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Mind the App: do European deposits react to digitalisation?

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Abstract

The March 2023 banking turmoil has intensified discussions whether social media and the digitalisation of finance have become significant factors in driving severe deposit outflows. We introduce the concept of *deposits-at-risk* and utilize quantile regressions for disentangling determinants of stressed outflows at the lowest tail of the distribution. For a sample of large banks directly supervised by the ECB, our findings indicate that an increased use of online banking services leads to a small amplification of extreme deposit outflows, but this effect is not further exacerbated by the availability of a mobile banking app. Online banking use and availability of a mobile app do not have a causal effect on deposit volatility in normal times. Finally, social media are impactful only in idiosyncratic cases.

JEL classification: G20, G21, G28.

Keywords: liquidity risk, deposit outflows, bank runs, banking regulation.

0 Non-technical summary

This paper investigates the impact of digitalisation and social media on deposit flows, particularly during periods of financial stress. The March 2023 banking turmoil, including the case of Silicon Valley Bank, highlighted how digital financial services and rapid news dissemination through platforms like X (formerly Twitter) can accelerate deposit outflows. Using a sample of large banks directly supervised by the European Central Bank (ECB), we leverage on granular supervisory data, web-scraped information on mobile app usage, Eurostat data on online banking penetration, and Bloomberg social media sentiment data. Our study contributes to the literature by providing a European perspective, complementing prior research focused on the U.S., such as Koont et al. (2024) and Erel et al. (2023).

We introduce the concept of "deposits-at-risk" (DaR) to examine extreme outflows at the lower tail of the distribution. By applying quantile regressions, we analyze the relationship between digitalisation, social media, and deposit volatility.

Our findings reveal that increased use of online banking services slightly amplifies extreme deposit outflows during stress periods, though this effect is not exacerbated by the availability of mobile banking apps. Importantly, neither online banking nor mobile app usage has a causal effect on deposit volatility during normal times. Furthermore, the role of social media in driving deposit outflows appears to be significant only in idiosyncratic cases, such as during the Silicon Valley Bank crisis, rather than being a systematic driver of instability.

To address endogeneity issues common in this literature, we implement a careful empirical identification strategy. This includes baseline regressions using banks mobile app availability as a proxy for digitalisation and advanced regressions combining bank-level data with country-level variation in digital banking use. We also incorporate fixed effects to account for unobserved heterogeneity at the bank and depositor levels.

As a robustness check, we conduct a case study on a subset of German banks to further control for depositor heterogeneity. Our results align with findings in the U.S. context, such as those by Koont et al. (2024), who examine digital bank runs, and Cookson et al. (2023), who explore social media as a catalyst for bank runs.

Our analysis extends the literature by examining various depositor classes and exploring how digitalisation impacts the interest rate sensitivity of deposit flows. While prior work, such as Erel et al. (2023), showed that digital banks may experience deposit inflows during monetary tightening due to higher deposit rate adjustments, our findings emphasize the nuanced role of digitalisation in amplifying outflows during crises.

This study has important implications for policymakers, particularly in managing liquidity risks and adapting Basel III liquidity regulations to account for the evolving digital landscape of banking.

1 Introduction

The digitalisation of finance and the role of social media are likely to increasingly influence retail depositor behaviour, a fact that has been recognised even before the 2023 banking turmoil. The deployment of widespread online banking services already began following the 2007-2009 financial crisis, only to accelerate following the Covid-19 period. By the end of 2024, around 85% of EU banks participating in the Single Supervisory Mechanism (SSM), so-called Significant Institutions (SIs), offered a mobile banking app. In addition, in conjunction with a rapid dissemination of news, for example via the platform X (formerly Twitter), discussions among policy makers have intensified as to whether the role of social media may have become an amplifier for the potential effects of digitalisation.[1]

The emerging technological advances in the banking landscape are multifaceted, complex and cover a wide range of issues. Recent developments include, among others, a growing use of online / mobile banking services, real-time access to bank accounts through an improved bank IT infrastructure, a more widespread use of digital wallets, and an increasing presence of 'digital only' financial institutions.[2] Traditional banking is also challenged by non-bank financial service providers offering 'Banking as a Service' (BaaS), or online deposit platforms and alternative financial products such as tokenised deposits. Banks have also expanded their digital communication channels, for instance via chatbots or social media presence. These technological advances might act as an amplifier and / or cause the propagation of liquidity stress to the broader financial system.

A more convenient and faster access to digital banking services (and to news related to their local bank) may make retail depositor behaviour more sensitive to any changes affecting their savings and investment decisions. During normal times, retail depositors may become more willing to move their funds to higher-yielding options when monetary policy tightens, and interest rates rise. During stress episodes, deposits may become flightier, further amplified by negative newsfeed as retail customers can react immediately by accessing their bank account online or via smartphone.

To which extent the observable trends in the digital financial transformation have

[1] See FSB (2024) and https://www.bis.org/speeches/sp241023a.htm.

[2] For example, Leitner et al. (2024).

resulted in an increased speed and scale of severe deposit outflows remains an empirical question. In a related report, the FSB concludes that recent deposit runs have occurred significantly faster than historical ones, while the scale remains comparable to historical outflows.[3] At the same time, in the euro area no major shift in the distribution of deposit flows towards more extreme values can be observed for a sample of SSM SIs between 2016 and 2024.[4]

In this paper, we first introduce 'deposits-at-risk' (DaR), and apply quantile regression techniques to disentangle tail effects from main trends in deposit flows. The application of quantile regression to gauge the impact of a certain variable on the (typically left) tail of the distribution of an outcome variable have been applied in the so-called value-at-risk (VaR) (see for example Andrews (1991) or Engle & Manganelli (2004)) and growth-at-risk (GaR) (see e.g. Adrian et al. (2022)) literature. In line with this literature, quantile regressions allow us to determine the impact of certain developments, such as digitalisation and social media, both on average deposit flows, but also on extreme inflows/outflows. This proves particularly useful in the absence of a commonly accepted quantitative definition of a bank run (as opposed to just measuring whether a bank run happens or not).

Second, this paper adds to the literature on digitalisation and deposit flows in the US by offering a European perspective (following Koont et al., 2024). Concretely, we leverage on granular bank-level data available in the ECB's supervisory statistics and match this data with web-scraped information on bank app use, country-level data from Eurostat on the use of online banking services, and bank-specific data on social media sentiment from Bloomberg. Given that banks under the supervision of the ECB operate in different countries, the advanced estimation strategy is adjusted to this set-up, which is different from the literature covering the US banking system. In addition, the paper provides evidence for several types of depositor classes.

Third, we employ a careful empirical identification strategy to address endogeneity problems which are common in this literature. Concretely, the level of digitalisation is typically correlated with unobserved characteristics of banks (e.g. outdated versus up-to-date IT infrastructures) and depositors (e.g. tech-savvy customers), thereby possibly leading to biased estimates, particularly if tech-savvy depositors are more reactive to

[3] See `https://www.fsb.org/uploads/P231024.pdf`.

[4] See `https://www.ecb.europa.eu/pub/pdf/scpops/ecb.op361~145e704503.en.pdf`.

shocks and more likely to adopt digital banking. Indeed, sophisticated investors are both more reactive to shock and more willing to move funds, and at the same time readier to adopt digitalisation and/or becoming client of more digitalised banks.

To address this question, we start running baseline regressions to test for correlations between digitalisation, social media and deposit flows. In this first step, we mainly rely on a bank's availability of a mobile banking app as measure of digitalisation. To account for unobserved heterogeneity at the bank and customer level, in a second step, we run advanced regressions that combine bank-level data on deposit flows with country-level data on digitalisation. By adding bank-time fixed effects to control for any unobserved heterogeneity at the bank level while using country-level variation in customers' use of online banking services, we argue that any remaining unobserved heterogeneity is minimised. As a robustness check for the advanced estimation approach, we run a case study at the regional level, specifically for a sub-set of German banks. This allows us to restrict customer heterogeneity further. Finally, we confirm results by also estimating how digitalisation affects the interest rate sensitivity of deposit flows, both of which are consistent with the results derived in our main regressions, and also with the magnitude of the effect in the US.

Our analysis indicates that digitalisation amplifies deposit flows at both tails of the distribution, i.e. it exacerbates both extreme inflows and outflows. When measuring digitalisation as the availability of a mobile banking app, this effect is particularly pronounced for uninsured retail deposits. The impact on deposit flows during normal times is close to zero. Conditional on being in the tail of the distribution, larger banks appear to have lower outflows in bad times and lower inflows in good times. The latter effect applies to all types of deposits. Once controlling for bank and country specific effects, the use of online banking services appears as the key variable driving results also for total deposits, whereas the availability of a mobile banking app does not further amplify the effect on extreme deposit flows.

The case study of German savings banks confirms the findings from the cross-country analysis. German *Sparkassen* share the same mobile banking app and serve a rather homogeneous customer base. As these specialised banks operate in regions with different online banking penetration, the case study allows us to isolate the effect of the use of online banking services while controlling for customer characteristics. The coefficient is consistent with the cross-country study, indicating that the use of online banking services amplifies severe outflows. We find that a 1% higher use of online banking services increases the most extreme deposit outflows by 0.28%. Consequently, the average increase of 20.7% in the use of online banking over the sample period is associated with a 5,8% amplification of extreme deposit outflows.

We also study the interest rate sensitivity of deposits with regard for more (less) digitalised banks. We find that for each 1 percentage point increase in the interest rate, digital banks experience a 0.02% reduction in their deposit growth rate compared to banks that do not offer a banking app, a result that echoes the work by Koont et al. (2024), while looking more at the tail of the distribution in our paper. We take this as further evidence that digitalisation has an amplification effect mainly in times of distressed outflows.

Finally, we find no effect of social media on deposit flows at monthly frequency, neither during normal times nor in stress episodes. This result holds for both count and sentiment indicators. Instead, the impact of social media on deposit outflows appears limited to idiosyncratic cases. While bank-level information available at monthly frequency is a key advantage of this study, it may not yet be high-frequent enough to capture flighty deposits similar to those observed during the March 2023 Banking Turmoil where severe outflows occurred within a few days only.

Our paper has direct policy implications. Not only since the March 2023 banking turmoil, policy makers are concerned that digitalisation may intensify severe deposit outflows or bank runs. Our paper confirms this conjecture. At the same time, and somewhat contrary to the ongoing policy debate, we do not find an amplifying effect for social media, which may however be related to the monthly frequency of the data.

Beyond Koont et al. (2024), our paper is related to the small literature arising from the 2023 banking turmoil, see for example Choi et al. (2023) and Beck (2024). The events in the US banks in 2023 have revived an older literature on the stickiness of deposits, see for example Drechsler et al. (2023). However, there is still relatively little literature on the nexus between the degree of bank digitalisation and the flightiness of bank deposits. Partly related to our work is also Erel et al. (2023), who show that 'more online' US banks transmit changes in the federal funds rate more strongly to rates that they offer on deposits. Erel et al. (2023) also show that during a monetary tightening online bank deposits experience inflows (due to rate movements), while traditional banks experience outflows. In this paper, we cannot isolate this channel due to lack of harmonised data on interest rates on deposits.

