | NFCRate Delta | HHRate Delta | DepRatio Growth | DepRatio Growth | DepRatio Growth |
| Digit × MonTight | -1.269*** | -1.624** | 0.016* | -0.005 | -1.447*** | 0.016* | 0.000 | -1.461*** | -1.854** | 0.016* | 0.000 | | | |
| | (0.478) | (0.648) | (0.008) | (0.004) | (0.478) | (0.009) | (0.005) | (0.399) | (0.624) | (0.009) | (0.005) | | | |
| Digit1 × MonTight | | | | | | | | | | | | -1.621** | | |
| | | | | | | | | | | | | (0.537) | | |
| Digit2 × MonTight | | | | | | | | | | | | | -1.622** | |
| | | | | | | | | | | | | | (0.703) | |
| Digit3 × MonTight | | | | | | | | | | | | | | -1.279* |
| | | | | | | | | | | | | | | (0.665) |
| Bank FE | x | x | x | x | x | x | x | x | x | x | x | x | x | x |
| BasicControls | x | x | x | x | x | x | x | x | x | x | x | x | x | x |
| Control for deposit instability | x | x | x | x | | | | | | | | x | x | x |
| Controls for deposit rates | x | x | x | x | | | | x | x | x | x | x | x | x |
| Digit | x | x | x | x | x | x | x | x | x | x | x | x | x | x |
| Month × Business model FE | x | x | x | x | x | x | x | x | x | x | x | x | x | x |
| N | 1589 | 1589 | 1589 | 1589 | 2591 | 1589 | 1589 | 1589 | 1589 | 1589 | 1589 | 1589 | 1589 | 1589 |
| R-sq | 0.20 | 0.23 | 0.45 | 0.51 | 0.17 | 0.45 | 0.51 | 0.20 | 0.22 | 0.45 | 0.51 | 0.23 | 0.23 | 0.23 |

**Source:** IBSI, IMIR, Google, Bloomberg.

**Notes:** Four bank-level monthly dependent variables including: (a) the growth rate of the deposit-to-assets ratio; (b) the growth rate of deposits; (c) the change in net NFC deposit rate, defined as the monthly change in the NFC deposit interest rate net of the monthly change in ECB rates; (d) the monthly net household deposit rate change. Digit is the treatment dummy separating digital banks from traditional ones. MonTight is the time dummy identifying the monetary tightening period, which takes the value of one in the post-June 2022 period.

$$\mathrm{Y}_{i,t} = \alpha + \beta(\mathrm{MonTight}_t \times \mathrm{Digit}_{i,t-1}) + \gamma(\mathrm{Digit}_{i,t-1}) + \theta(\mathrm{X}_{i,t-1}) + \mathrm{bankFE}_i + (\mathrm{monthFE}_t \times \mathrm{BusinessModelFE}_i) + \epsilon$$

Table 4: **Impact of digitalisation on deposit flows and rates during the monetary tightening, with fixed effects, control variables and re-balancing a' la Hainmueller (2012)**

| | (1) DepRatio Growth | (2) NFCRate Delta | (3) HHRate Delta | (4) DepRatio Growth | (5) NFCRate Delta | (6) HHRate Delta | (7) DepRatio Growth | (8) NFCRate Delta | (9) HHRate Delta |
|---|---|---|---|---|---|---|---|---|---|
| Digit × MonTight | -2.452*** | 0.014 | -0.004 | -1.772*** | 0.019** | -0.001 | -1.722*** | 0.018** | -0.001 |
| | (0.785) | (0.009) | (0.006) | (0.536) | (0.008) | (0.005) | (0.503) | (0.008) | (0.005) |
| Digit | 0.851 | -0.005 | -0.004 | 0.745 | -0.008** | -0.006** | 0.720 | -0.008** | -0.006** |
| | (0.586) | (0.004) | (0.003) | (0.450) | (0.004) | (0.003) | (0.440) | (0.004) | (0.003) |
| Bank FE | x | x | x | x | x | x | x | x | x |
| BasicControls | x | x | x | x | x | x | x | x | x |
| Control for deposit instability | x | x | x | x | x | x | | | |
| Controls for deposit rates | x | x | x | | | | | | |
| Hainmueller (2012) | x | x | x | x | x | x | x | x | x |
| Month × Business model FE | x | x | x | x | x | x | x | x | x |
| N | 1589 | 1589 | 1589 | 2591 | 1589 | 1589 | 2591 | 1589 | 1589 |
| R-sq | 0.51 | 0.50 | 0.55 | 0.19 | 0.47 | 0.52 | 0.19 | 0.47 | 0.52 |

**Source:** IBSI, IMIR, Google, Bloomberg.

**Notes:** Four bank-level monthly dependent variables including: (a) the growth rate of the deposit-to-assets ratio; (b) the growth rate of deposits; (c) the change in net NFC deposit rate, defined as the monthly change in the NFC deposit interest rate net of the monthly change in ECB rates; (d) the monthly net household deposit rate change. Digit is the treatment dummy separating digital banks from traditional ones. MonTight is the time dummy identifying the monetary tightening period, which takes the value of one in the post-June-2022 period.