The remainder of this paper is organised as follows. Section 2 describes the data. Section 3 introduces the concept of deposits-at-risk, presents our empirical identification strategy and a series of robustness checks. Section 4 looks at the impact of interest rates on deposits and the intermediating role of digitalisation. Section 5 concludes.

2 Data and variables definition

The key variables of interest relate to supervisory data (see Section 2.1) on banks' monthly deposit stocks. We leverage on supervisory data collected for Significant Institutions (SIs), i.e. those banks directly supervised by ECB Banking Supervision. The cleaned dataset comprises a balanced sample of 110 SIs. It spans over the period September 2016 to February 2024, at a monthly frequency.[5] From the monthly stock of deposits, we compute flows by calculating the month-on-month growth rate of the stock value. The monthly data set covers several types of deposit classes. Importantly, this data set is available at the highest level of consolidation for each banking group; thus we cannot simply collapse it into country level data to merge with one of the digitalisation proxies which is available at the country level only.

For the country-level regression analysis which provides a better set-up for controlling for unobserved heterogeneity, we therefore also draw on a second source of supervisory reporting data which provides data on total deposit flows at the country level, albeit only at quarterly frequency. This data set also provides information on bank characteristics such as size, capitalisation, funding, and profitability.

The proxies for digitalisation (see Section 2.2) are available at the bank level and monthly, and at the country level and annually. The first digitalisation proxy, web-scraped information on bank app use, is available at the bank and the monthly level. The second

[5] The addition of other data sources reduces the sample in the baseline econometric specification to 90 SIs, mainly due to limitations in the digitalisation proxies.

digitalisation proxy is available at the country level, but only annually.

The proxies covering social media and newsfeed indicators from Bloomberg are available at a daily frequency.

2.1 Supervisory data reporting sources

Supervisory reporting templates contain data on financial statements and balance sheets that banks under direct supervision by the ECB are required to periodically disclose to the relevant competent authorities. Both the Common Reporting Framework (COREP) templates and the Financial Reporting Standard (FINREP) templates collect granular deposit data.[6] For instance, the COREP template collects monthly data on certain specific deposit classes that are relevant for the computation of the Liquidity Coverage Ratio (LCR). These include a split between retail and non-financial corporation (NFC) counterparts and between accounts covered and not covered by a deposit guarantee scheme (DGS).[7] Further details on this data source, the thorough data cleaning process for misreporting and handling of mergers & acquisitions can be found in Fascione et al. (2024).

By contrast, the FINREP template collects deposits at quarterly frequency with a bank-individual breakdown by counterparty type and geographic location.[8] We use the reported overnight deposits and deposits with a maturity of less than 30 days to compute month-on-month percent changes in the stock of outstanding amounts for total deposits.

2.2 Non-supervisory data

2.2.1 Web-scraped data on mobile banking apps

In this paper, we define a bank to be digital from the point in time it offers a mobile banking app to its customers. We web-scrape data retrieved from Google Play to obtain bank-individual information for a corresponding banking app on its (i) total downloads,

[6] See, in particular, COREP C.73.00 and FINREP F.20.06.

[7] In particular, the LCR standards assumptions break deposits down (per definition) into the following key classes, among more minor others: derogated stable retail deposits, retail stable (insured) deposits, retail less stable (uninsured) deposits, (un)insured operational deposits, (un)insured non-operational deposits, excess operational deposits by financial customers, (un)insured excess operational deposits by non-financial customers.

[8] In particular, the FINREP template reports carrying amounts of deposits of central banks, general governments, credit institutions, other financial corporations, non-financial corporations, and households.

(ii) total reviews and (iii) total reviews with comments. While the variables are only available for the point in time of retrieval, and thus do not allow building a time series, the commented reviews have a time stamp and thereby allow us to track the exact moment of the commented review. As a result, we can build a time series of a variable capturing the cumulative reviews (with comments) over time for the period 2016-2024. We call this variable $Reviews_{bt}$ for each period t and bank b. From this we construct a binary variable switching to 1 when the banking app has its first review. We define whether a bank provides digital banking services as follows:

$$\mathtt{Digital}_{bt} = 1 \ \ \mathtt{if} \ \ Reviews_{bt} > 0$$

and 0 otherwise. In doing so, we aim for a definition as close as possible to the true launch day of the app. While the literature employs also different versions of this variable (e.g. continuous variable definitions), we show in Appendix 5 that these variants are subject to non-negligible limitations and may lead to erroneous interpretation.

2.2.2 Eurostat data on the use of online banking

While only about half of retail customers regularly used online banking back in 2016, the demand for digitalised banking services has increased to around 85% by end-2024. This observable trend was not least because of the various lockdowns during the Covid-19 period, where people necessarily had to switch to alternative online options to access their local bank. The Eurostat database collects the share of customers using internet banking within the last three months per country in the European Union on an annual basis. This includes typical online banking services (such as electronic bank transfers) as well as the use of mobile banking apps. The indicator is also available at regional level (called NUTS 1 regional classification) which we use for our case-study of German savings banks (see Section 3.5).

The analysis using data on online banking penetration is subject to one limitation. Eurostat notes a structural break for Germany and Ireland in 2021 when Eurostat changed its methodology for those two countries (see Appendix 5). We address this problem by extending the 2020 value to years 2021-2023 for these two countries. However, this implies that the effect of customer banking internet literacy could be even bigger (smaller) if outflow where higher (lower) in the last years of the sample and the online banking penetration increases for these two countries during 2021-2023.[9]

2.2.3 Bloomberg data on social media newsfeeds

Nowadays, banks are increasingly present on various social media platforms such as Facebook, Instagram and, primarily, X (formerly Twitter). This way of connecting to its customer base can be understood as a new form of relationship banking, with the aim to strengthen customer loyalty and, ideally, to generate new revenue opportunities. This may be carried out via targeted advertising based on the collection of personal information, possibly supported by generative Artificial Intelligence (AI). However, a strong online presence may make the bank also more vulnerable to negative newsfeeds, possibly resulting in private customers moving their deposits or funds quickly.

The rapid dissemination of news via social media may act in two different ways. To capture the potential amplification of negative news, we use a Bloomberg count indicator collecting the total number of tweets associated with the bank (i.e. how much people talk about each bank over time on X (formerly Twitter)). Available daily observations for the count variable are cumulated up to monthly frequency. To gauge the potential causal effect of negative news about the bank itself, we use a Bloomberg sentiment indicator, which ranges from -1 (bad comments about the bank) to 1 (good comments about the bank). We aggregate available daily data to monthly frequency by taking the average over the sentiment variable.

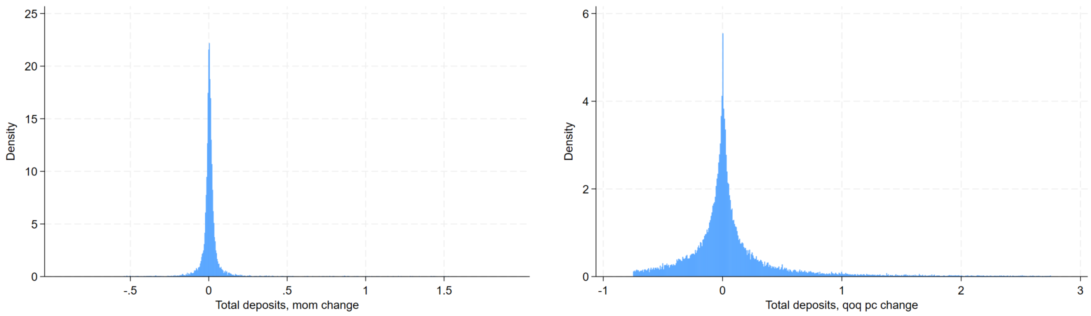
3 The impact of digitalisation on DaR

3.1 Descriptive evidence

Since our baseline and advanced estimation approach rely on two different data sources, we start by showing that the distribution of both measures of total deposits is similar, and follows the structure described in Fascione et al. (2024). Figure 1 shows the distribution of the two main dependent variables. We use the month-on-month change in the stock of deposits as recorded in COREP reporting (Panel A) and the quarter-on-quarter change in

[9] As a robustness check, we re-run the regression for the period 2021-2023. This regression for a shorter time period gives similar results as the regression for the whole sample period.

the stock of deposits as reported in FINREP reporting (Panel B). Since the sub-categories of deposits differ between the COREP and FINREP reporting templates, we show the distribution for total deposits, which is the only category that matches between the two templates.



(a) Panel A: Distribution of the m-o-m change in total deposits (COREP)

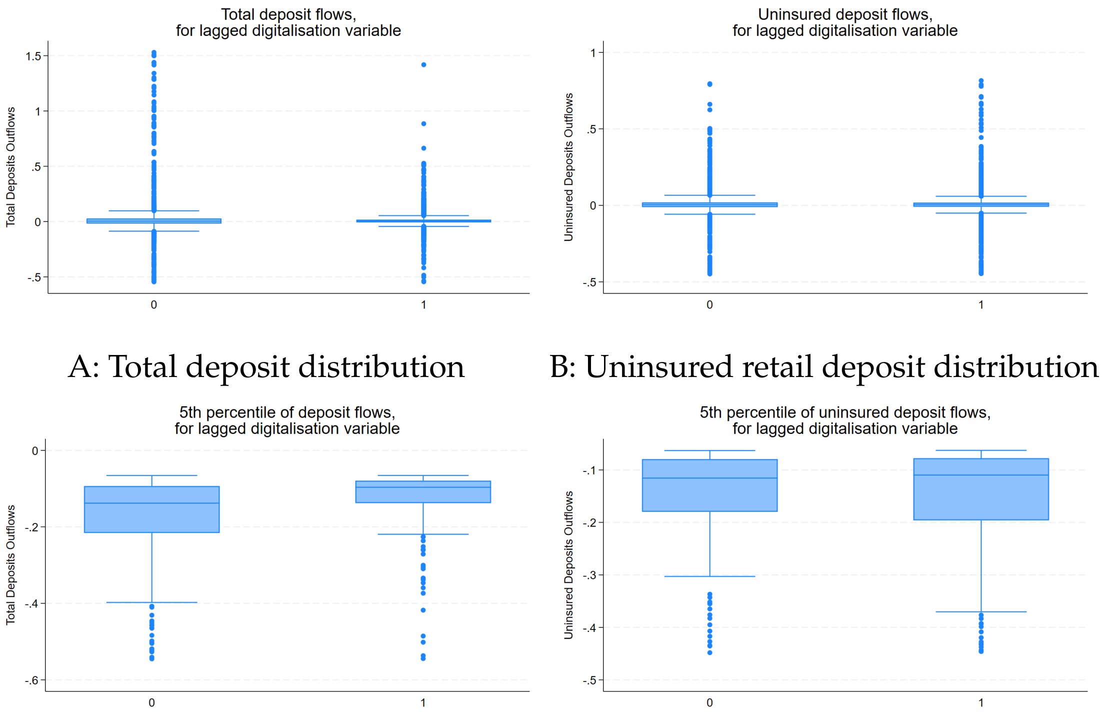
(b) Panel B: Distribution of the q-o-q change in total deposits (FINREP)

Figure 1: Distribution of the dependent variable in the baseline and the advanced regression

Sources: COREP and FINREP data on deposits.

Both distributions display the inverse t-shape described in Fascione et al. (2024). Figure 1 also illustrates that total deposits from the FINREP template display wider and somewhat fatter tails. The underlying reason for this difference is that the FINREP data we use is consolidated at the bank-country level while COREP data is consolidated at the bank (group) level. This results in larger and more disparate values in the FINREP data. Consider e.g. a bank with deposits in several countries. It is possible that this stock of deposits is concentrated in one country but still with sizeable deposits also in other countries. The fatter tails for the FINREP data make inference at the tails somewhat more challenging than for COREP data.

3.1.1 Descriptive evidence on the impact of the availability of an app



A: Total deposit distribution — B: Uninsured retail deposit distribution

C: Total Deposits tail distribution — D: Uninsured retail deposits tail dist.

Figure 2: Digital (1) and Non Digital (0) banks deposit distribution

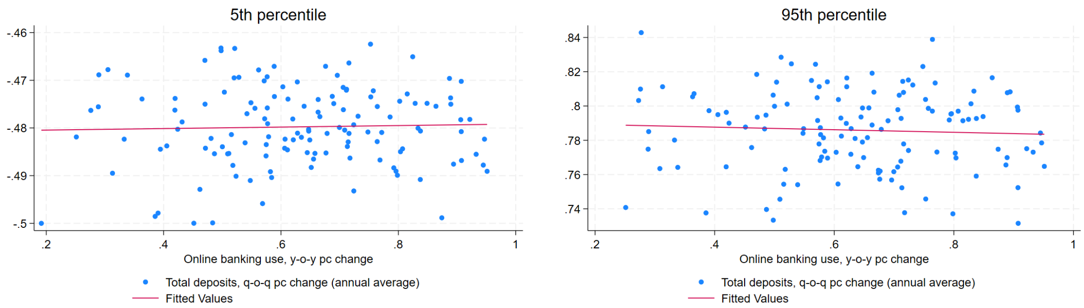
Notes: We divide our sample in 5 groups (quintiles) according to each bank characteristic. Then, we plot the correlation between the internet level penetration at the country level and the 5% for the lowest and highest groups.

Figure 2 uses boxplots to illustrate the difference in deposit flows for digitalised verus non-digitalised banks based on the availability of a mobile banking app. Panel A and Panel B show the difference for total depost flows (Panel A) and uninsured retail deposit flows (Panel B). While there is no significant difference in the median for both types of flows, non-digitalised banks seem to display more total inflows while the digitalised banks seem to record more uninsured retail inflows. For extreme outflows it is difficult to discern any difference from the total distribution.

Therefore, Panels C and D of figure 2 show boxplots only for the left tail of the distribution. Here, the tail seems flatter for total deposits for digitalised banks (Panel C), but their tail is fatter for uninsured retail deposits for digitalised banks (Panel D). As a consequence, an effect for digitalised banks seems to be present for extreme outflows of uninsured retail deposits.

3.1.2 Descriptive evidence on the impact of the use of online banking

To investigate for potential links between the use of online banking and FINREP deposits, we look at the correlation between annualised total deposit flows and online banking penetration for the lower and the upper tail of the distribution. Correlations are shown at country-level for the available annual frequency.



(a) Panel A: Internet penetration effect β_1 (b) Panel B: Digitalisation Effect β_2

Figure 3: Correlation between online banking use and total deposit flows, 5th and 95th percentiles

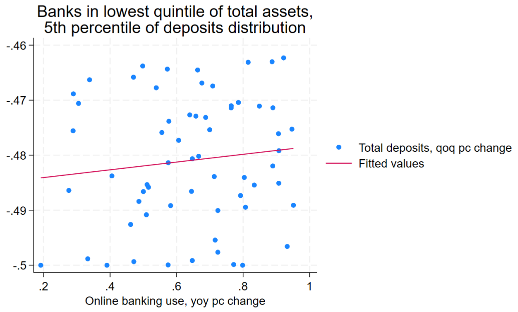
Notes: This figure shows the correlation between internet banking use and total deposits from FINREP data. Panel A depicts the 5th percentile of the distribution of deposit flows and Panel B depicts the 95th percentile of the distribution of deposit flows.

Figure 3 shows correlations for the 5th and 95th percentile of the distribution of total deposit flows. There is hardly any correlation for extreme outflows, and if at all a slightly positive correlation for extreme inflows (implying more inflows when there is a more widespread use of online banking).

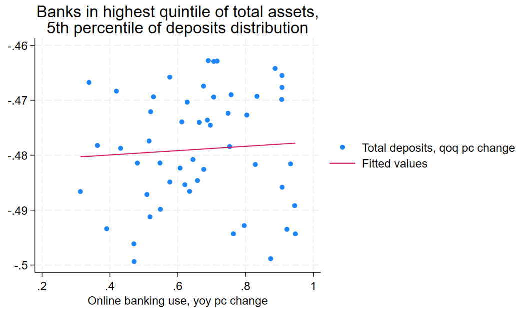
However, since we expect deposit flows to be strongly determined by bank and depositor characteristics, it is possible that the effect of online banking use is masked by the heterogeneity in the sample of banks. Therefore, we split the data further by bank characteristics. Specifically, we look at the highest versus lowest quintile of total assets, return on assets, and cost-to-income ratio.

Figure 4 provides such correlations for the lower tail of the distribution, additionally for the lowest and highest quintile of different variables capturing bank characteristics. There does not seem to be a strong correlation for a split by total assets (Panels A and B). We observe a negative correlation between the use of online banking and deposit flows for low ROE banks and high cost-to-income banks (Panels C and F). The opposite is true for high ROE banks and low cost-to-income banks (Panels D and E).

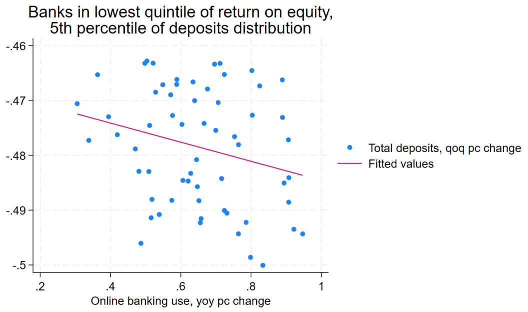
While we do not find a strong correlation between total deposits and the extreme tails of total deposit flows at the annual frequency, splitting the sample by bank characteristics confirms that the relationship is likely to differ depending on the characteristics of the bank. This confirms the typical potential endogeneity bias inherent in this literature which is about the unobserved heterogeneity at bank- or customer level. We adjust our regression approach to account as much as possible for this type of heterogeneity.



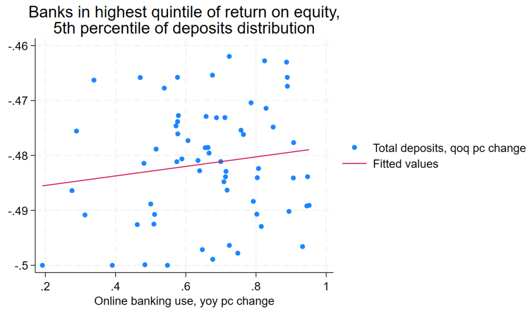
Panel A: Digitalisation and low assets



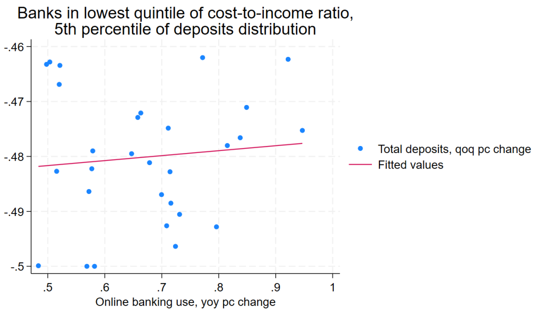
Panel B: Digitalisation and high assets



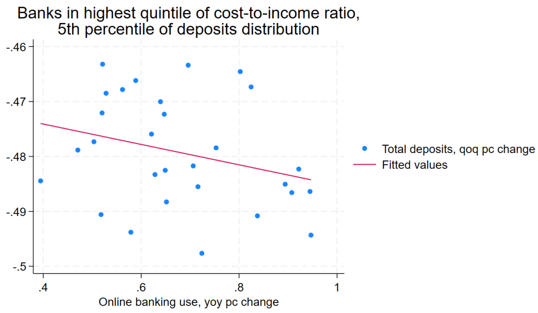
Panel C: Digitalisation and low ROE



Panel D: Digitalisation and high ROE



Panel E: Dig. and low cost to income



Panel F: Dig. and high cost to income

Figure 4: Correlation between use of online banking and total deposit outflows by bank characteristics

Notes: We divide our sample in 5 groups (quintiles) according to each bank characteristic. Then, we plot the correlation between the internet level penetration at the country level and the 5% for the lowest and highest groups.

3.2 Identification

Given the imperfect data sources, the main challenge for identification is endogeneity bias from the correlation of the digitalisation variable with unobserved characteristics of the bank. For example, whether a bank provides a mobile banking app might be correlated with unobserved characteristics of the bank, or it might align with specific depositor traits; banks are more likely to develop an app if their depositors are inclined to use electronic methods because, say, they are more sophisticated. In addition, the use of the app itself might be related to customer characteristics, which are also related to their demand for online banking services.

While we are not able to address this issue with a direct control, we adopt a sequential approach to establish the robustness of our results to plausible variation in unobserved traits. First, we incorporate a binary digitalisation indicator based on app use into the estimation equation (Section 3.3). Second, we enhance the approach by utilising the available bank-country breakdown of deposit flows. Since FINREP provides deposits by bank but also by country, we can leverage on both the within-bank variation and the between country variation. We use the between-country variation for drawing inference, while using within-bank variation to control for unobserved heterogeneity. Specifically, we add to the regression bank-time fixed effects. These time-varying bank fixed effects capture all characteristics for a bank which are bank-specific, even if they change over time. The only type of heterogeneity which this approach cannot cover is if a bank has different types of customers in different countries, in particular changes in a bank's customer base *between countries* over time (since one bank may operate in more than one country). However, for the period of our analysis one can argue that most of the time span was characterised by very low interest rates, providing limited incentives for large-scale shifts in a bank's customer base between countries. Note that changes in customer characteristics only related to the bank would be covered as the fixed-effects are time-varying (bank-time fixed effects). For the estimation using country-level variation, we include a second digitalisation proxy, the use of banking services at the country level for each year, as an additional explanatory variable (Section 3.4).