$$\mathrm{Y}_{i,t} = \alpha + \beta(\mathrm{MonTight}_t \times \mathrm{Digit}_{i,t-1}) + \gamma(\mathrm{Digit}_{i,t-1}) + \theta(\mathrm{X}_{i,t-1}) + \mathrm{bankFE}_i + (\mathrm{monthFE}_t \times \mathrm{BusinessModelFE}_i) + \epsilon$$

Table 5: **Impact of digitalisation on deposit flows and rates during the monetary tightening, with fixed effects and non-linear control variables**

| | (1) DepRatio Growth | (2) NFCRate Delta | (3) HHRate Delta | (4) Dep Growth | (5) DepRatio Growth | (6) DepRatio Growth | (7) DepRatio Growth |
|---|---|---|---|---|---|---|---|
| Digit x MonTight | -1.535** | 0.013 | -0.003 | -1.380*** | -1.798** | | |
| | (0.676) | (0.008) | (0.005) | (0.418) | (0.652) | | |
| Digit x DeltaMRR | | | | | | -3.336** | |
| | | | | | | (1.362) | |
| Digit x MRR | | | | | | | -0.306* |
| | | | | | | | (0.154) |
| Bank FE | x | x | x | x | x | x | x |
| BasicControls | x | x | x | x | x | x | x |
| Control for deposit instability | x | x | x | | | x | x |
| Controls for deposit rates | x | x | x | x | x | x | x |
| Controls × MonTight | x | x | x | x | x | x | x |
| Month × Business model FE | x | x | x | x | x | x | x |
| N | 1589 | 1589 | 1589 | 1589 | 1589 | 1589 | 1589 |
| R-sq | 0.23 | 0.47 | 0.54 | 0.20 | 0.22 | 0.22 | 0.22 |

**Source:** IBSI, IMIR, Google, Bloomberg.

**Notes:** Four bank-level monthly dependent variables including: (a) the growth rate of the deposit-to-assets ratio; (b) the growth rate of deposits; (c) the change in net NFC deposit rate, defined as the monthly change in the NFC deposit interest rate net of the monthly change in ECB rates; (d) the monthly net household deposit rate change. Digit is the treatment dummy separating digital banks from traditional ones. MonTight is the time dummy identifying the monetary tightening period, which takes the value of one in the post-June-2022 period.

$$\begin{aligned} \mathrm{Y}_{i,t} = \alpha + \beta(\mathrm{MonTight}_t \times \mathrm{Digit}_{i,t-1}) + \gamma(\mathrm{Digit}_{i,t-1}) + \theta(\mathrm{X}_{i,t-1}) + \rho(\mathrm{MonTight}_t \times \mathrm{X}_{i,t-1}) \\ + \mathrm{bankFE}_i + (\mathrm{monthFE}_t \times \mathrm{BusinessModelFE}_i) + \epsilon \end{aligned}$$

Table 6: **Impact of Twitter sentiment ratio on deposit flows and rates, with fixed effects, control variables and re-balancing a' la Hainmueller (2012)**

| | (1) DepRatio Growth | (2) NFCRate Delta | (3) HHRate Delta | (4) DepRatio Growth | (5) DepRatio Growth | (6) DepRatio Growth | (7) NFCRate Delta | (8) HHRate Delta | (9) DepRatio Growth |
|---|---|---|---|---|---|---|---|---|---|
| Tweet Neg | -1.358* | -0.002 | 0.005 | -1.437** | -1.381* | -1.450* | 0.001 | -0.001 | -1.199 |
| | (0.786) | (0.006) | (0.004) | (0.560) | (0.784) | (0.832) | (0.003) | (0.003) | (0.795) |
| News Neg | 0.042 | 0.000 | 0.002 | 0.129 | 0.058 | | | | 0.277 |
| | (0.457) | (0.004) | (0.002) | (0.409) | (0.460) | | | | (0.468) |
| Digit | | | | | -0.351 | | | | |
| | | | | | (0.427) | | | | |
| Tweet Pos | | | | | | | | | 0.257 |
| | | | | | | | | | (0.594) |
| News Pos | | | | | | | | | 0.440 |
| | | | | | | | | | (0.617) |
| Bank FE | x | x | x | x | x | x | x | x | x |
| BasicControls | x | x | x | x | x | x | x | x | x |
| Control for deposit instability | x | x | x | | | x | x | x | x |
| Controls for deposit rates | x | x | x | | x | x | x | x | x |
| Controls × MonTight | x | x | x | x | x | x | x | x | x |
| Hainmueller (2012) | | | | | | x | x | x | |
| Month × Business model FE | x | x | x | x | x | x | x | x | x |
| N | 1589 | 1589 | 1589 | 2591 | 1589 | 1589 | 1589 | 1589 | 1589 |
| R-sq | 0.23 | 0.45 | 0.51 | 0.17 | 0.23 | 0.26 | 0.46 | 0.55 | 0.23 |