Third, we conduct a case study on German savings banks, which allows us to build on a more granular breakdown of the second digitalisation proxy (Section 3.5). We repeat all regressions for various deposit categories, such as retail versus non-financial corporation (NFC) deposits and uninsured versus insured deposits. Finally, additional robustness checks to validate our findings are discussed in Section 3.7.

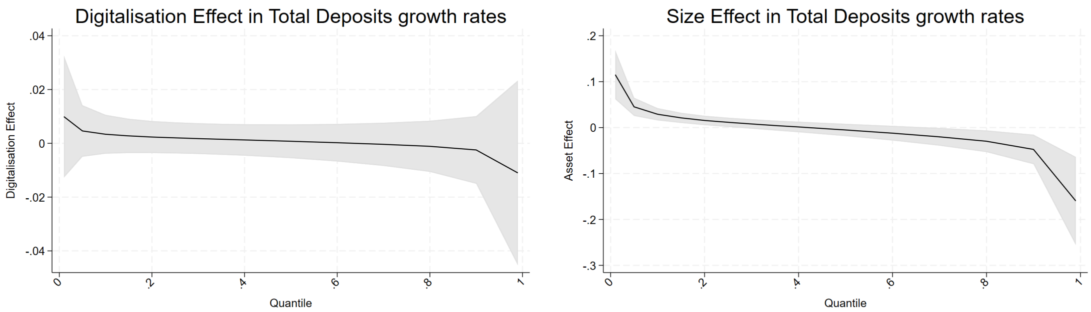
3.3 Baseline estimation approach

We start with the most simple regression specification. We regress the monthly growth rate of deposits for each bank on a measure of the size (total assets), a measure of profits (change in ROA) and our binary digitalisation variable. We follow the estimation procedure of Rios-Avila et al. (2024) which allows us to use quantile regression and control for multiple fixed effects (month-year and bank):

$$d_{bt} = \alpha_b + \alpha_t + \beta_1 \mathtt{Digital}_{b,t-1} + \beta_2 \log(Assets_{b,t-1}) + \beta_3 \Delta ROA_{b,t-1} + \epsilon_{b,t}. \quad (1)$$

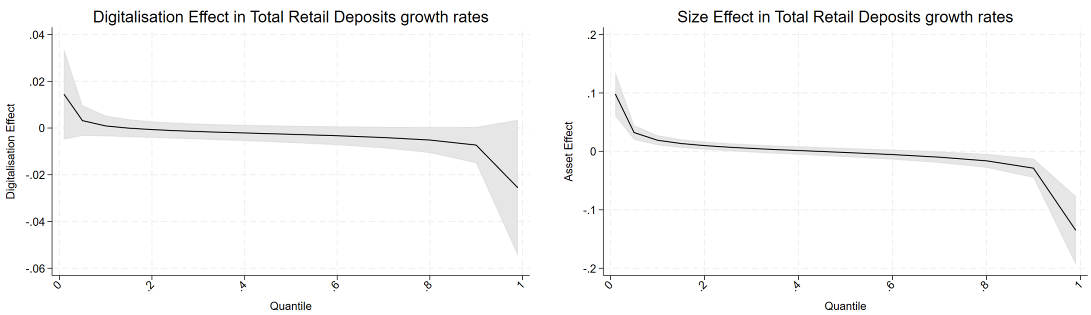
Equation 1 describes the baseline regression. d_{bt} denotes the deposit growth rate of bank b in period t. In this equation, the coefficient β_1 describes the key digitalisation effect of interest. Since the baseline regression is at the monthly frequency and bank level only, it includes bank fixed effects α_b and time-fixed effects α_t separately. β_1 is the coefficient of interest on the digitalisation proxy $\mathtt{Digital}_{b,t-1}$ which is added with a lag. We also control for a bank's growth ($\log(Assets_b, t-1)$) which is also added with a lag. Finally, we also control for lagged first differences in a bank's profitability ($\Delta ROA_{b,t-1}$).

Figure 5 provides an illustration of the two coefficients β_1 and β_2 for three different breakdowns of deposits: total deposits, total retail deposits and uninsured retail deposits. The quantiles of the distribution of (net) deposit flows shown in the figures range from severe negative outflows (i.e. the lowest tail of the distribution is characterised by an outflow rate of 21.7% and 20% at the 1st percentile for uninsured retail deposits and total deposits respectively) to extreme positive inflows (i.e. the highest tail of the distribution is marked by an inflow rate of 21.3% and 33% at the 99st percentile for uninsured retail and total deposits respectively). This affects the interpretation of the sign for each point estimate per quantile. Note that the estimation yields a coefficient β_2 of 0.1 and 0.04 for the 1% and 5% quantile respectively. This means that a 1% larger bank experiences 0.1 percentage points fewer extreme outflows (i.e. those at the 1% quantile), which is an economically small effect.



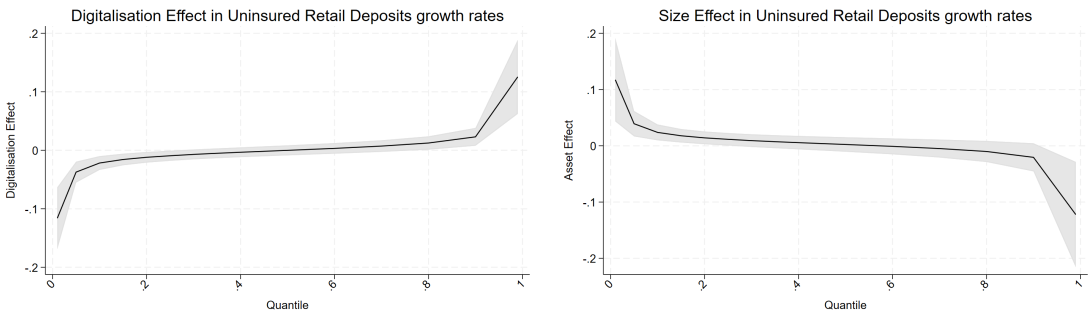
Panel A: Digitalisation and Deposits Panel B: Size and Deposits

Quantile Estimation on Total Deposits



Panel C: Digitalisation and Retail Dep. Panel D: Size and Retail Dep.

Quantile Estimation on Total Retail Deposits



Panel E: Dig. and Uninsured Retail Panel F: Size and Uninsured Retail

Quantile Estimation on Uninsured Retail Deposits

Figure 5: Quantile regression effects

Notes: Point estimates from Equation 1 and 5% confidence interval. Panel B shows the bank size effect on deposit growth. The positive coefficient in the left tail of the distribution implies smaller (i.e. less negative) growth rates for larger banks. E.g., a point estimate of $\beta_2 = 0.1$ implies that at the very left tail, a 1% increase in the size of the banks correlates with a reduction of outflows by 0.1 percentage points. Panel A shows the digitalisation effect, i.e. the coefficient β_1. The coefficient in the very left tail of the distribution is positive, through not statistically significant. The same results can be observed when regressing total retail deposits on size and digitalisation (Panels D and C). Panel E shows the coefficient β_1 for uninsured retail deposits, which is negative and different from zero for the very left tail of the distribution, i.e. negative growth rates are more negative for digitalised banks. E.g., a coefficient of -0.1 on the very left tail of the distribution for the binary digitalisation variable implies that banks that provide a digital app record 0.1 percentage points higher outflows than banks which does not provide a digital app.

We do not find an effect of the binary digitalisation variable on total deposits and insured retail deposits, albeit without claiming causality. This holds both for the tails and for normal times. Conditional on being in the tail of the distribution, larger banks appear to have lower outflows in bad times and also lower inflows in good times. We find the same effect for all different types of deposits in terms of size (see left-hand side panels of Figure 5).

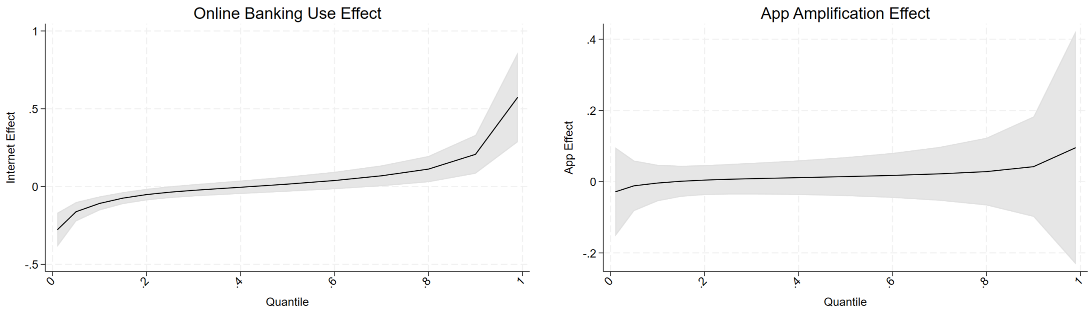
At the same time, looking instead at the most unstable type of deposits, we find an amplification effect for the impact of digitalisation on uninsured retail deposit flows at both tails of the distribution. In other words, during periods of high deposit outflows (inflows), providing a mobile banking app increases the amount of outflows (inflows). The effect is statistically significant and meaningful for uninsured retail deposits at both tails of the distribution.

3.4 Controlling for bank-time fixed effects

We turn to sharpening the identification strategy by exploiting the bank-country breakdown of the FINREP deposit data and introduce bank-time fixed effects as well as a second digitalisation proxy. (see Section 2.1). This allows us to include the (country-specific) customer demand for online banking services into the estimation equation and study its potential impact on (country-specific) deposit flows, while controlling unobserved heterogeneity and expected omitted variable bias through the addition of bank-time fixed effects:

$$d_{bc,t} = \alpha_{bt} + \beta_1 \mathtt{internet}_{c,t} + \beta_2 \mathtt{internet}_{c,t} \mathtt{Digital}_{b,t-1} + \epsilon_{bc,t}. \quad (2)$$

Here, β_1 captures the effect of the use of online banking, while β_2 captures the effect of providing an app conditional on the use of online banking services. In this setup, d_{bct} is the change in deposits of bank b in country c at time t. Note that we are controlling for time-varying bank fixed effects, which allows us to address the main endogeneity problem better than with a regression at the bank level only, controlling for any characteristic which is bank-specific (including the customer base, unless it changes for the same bank *between* countries). As a result, the cross-sectional heterogeneity between banks provides identification, similar to Koont et al. (2024). We run the regression only for total deposits as the other breakdowns of the data do not give sufficient coverage for a meaningful sample size.



(a) Panel A: Distribution of β_1 (b) Panel B: Distribution of β_2

Figure 6: Quantile Estimation on Total Deposits 2016-2023

Notes: This figure shows the effect of online banking use (base effect, β_1) and digitalisation (amplification effect, β_2) on the change in deposits for different quantiles.

We find that an increased use of online banking services amplifies severe deposit outflows, but this effect is not further exacerbated by the availability of a mobile banking app. Panel A of figure 6 shows that a higher share of the population using online banking services is associated with negative coefficients for the lower quantiles of the distribution. The use of online banking is measured in percentages. Therefore, the coefficient β_1 gives the estimated percentage point impact on the dependent variable of an increase in online banking use by 1 percentage point. The estimated coefficient for the lowest (1%) quantile is $\beta_1 = -0.278$. This implies that outflows increase by 0.278 percentage points for a 1 percentage point increase in online banking use. The effect reduces to approximately 0.16 percentage points at the 5% quantile. Magnitudes are similar at the upper tail of the distribution. During normal times the effect is economically and statistically close to zero.

To gauge the economic significance of the effect, it is useful to consider the distribution of online banking use. The variable ranges from 19% to 95% in the full sample. The standard deviation of online banking use over time within country ranges from 1.89% (EE) to 15.9% (CY), depending on the country. The average standard deviation within country (over time) is 6.75%. The average standard deviation *between* countries is 15.99%, which is rather stable over time. The maximum change in online banking use for the sample period is recorded in CY (+43%) and the smallest change in online banking use is recorded for Estonia (+6.3%). The average increase during the sample period is 20.7%. Using this information to put the estimated coefficient into perspective, for the average increase in the use of online banking, i.e. 20.7%, the average impact at the very low end of the tail can be expected in the range of $0.278 * 20.7 = 5.76$ percentage points, indicating that an increased use of online banking can exacerbate bank runs. For total deposits, the standard deviation is 42% while the variance is 17.8% squared. This implies that the amplification effect at the extreme tail is smaller than the variance of the full distribution.

By comparison, Panel B shows how having a mobile banking app would amplify the effect of online banking use (β_2). The coefficient is not statistically different from zero for any part of the distribution. As such, we conclude that the channel through which internet-savvy depositors move their funds quickly in times of stress is more relevant than the level of digitalisation measured by the availability of a mobile banking app. As a robustness check, to confirm that the mobile banking app variable as such becomes insignificant, we re-run the regression without the bank-time fixed effects (which otherwise capture a bank's supply of an app) but include the mobile app variable separately, together with bank-specific control variables such as size or profitability. In this exercise the mobile banking app dummy indeed is insignificant.

In sum, our results are supportive of the customer channel (i.e. an increased use of online banking services) in exacerbating severe deposit outflows. Our baseline regressions find a correlation between digitalisation (i.e. measured via the mobile banking app) and net deposit flows, and the effect is statistically significant for uninsured deposits. In addition, in the appendix we show that the continuous version of this variable (i.e. a count indicator of app reviews) which is used in other studies (e.g. Koont et al. (2024)) is subject to non-negligible biases. Once we add bank-time fixed effects in our advanced estimation approach, and add the country-wide customer penetration of online banking, we do find a statistically significant and robust effect of online banking use amplifying extreme outflows.

3.5 The Sparkassen case study

Since we use country-level data for the use of online banking, we cannot fully rule out potential heterogeneity across retail customers' preference for technologically advanced banking services *within* each country. For example, as regional Eurostat data at NUTS1 level suggests, e.g. the online banking penetration in the North of Italy is considerably higher than in the South (see Appendix 5). If this heterogeneity changes between countries over time, it may result in slightly biased results. Therefore we conduct a dedicated case study for the German savings banks sector whose special features can help us to partially address this problem.

Specifically, we make use of three special features of the German banking system. First, we exploit the so-called *Regionalprinzip*. The *Regionalprinzip* implies that, by legal definition, savings banks do not compete at the regional level but each *Sparkasse* is allowed to collect retail deposits only in the region where its headquarter is operating. By splitting the savings banks deposits into NUTS1 regions according to the address of the Sparkassen headquarter, we can account for customers use of online banking at the regional level.

Second, in our data set, each Sparkasse is assigned to one NUTS1 region, while one NUTS1 region (state) has more than one bank. As a consequence, for identification we exploit the heterogeneity between regions, but not between banks. For this identification to work we need to assume that the *Sparkassen* and their customers are relatively similar in one region. *Sparkassen* (savings banks) are predominantly owned by the public sector and fulfill their public mandate of supporting access to banking services to the population as well as providing tailored banking services for small and medium-sized enterprises.[10] This implies that their customer-base is rather homogeneous. Figures 13 and 14 in Appendix 5 present key descriptive data for the German savings banks case study, with a particular emphasis on the variation from which we draw inference.

Third, all *Sparkasssen* use the same app, irrespective of the region. This means by focussing on the *Sparkassen* only, we can keep constant the information on the availability of an app. According to its first Google Play review, this general app has has been active since 2011.

[10] The German banking system is subdivided into a three-pillar structure of savings banks and so-called *Landesbanken* (regional banks), cooperative banks and their central institutions, as well as commercial banks.

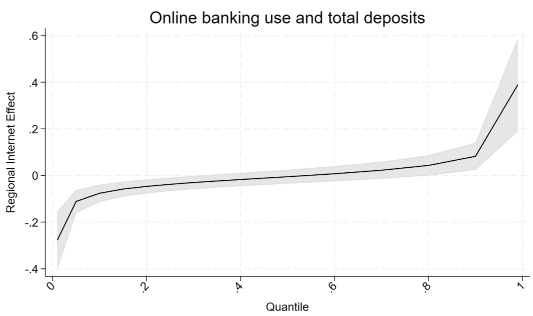
For this case study we re-run the same regressions as in Section 3.3. In particular:

$$d_{bc,t} = \alpha_b + \alpha_t + \beta_1 \text{internet}_{c,t} + \epsilon_{bc,t} \tag{3}$$

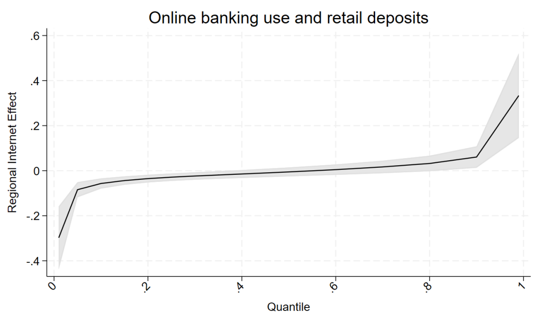
where $d_{bc,t}$ denotes the deposit growth rate of the bank b in region c at time t. By definition, each bank b has deposits only in one region c, but each region has more than one bank.

Figure 7 displays case study results for total deposits (Panel A) and retail deposits (Panel B). The panels show coefficient β_1, i.e. the effect of the variable measuring the use of online banking on deposit flows. Both for total deposits and retail deposits a more widespread use of online banking amplifies deposit flows at the tails, although the effect is statistically significant but quantitatively rather small. In other words, a higher share of online banking in one region intensifies extreme outflows and extreme inflows with a zero effect during normal times.

The results both confirm and extend the country-level analysis. The results for total deposits (Panel A) confirm the country-level results. The coefficient β_1 for total deposits for the 1% quantile is at -0.277. In addition, with the case study we can confirm the effect also for retail deposits (Panel B). β_1 for retail deposits stands -0.297 for the 1% quantile of retail deposits, which is consistent with the effect for total deposits and thus also with the coefficient for the cross-country study, providing a further indication of the robustness of results.



A: β_1 for total deposits



B: β_1 for retail deposits

Figure 7: Effect of internet banking penetration on deposit flows: *Sparkassen* case study

Notes: Panels display distribution of point estimates for β_1 from Equation 3, with a 5% confidence interval. Panel A shows β_1 for total deposits, Panel B shows β_1 for retail deposits.

3.6 Social media and severe outflows

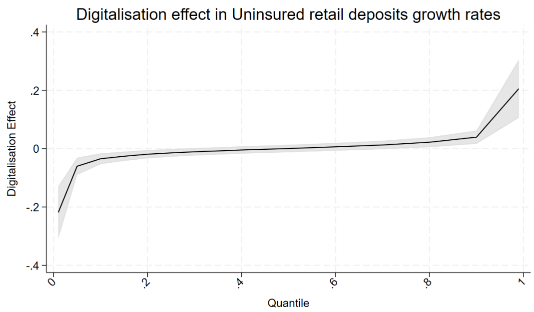
Finally one may argue that rather than digitalisation, the use of social media is most relevant in amplifying deposit outflows. The information-sharing on both private chat groups and X (formerly Twitter) on Silicon Valley Bank has been identified as a key driver of speedy deposit outflows which led to its failure. In the case of Credit Suisse, the banks depositor base also reacted quickly to the rapid dissemination of news via social media, with total deposit outflows amounting to 21% over a 90-day period.[11]

A test of this hypothesis for the banking union banks remains challenging, because the social media coverage for banking union SIs remains low to this date. We use two different approaches to approximate social media coverage, using Bloomberg data. First, we use the number of tweets which mention on X (formerly Twitter) a specific bank during a certain month. This indicator can be interpreted as a measure of how strongly news on a specific bank are amplified. Second, we use the average X (formerly Twitter) sentiment regarding a specific bank during a month. This second measure can be interpreted as a reflection of a more sustained negative or positive sentiment about a bank, reflecting, for instance, the disclosure of e.g. financial statements. There is limited data coverage of the two indicators, covering approximately 50 banks comprising a total of 4237 observations. We re-run our regressions for this subsample, importantly not only including the social media variables but also the use of online banking variable:

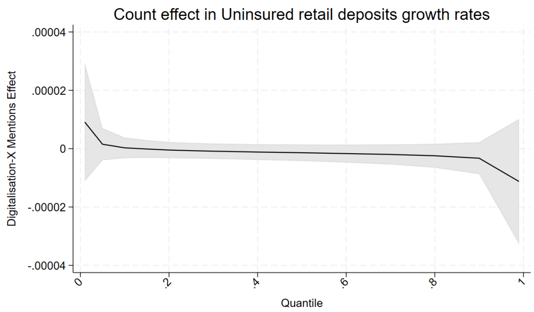
$$\begin{aligned} d_{bt} = {} & \alpha_b + \alpha_t + \beta_1 Digital_{b,t-1} + \beta_2 Count_{b,t-1} \times Digital_{b,t-1} \\ & + \beta_3 AvgSentiment_{b,t-1} \times Digital_{b,t-1} + \beta_5 log(Assets_{b,t-1}) \\ & + \beta_6 \Delta ROA_{b,t-1} + \epsilon_{bt}, \end{aligned} \tag{4}$$

where where d_{bt} denotes the deposit growth rate of bank b at time t, α_b denotes the bank FE, α_t denotes the time FE. The variables of interest are Count and Sentiment. To avoid contemporaneous problems, we use the lagged value for both of them. Figure 8 displays the coefficients β_1, β_2 and β_3:

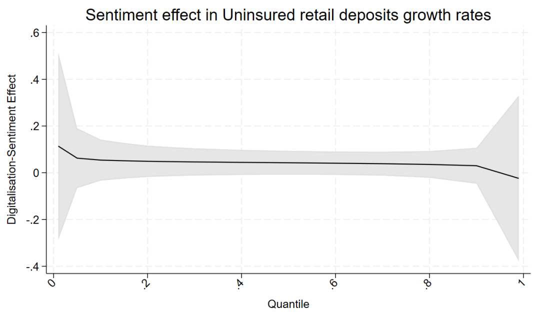
[11] See BCBS (2023a).