**Source:** IBSI, IMIR, Google, Bloomberg.

**Notes:** Three bank-level monthly dependent variables including: (a) the growth rate of the deposit-to-assets ratio; (b) the change in net NFC deposit rate, defined as the monthly change in the NFC deposit interest rate net of the monthly change in ECB rates; (c) the monthly net household deposit rate change. Tweet (and News) are dummy variables identifying banks with Twitter (and News) sentiment ratios worse than the country-level median.

$$\begin{aligned} \mathrm{Y}_{i,t} = \alpha + \beta(\mathrm{UnfavourableTwitter}_{i,t-1}) + \gamma(\mathrm{UnfavourableNews}_{i,t-1}) \\ + \theta(\mathrm{X}_{i,t-1}) + \mathrm{bankFE}_i + (\mathrm{monthFE}_t \times \mathrm{BusinessModelFE}_i) + \epsilon \end{aligned}$$

Table 7: **Impact of Twitter sentiment ratio on deposit flows and rates during tightening and 2023 bank turmoil, with fixed effects, control variables and re-balancing a' la Hainmueller (2012)**

| | (1) DepRatio Growth | (2) NFCRate Delta | (3) HHRate Delta | (4) DepRatio Growth | (5) NFCRate Delta | (6) HHRate Delta | (7) DepRatio Growth | (8) NFCRate Delta | (9) HHRate Delta | (10) DepRatio Growth | (11) NFCRate Delta | (12) HHRate Delta |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tweet × MonTight | -1.201 | -0.005 | 0.003 | 0.786 | 0.002 | -0.001 | | | | | | |
| | (0.972) | (0.011) | (0.008) | (0.811) | (0.010) | (0.008) | | | | | | |
| Tweet × March | | | | | | | -4.712** | -0.002 | 0.022* | -5.132** | -0.001 | 0.018 |
| | | | | | | | (2.065) | (0.033) | (0.012) | (2.310) | (0.036) | (0.012) |
| Tweet | -1.345* | 0.003 | 0.000 | -1.589 | 0.004 | -0.001 | 1.976 | -0.009 | -0.021** | 2.921* | 0.005 | -0.016* |
| | (0.734) | (0.005) | (0.004) | (1.041) | (0.004) | (0.003) | (1.515) | (0.022) | (0.010) | (1.667) | (0.020) | (0.009) |
| News × MonTight | -1.477* | 0.000 | -0.005 | | | | | | | | | |
| | (0.740) | (0.008) | (0.003) | | | | | | | | | |
| News | 0.704 | 0.000 | 0.001 | | | | | | | | | |
| | (0.452) | (0.003) | (0.002) | | | | | | | | | |
| Bank FE | x | x | x | x | x | x | x | x | x | x | x | x |
| BasicControls | x | x | x | x | x | x | x | x | x | x | x | x |
| Control for deposit instability | x | x | x | x | x | x | x | x | x | x | x | x |
| Controls for deposit rates | x | x | x | x | x | x | x | x | x | x | x | x |
| Controls × MonTight | x | x | x | | | | | | | | | |
| Hainmueller (2012) | | | | x | x | x | x | x | x | x | x | x |
| Month × Business model FE | x | x | x | x | x | x | x | x | x | x | x | x |
| N | 1589 | 1589 | 1589 | 193 | 193 | 193 | 193 | 193 | 193 | 193 | 193 | 193 |
| R-sq | 0.24 | 0.52 | 0.56 | 0.44 | 0.58 | 0.75 | 0.49 | 0.67 | 0.81 | 0.45 | 0.64 | 0.75 |

**Source:** IBSI, IMIR, Google, Bloomberg.

**Notes:** Three bank-level monthly dependent variables including: (a) the growth rate of the deposit-to-assets ratio; (b) the change in net NFC deposit rate, defined as the monthly change in the NFC deposit interest rate net of the monthly change in ECB rates; (c) the monthly net household deposit rate change. Digit is the treatment dummy separating digital banks from traditional ones. Tweet (and News) are dummy variables identifying banks with Twitter (and News) sentiment ratios worse than the country-level median. MonTight is the time dummy identifying the monetary tightening period, which takes the value of one in the post-June-2022 period. March is the time dummy identifying the March and April 2023 period, against the January and February 2023 period.

$$\begin{aligned} \mathrm{Y}_{i,t} = \alpha + \beta(\mathrm{Post}_t \times \mathrm{UnfavourableTwitter}_{i,t-1}) + \gamma \mathrm{UnfavourableTwitter}_{i,t-1} \\ + \theta \mathrm{X}_{i,t-1} + \mathrm{bankFE}_i + (\mathrm{monthFE}_t \times \mathrm{BusinessModelFE}_i) + \epsilon \end{aligned}$$

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For specific terminology please refer to the **ESRB glossary** (available in English only).

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