A: Digitalisation coefficient (β_1)



B: Number of tweets coefficient β_2



C: Sentiment coefficient (β_3)

Figure 8: Digitalisation, number of tweets and sentiment coefficients

Notes: Distribution of point estimates from Equation 4 and 5% confidence interval.

Figure 8 shows that we do not find a causal effect of social media on deposit flows, neither during normal times, nor during stress episodes. Panel A shows the app effect on uninsured retail deposits. Similar to the baseline regression, we obtain a negative coefficient at the tail of the distribution. The coefficient in the left tail of the distribution (where all growth rates are negative) is negative, meaning that the negative growth rates are even more negative for banks that provide a banking app. Our results hold for both the count and sentiment indicators. Further, we still find the same coefficient in the left tail of the distribution for the digitalisation variable, rendering further support for our hypothesis that the effect of the use of online banking on extreme deposit flows is robust across deposit categories and samples. In sum, we take these findings as evidence for the overall conclusion about the March 2023 banking turmoil in that that the turmoil was limited to idiosyncratic cases.

This analysis is however subject to one limitation. Typically, bank-level information is available at quarterly (or lower) frequency. In this regard, the availability of granular bank information at monthly frequency is a key advantage of this study. Yet, we cannot exclude that extremely flighty deposits over the span of only a few days as they occured amid the March 2023 banking turmoil would not yield a more accurate picture when it comes to analysing the potential impact of social media which has a tendency to spread news in quasi real-time.

3.7 Sensitivity to the size of the tails

As detailed in Section 2, the distribution of deposit flows takes an inverse t-shape with very long tails. As a consequence, results can be sensitive to the number of large observations in the tails. To investigate how sensitive results are to the values in the tails and the size of the tails more generally, we also re-run the baseline regressions for a different cut-off point for the tails.

Specifically, since the FINREP data set has larger tails, i.e. a stronger dispersion than the COREP data set due to its aggregation also at country level, we also estimate the advanced model cutting 5% of observations at each tail as a robustness check. As mentioned in section 2 the FINREP data by definition displays more extreme values than the COREP data due to the combination of consolidation at the group level and then additionally providing a breakdown by country. To investigate whether our results are driven by including these extreme values, we also cut 5% of each tail instead of the 2.5% common in the literature. Figure 15 in Appendix displays the distribution of the coefficients β_1 and β_2 for this exercise.

Not surprisingly, after cutting at the 1% quantile the coefficient β_1 stands at -0.149, which is close to the coefficient at the 5% quantile if we do not cut the tails at 5%. Therefore, the exercise confirms the robustness of the effect, and that it approximately halves when we remove the most extreme dispersion from the data. The coefficient β_2 is marginally significant for the 1% quantile of the distribution when cutting 5% of the tails. However, most coefficients β_2 also remain insignificant when cutting 5% of the tails.

4 The effect of digitalisation on the interest rate sensitivity of deposits

One key finding in Koont et al. (2024) is that the sensitivity of deposit flows to changes in interest rates also depends on digitalisation, i.e. that interest rate sensitivity has increased with digitalisation. In other words, conditional on observing a higher interest rate in the market, deposits of more digital banks are more prone to flight to other type of assets. We therefore conduct a similar analysis for estimating the interest rate sensitivity of deposits conditional on the level of digitalisation of the bank.

We proceed in two ways. In Section 4.1 we use an ECB dataset on the digitalisation level for a subset of banks. In Section 4.2 we use the same mobile app data as in our baseline model and merge it with the average 10-year sovereign bond yields for the 19 euro area countries for which the ECB sets monetary policy rates, and run the regression for the period 2016-2024.

4.1 ECB digitalisation data and interest rate sensitivity

This section builds on ECB digitalisation data for 28 banks in 2023. This data has been collected directly from supervised banks by the ECB in its supervisory function. Digitalisation is measured as the percentage of bank customers who used any virtual method for a transaction with the bank in the last three months.

Figure 9 displays the distribution of bank-specific digitalisation levels. Even though only 28 banks are covered, there is discernable variation in the level of digitalisation.

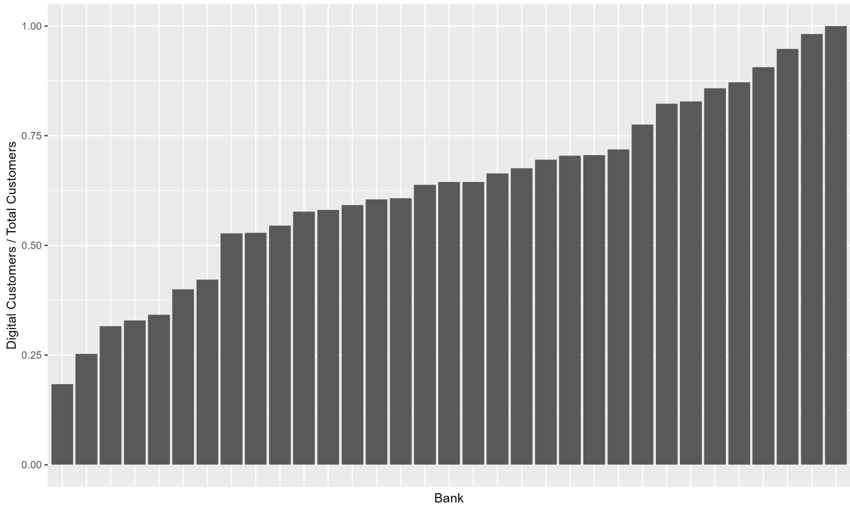


Figure 9: Bank-specific digitalisation level

Note: The bank-specific digitalisation level is defined as the percentage of bank customers who used any virtual method for a transaction with the bank in the last three months. Source: The data has been collected by the ECB directly from banks.

Identification is derived from comparing deposit flows between banks. The bank-level digitalisation variable is available only for one point in time. Therefore, we can assign different levels of digitalisation to each bank in the sample, something which is not possible for the country-level use of online banking variable which we use in the previous section. At the same time, this is an improvement compared to the binary digitalisation variable based on the use of an app. Nevertheless, we can only derive identification from a between-bank comparison.

Given that the sample of banks is small and in view of the fact that we need variation in the interest rate to identify an effect of interest rate changes on deposit flows, we use monthly data on changes in 10-year sovereign bond yields from the FRED data base[12] to capture changes in the long-term interest rates. We focus on the period between 2020-2024, a time window for which we assume that digitalisation levels between banks have not changed significantly. A further complication is the fact that interest rates by definition only vary over time, but not between banks, as all banks are within the jurisdiction of the European Central Bank (euro area). Since we want to essentially capture the effects of monetary policy, we do not use country-specific yields as these also reflect differences in countries' fiscal policies. Therefore, the regression compares deposit

[12]https://fred.stlouisfed.org/series/IRLTLT01EZM156N

flows between banks conditional on the overall level of interest rates.

To estimate the effect, we regress deposit flows at time t, $d_{b,t}$, on time and bank fixed effects α_t and α_b, the change in 10 year yields in month $t-1$ (to address autocorrelation) interacted with the bank's digitalisation level $Digital_b$, as well as on the bank's size approximated by asset growth in $t-1$, $log(Assets_{b,t-1})$, as well as an interaction of the bank's size with the change in interest rates in $t-1$, and on the bank's return in asset growth in $t-1$, $\Delta ROA_{b,t-1}$. The model is estimated with OLS, includes time and bank fixed effects, and robust standard errors.

$$\begin{aligned} d_{b,t} &= \alpha_t + \alpha_b + \beta_1 \Delta i_{t-1} \times Digital_b + \beta_2 \Delta i_{t-1} \times log(Assets_{b,t-1}) + \\ &\quad \beta_3 log(Assets_{b,t-1}) + \beta_4 \Delta ROA_{b,t-1} + \epsilon_{b,t} \end{aligned} \tag{5}$$

Table 1 displays the estimated coefficients when using total deposit growth and uninsured retail deposits as a dependent variable. We estimate the effect without time fixed effects in column (1) and with time fixed effects in column (2). We show the column (1) results to provide an idea of the sign of the coefficient on interest rates which is hidden in the time fixed effects in column (2). The sign of this coefficient is relevant for determining whether interest rate sensitivity is higher or lower for more digitalised banks. The coefficient β_1 is negative, which would indicate lower sensitivity to interest rates for more digitalised banks, but neither of the two coefficients is statistically different from zero.

Table 1: Digitalisation and Interest Rate Sensitivity on Deposits

	Total Deposits		Uninsured Retail Deposits	
	(1)	(2)	(3)	(4)
Coefficient on:	Growth Rate	Growth Rate	Growth Rate	Growth Rate
Δi_{t-1}	0.0512		0.0570	
	(0.95)		(0.72)	
$\Delta i_{t-1} \times \mathrm{Digital}_b$	-0.0296	-0.0280	-0.0403	-0.0475*
	(-1.27)	(-1.26)	(-1.63)	(-1.77)
$\Delta i_{t-1} \times \log(\mathrm{Assets}_{b,t-1})$	-0.00110	-0.00740	-0.00150	-0.00185
	(-0.55)	(-0.37)	(-0.53)	(-0.62)
$\log(\mathrm{Assets}_{b,t-1})$	-0.0697**	-0.0563***	-0.0264*	0.00720
	(-7.33)	(-8.29)	(-1.74)	(0.78)
$\Delta \mathrm{ROA}_{b,t-1}$	-0.0374	0.253	0.428	0.874**
	(-0.18)	(1.02)	(1.42)	(2.16)
Observations	1473	1473	1416	1416
R-squared	0.0421	0.139	0.00779	0.0620
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes

Notes: Columns (1) and (2) show results for total deposit growth, while columns (3) and (4) show results for uninsured retail deposit growth. A positive coefficient on Δi_{t-1} indicates higher deposit growth for a 1pp change in the interest rate. A negative coefficient on $\Delta i_{t-1} \times \mathrm{Digital}_b$ indicates that digitalised banks are less sensitive to the change in interest rates, i.e. digitalisation dampens the effect. *t* statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Given that the digitalisation effect is insignificant for total deposits also in our baseline analysis (i.e. when we only use the binary indicator on app availability), we repeat the same analysis for uninsured retail deposits, the results of which are shown in Columnns (3) and (4). Here, we also find a positive sign for the interest rate effect alone, while the sign for interest rate sensitivity conditional on higher levels of digitalisation is negative. The latter coefficient is marginally significant.

4.2 Google Play data and interest rate sensitivity

To expand the sample and to introduce a time-varying digitalisation variable we use the availability of the app as measure for digitalisation. As a consequence we can use the full sample of banks used in Section 3.3. The digitalisation variable changes at least once per bank at the point in time when there is a review of its app in the Google Play Store. Given that the Covid period saw a surge in digital solutions, we add a dummy variable for April 2020 to control for such a Covid effect in the regressions where we do not include time fixed effects.

$$
\begin{aligned}
d_{b,t} \quad = \quad & \alpha_b + \alpha_t + \beta_1 \Delta i_{t-1} + \beta_2(\Delta i_{t-1} \times \mathrm{Digital}_{b,t-1}) + \beta_3(\Delta i_{t-1} \times \\
& \log(\mathrm{Assets}_{b,t-1})) + \beta_4 \log(\mathrm{Assets}_{b,t-1}) + \beta_5 \Delta \mathrm{ROA}_{b,t-1} + \beta_6 \mathrm{April2020} \\
& \times \mathrm{Digital}_{b,t-1} + \epsilon_{bt}
\end{aligned} \tag{6}
$$

The main difference between equation 6 and 5 is that the digitalisation variable (dummy) changes over time for each bank. As a result, we can control for bank FE and extend our sample to include all banks in the COREP sample.

Table 2 shows results. Column (1) again shows the regression excluding time fixed effects and column (2) shows results including time fixed effects, for total deposit growth. Results differ from the analysis in Table 1 in one key way. The coefficient on interest rate changes is negative, which indicates that deposit outflows are larger for larger changes in interest rates. The negative coefficient on interest rate changes conditional on digitalisation implies that for more digitalised banks this outflow effect is amplified. For example, for each 1% increase in the interest rate, *digital* banks experience a 0.02% reduction in their deposit growth rate compared to banks that do not offer a banking app. Other coefficients are also in line with expectations. For example, larger banks are less sensitive to changes in interest rates, whereas banks that provide a banking app are more sensitive.

Table 2: Interest rate sensitivity and digitalisation: full sample

Coefficient on:	(1) Growth Rate	(2) Growth Rate
Δi_{t-1}	-0.105**	
	(-2.06)	
$\Delta i_{t-1} \times \log(Assets_{b,t-1})$	0.00477**	0.00481**
	(2.33)	(2.33)
$\Delta i_{t-1} \times Digital_{b,t-1}$	-0.0190	-0.0196*
	(-1.63)	(-1.67)
$Digital_{b,t-1}$	-0.00349	0.00190
	(-1.41)	(0.53)
$\log(Assets_{b,t-1})$	-0.00957	-0.00574
	(-1.45)	(-0.68)
$\Delta ROA_{b,t-1}$	-0.516***	-0.574***
	(-2.70)	(-3.58)
Covid (April 2020)	0.146***	
	(2.70)	
$Covid \times Digital_{b,t-1}$	-0.0739	-0.0748
	(-1.32)	(-1.32)
Observations	9174	9174
R-squared	0.0152	0.0325
Bank FE	Yes	Yes
Time FE	No	Yes

Notes: Columns (1) and (2) show results for total deposit growth. A negative coefficient on Δi_{t-1} indicates lower deposit growth for a 1% change in the interest rate. A negative coefficient on $\Delta i_{t-1} \times Digital_b$ indicates that for digitalised banks deposit growth falls less in response to a 1% change in interest rates.
t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusions

This paper introduces deposits-at-risk (DaR) as a novel approach for assessing the determinants of severe deposit outflows. The frequency and intensity of deposit outflows vary between normal periods and stress episodes, and may in rare cases turn into classic bank runs. Without a clear definition of when an outflow constitutes or transitions into a bank run, relying on a well-accepted statistical method for analysing the tails of a distribution can provide clarity on the determinants of severe outflows without having to define a cutoff point for a bank run. In this study we review how common determinants, such as bank-specific characteristics, digitalisation and the role of social media affect the tails of deposit flows for a sample of European banks.

Given the potential endogeneity bias inherent in this literature, associated with the level of digitalisation possibly correlating with unobserved characteristics of banks and depositors, we employ a careful identification strategy to minimize any potentially remaining bank or customer heterogeneity and employ several robustness checks (including a case study at regional level) to validate our results.

In our baseline estimation approach when measuring digitalisation as the availability of a mobile banking app we only find an amplifying effect for uninsured retail deposits and the effect is quantitatively rather small although statistically significant. Moreover, when improving the identification strategy by accounting for unobserved time-varying bank characteristics we find that an increased use of online banking services amplifies severe outflows also for total deposits. At the same time, we do not find an additional amplifying effect for banks having a mobile app when we include the measure of use of online banking services.

The digitalisation effect is robust across different samples. During normal times, neither the use of online banking nor a mobile banking app exert a meaningful effect on deposit flows. When zooming into one country, Germany, and controlling for the use of online banking at the regional level, we also find significant results for total deposit flows, consistent with the cross-country study. The digitalisation effect remains present in the data when adding interest rates as another key determinant of deposit flows. The amplification effect at the extreme tail (1% quantile of the distribution) amounts to 0.28% for a 1% increase in the use of online banking. For the 20.7% average increase in digitalisation for the sample period, this implies a 5.8% amplification effect at the 1% tail. Finally, our analysis does not reveal any amplifying effects for the role of social media on deposit flows at monthly frequency.

More generally, while our study confirms that digitalisation affects deposit flows, it also highlights the need for more comparable bank-level data on digitalisation to robustly discern its effect. Notably, while the availability of a banking app is often used in studies aiming to estimate the impact of digitalisation, at least for determining the impact of digitalisation on deposit flows among European banks, it seems that the general penetration of online banking services is a more relevant predictor. Further research to better measure the multifaceted aspects of digitalisation is key to better understanding its effects.

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Appendix A: Data Construction

Supervisory banking data

To measure deposit flows we use European supervisory data that is collected for banking union banks directly supervised by the European Central Bank. Supervisory reporting templates contain data on financial statements and balance sheets that banks are required to periodically disclose to the relevant competent authorities. The main variables relate to banks' deposit stocks as well as balance sheet data, combined with data from other sources. We focus on two templates which require banks to report deposit data, Common Reporting Framework (COREP) template C.73.00.a and Financial Reporting Framework (FINREP) template F.20.06. The COREP template contains monthly data on specific deposit classes that are relevant for the computation of the Liquidity Coverage Ratio (LCR), including a split between retail and non-financial corporate (NFC) counterparts and between accounts covered and not covered by a deposit guarantee scheme (DGS).

The COREP data set constitutes a balanced sample of 110 Significant Institutions (SIs), i.e. banks supervised directly by ECB Banking Supervision, at the highest level of consolidation across SSM jurisdictions, spanning the period September 2016 to June 2024 on a monthly basis. To address outliers, we delete the highest (lowest) 40 observations. We apply different forms of winsorisation as robustness checks. Fascione et al. (2024) details the data-cleaning process. The FINREP template reports deposits at a quarterly frequency with a breakdown by country for each bank. As detailed in the paper, the breadown by country is associated with a larger dispersion of data points as well as somewhat longer and fatter tails. Therefore, in line with the literature, we remove 2.5% of each tail to address outliers.

Digitalisation proxy based on app use

We construct the digitalisation proxy based on app use as a variable related to the point in time when its app receives at least one review:

$$\mathtt{Digital}_{bt} = 1 \ \mathtt{if} \ \text{Reviews}_{bt} > 0$$

where *Reviews* is the number of reviews that the bank received in Google Play at a given point in time. If we find an app for a bank but there are no reviews on it, then we assume that the app does not exist (Digital = 0). In 2016, this approach classifies 63 out of 104 banks as digital, while in 2023 this approach classifies 88 banks as digital.

We note that the literature uses a second perturbation of digitalisation proxied by app use, from which we refrain in this paper. Specifically, the literature uses a digitalisation proxy constructed as:

$$\mathtt{Digital}^{C}_{bt} = \frac{\mathtt{Reviews}_{bt}}{\text{Average Total Retail Deposits}_{b}}.$$

Typically, this specification of the proxy is used to also have a continuous variable measuring digitalisation based on app use. However, this definition of the digitalisation variable adds variation mainly driven by the size of the bank. Figure 10 shows the variable $\mathtt{Digital}^{C}_{bt}$ over time, after normalising so that it ranges between 0 and 1.

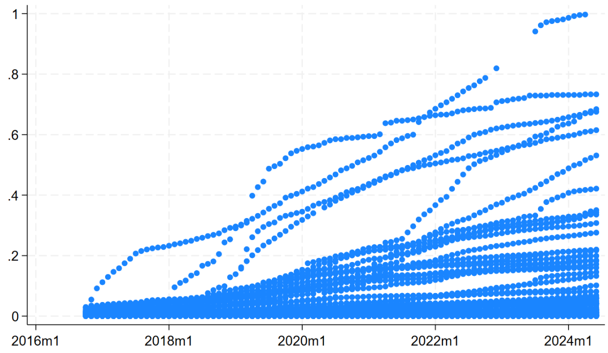


Figure 10: Time-varying digitalisation proxy based on app use

To assess whether the large differences between banks shown in Figure 10 are related to digitalistion rather than bank size, we compare this dataset with the ECB digitalisation data which we use for the case study on German savings banks. Since this data has been directly collected by the ECB's supervisors in 2023 we consider it as close as possible to a bank's true digitalisation level. In the ECB data set there are banks at most 3 to 4 times more digital than others.

Figure 11 shows the correlation between the continuous proxy based on app use and digitalisation level as reported by banks to the ECB in 2023. Given significant outliers in the app data set, we winsorise at 5% to be better able to gauge the correlation. As Figure 11 shows, there is no strong correlation between the bank-reported digitalisation variable and the continuous variable based on app reviews.

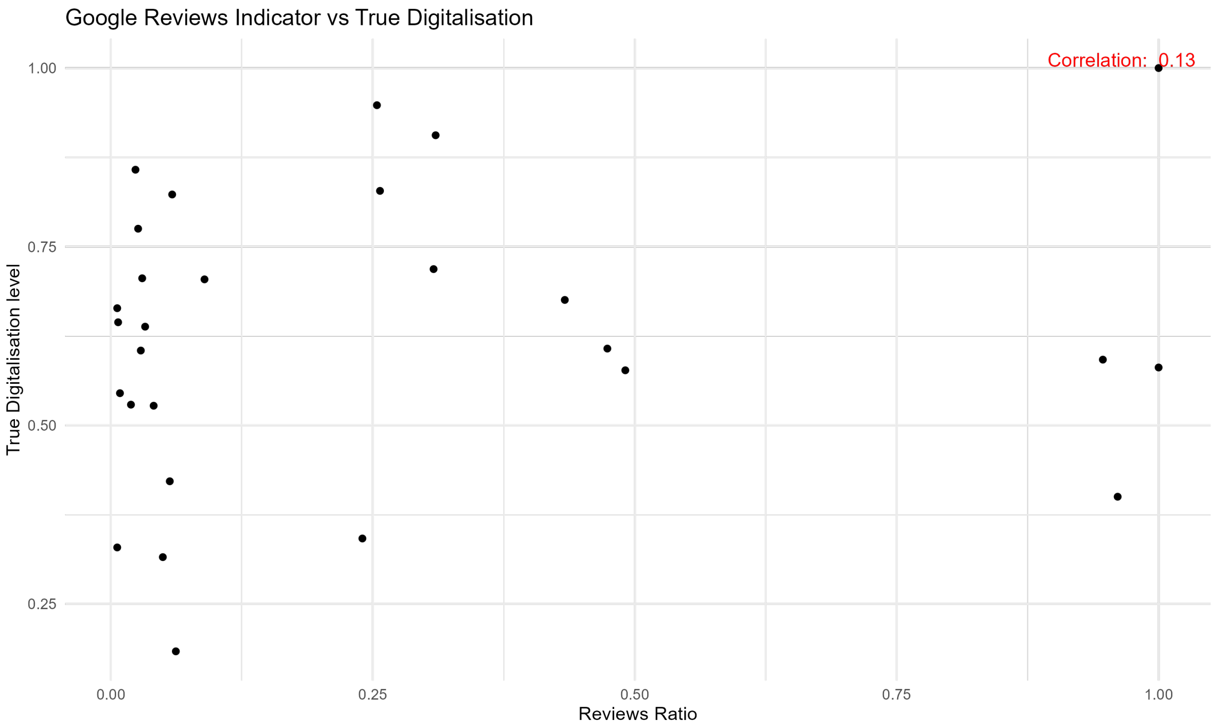


Figure 11: $\mathtt{Digital}^{C}_{bt}$ compared to true digitalisation level

We support this finding by running a simple OLS regression to quantify the degree of correlation between the two variables:

$$\text{True Dig}_b = \alpha + \beta \textbf{Google Review Dig}_b + \epsilon_b,$$

where $TrueDig_b$ is the bank-reported measure of digitalisation, and $GoogleReviewDig_b$ is the continuous digitalisation variable based on app reviews. This exercise renders an R^2 of 0.12 and a correlation coefficient β equal to 0.079 with a p-value of 0.505.[13] As a consequence, we do not use the continuous app-based digitalisation proxy, despite its use in the literature.

Appendix C: Data on the use of online banking services

Data on online banking use from Eurostat is available at an annual basis. We match it with quarterly data from FINREP on total deposits for 88 banks in all EU member

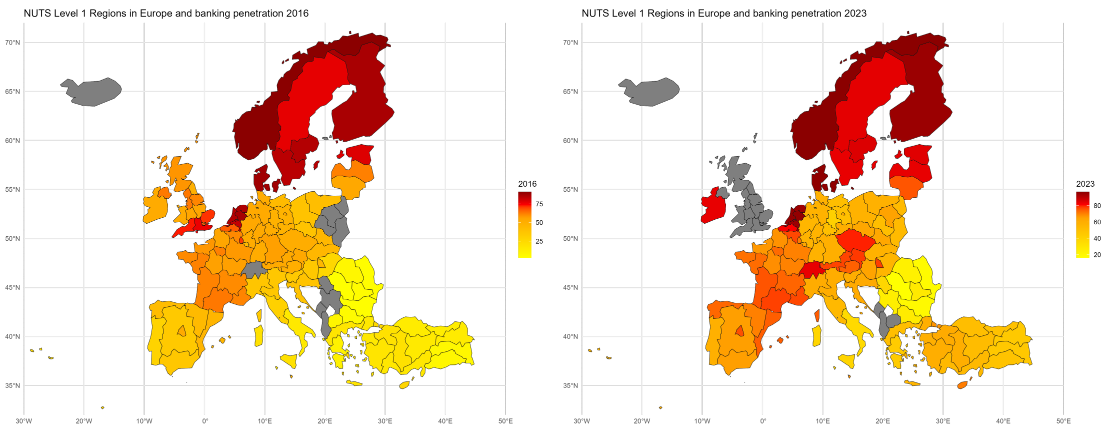
[13] If we keep the outliers, β takes a value of 0.38 with a p-value if 0.0643. However, comparing this to the insignificant and very small correlation coefficient for the winsorised sample, the correlation seems to be driven by very few outliers.

countries. We cut the tails at the 2.5% level.

For the case study on German savings banks, we use monthly supervisory data for 351 German banks. The German regions are assigned an online banking penetration level based on the annual Eurostat information. Given that the dispersion of values in this sample is more homogeneous, we delete only extreme values in each tail, accounting for less than 0.1% of each tail. We combine this data with the Eurostat data on online banking use for each NUTS1 region in Germany, i.e. German states. We match each Sparkasse according to the state in which its headquarter is located (based on the address of the headquarter).

Note that because of a Eurostat change in the calculation of the variable as of 2021, we set the value for 2021 to 2023 to the value of 2020 for each region.

Figure 12 shows the variation in the use of online banking across the EU for the years 2016, the start of our sample, and the year 2023, the last year in our sample. Both panels highlight persistent differences between EU countries, providing sufficient variation in the variable for identification. The comparison of the panels for 2016 and for 2023 illustrates that the use of online banking has also changed over time within countries, providing additional variation for identification.



2016 2023

Figure 12: Variation in the use of online banking across Europe

Figures 13 and 14 present key descriptive data for the German savings banks. Figure 13 shows the online banking penetration variable over time. This figure illustrates that the variable displays variation over time. The figure also shows the structural break in

2021 which Eurostat reports for Germany and Ireland due to revised calculation methods.

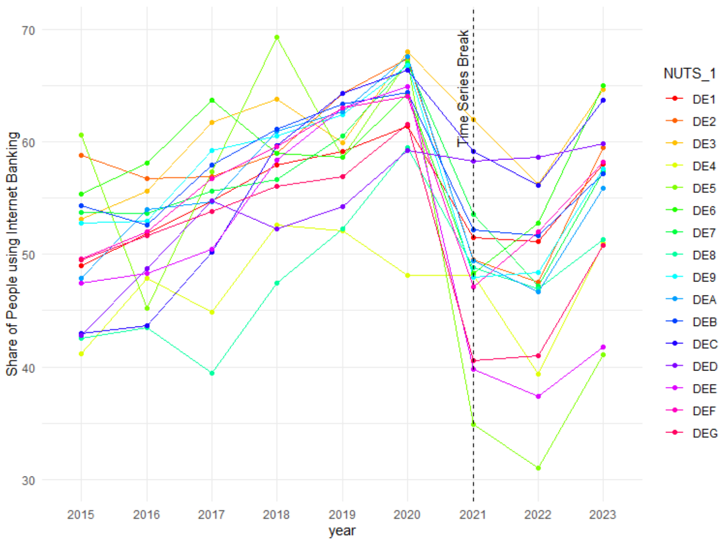
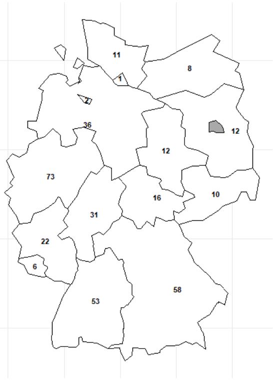
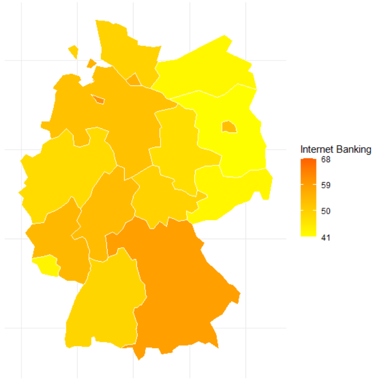


Figure 13: Evolution of internet banking penetration by region

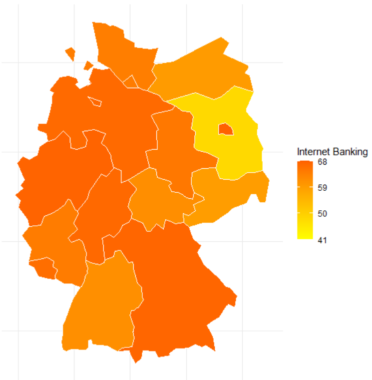
Figure 14 illustrates the variation in online banking penetration across German regions. Panel A shows the number of savings banks for the regional breakdown of the use of banking services variable. Panels B-D show the distribution of the use of online banking services across German states for different points in time. These panels highlight that there is considerable variation across states and also over time.

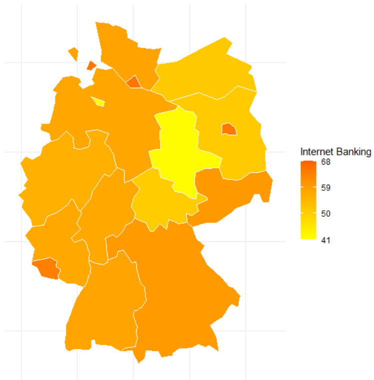




A: German savings banks per region

B: Use of internet banking 2015



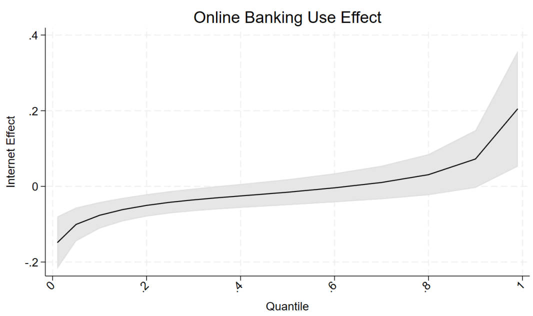


C: Use of internet banking 2020

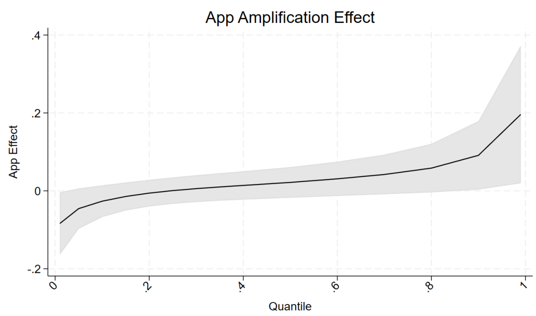
D: Use of internet banking 2023

Figure 14: Number of savings banks and use of online banking in Germany

Appendix D: Additional robustness checks



(a) Panel A: Distribution of β_1



(b) Panel B: Distribution of β_2

Figure 15: Quantile Estimation on Total Deposits 2016-2023

Notes: This figure shows the effect of internet penetration (base effect) and digitalisation (amplification effect) on deposit growth rates for different quantiles. The charts provide a depiction of the within-bank effect as the equation exploits the cross section heterogeneity within banks. Panel [B] shows the confidence interval for the app effect of digitalisation (β_2) on net deposit growth.

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