NBER WORKING PAPER SERIES

DESTABILIZING DIGITAL "BANK WALKS"

Naz Koont
Tano Santos
Luigi Zingales

Working Paper 32601
http://www.nber.org/papers/w32601

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
June 2024, Revised August 2025

We thank our discussants, Mark Egan, Bill English, Thomas Philippon, Maryam Farboodi, and Sarin Schuermann, and participants to the 2023 Summer NBER, the 2024 Five Star Conference, the 2025 Brazilian Finance Association Meetings, and seminars at University of Maryland, the OCC, the Chicago Fed, Yale Law School, and the IESE Workshop on Banking Turmoil and Regulatory Reform. We are thankful to Yiming Ma and Rafael Repullo for extensive comments in successive versions of the paper. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Destabilizing Digital "Bank Walks"
Naz Koont, Tano Santos, and Luigi Zingales
NBER Working Paper No. 32601
June 2024, Revised August 2025
JEL No. G21

ABSTRACT

We develop a model of “stickiness” of bank deposits to study the effect of digitalization on the size and duration of the value of the deposit franchise and, ultimately, on banks’ stability. The model predicts that digitalization increases the sensitivity of deposit levels and rates to changes in the Fed funds rate. We test these predictions using data on the U.S. banking sector, and find that, when interest rates rise, deposit outflows, or “walks”, and deposit rate pass-through are significantly larger at banks with mobile apps and brokerage services. We use these estimates to predict the effects of digitalization on bank stability. Digitalization has ambiguous effects on the value of the deposit franchise, depending on the magnitude of the reduction in the marginal cost of servicing deposits. Still, it unambiguously increases the deposit franchise duration, undermining bank stability.

Naz Koont
Stanford University
Columbia Business School
nazkoont@gmail.com

Tano Santos
Columbia University
Graduate School of Business
and NBER
js1786@columbia.edu

Luigi Zingales
University of Chicago
Booth School of Business
and NBER
luigi.zingales@ChicagoBooth.edu

1 Introduction

Digitalization is changing the nature of the service industry by reducing the importance of location and reshaping cost structures, enabling economies of scale that were once achievable only in the manufacturing sector (Hsieh and Rossi-Hansberg, 2023). This transformation challenges our current understanding of the functioning of many service industries. Is it possible to introduce digitalization in a simple, tractable way into traditional models to provide useful guidance for policymakers in this new digital era?

In this paper, we explore this issue in a key service sector: banking. We study the impact of digitalization on the liability side, specifically, the value of banks' deposit franchise, and the resulting implications for bank stability. A bank's deposit franchise value is the "intangible asset that arises from the bank's ability to pay below-market rates on deposits" (Drechsler et al., 2023b), which stems from the fact that deposits are relatively insensitive, or "sticky", with respect to interest rates (Drechsler et al., 2021). This "stickiness" is central to banks' business model of maturity transformation (Kashyap et al., 2002; Hanson et al., 2015). If this stickiness is sufficiently large that the deposit franchise value of a bank rises with interest rates, it will help hedge losses on rate-sensitive assets, increasing bank stability. Digitalization is likely to reduce stickiness by enabling depositors to walk away to higher-yielding alternatives with just a few taps on a mobile app, all without leaving their sofa. Are these features sufficient to undermine the stickiness of deposits and, in so doing, jeopardize banks' stability?

To answer this fundamental question, we need a model of deposit stickiness to analyze how digitalization impacts this stickiness. We need to test the predictions of this model empirically and estimate its key parameters. Then, we need to use this model and the estimated parameters to predict the level and the duration of the deposit franchise value at different levels of digitalization. This is what we do in this paper.

We begin by modeling explicitly where deposit stickiness comes from. Agents can save either through banks or money market funds (MMFs), based on the classical Salop model of competition (Freixas and Rochet, 2008). Banks offer services unavailable from MMFs but pay lower rates, while agents value proximity, service quality, and rates. We extend the model by introducing heterogeneity in the extent to which depositors are locked in banks, impairing their willingness to explore alternative investments, in line with recent work on depositor behavior (Xiao, 2020; Lu et al., 2024b; Blickle et al., 2024; Egan et al., 2025). In this framework, deposit stickiness arises from agents' desire for proximity and services, as well as the extent to which they are locked in banks, either due to the cost of migrating away from them or due to obstacles in exploring alternatives.

Digitalization has three effects. First, it reduces the cost of accessing distant banks, broadening the effective competitive set. Second, it lowers the barriers to reallocating funds into MMFs, especially when the bank offers integrated brokerage services. It reduces depositors' lock-in and makes them more sensitive to higher-yielding alternatives. Third, it reduces the marginal cost of servicing those deposits.

The model yields two testable predictions: digitalization (i) increases the outflows or "walk" of deposits when the federal fund rate (FFR) increases, and (ii) increases the sensitivity of bank deposit rates to changes in the FFR, or banks' deposit "betas".

We test the model's predictions with data on the U.S. banking sector, beginning with how digitalization affects deposit "walks" in response to hikes in the Fed funds rate. In the cross-section of banks, we find that banks that have a mobile app see greater deposit outflows as the Fed funds rate increases. We find that a 425bps increase in the Fed funds rate, roughly what the Fed increased rates in 2022, leads to a differential drop in deposit growth of 7.2% for non-digital banks, but between 10.6% and 16.6% for digital banks, depending on our definition of digital banks.

Because banks' decisions to offer a mobile app or brokerage services may correlate with other factors that influence deposit outflows, we next analyze deposit flows across branches within bank-year to isolate the role of digitalization. We use internet penetration as a proxy for the extent to which local customers engage in digital banking. Specifically, we examine whether, for a given bank, deposit outflows are more sensitive in counties that have higher internet usage, depending on whether the bank is digital or not. By also comparing banks within the same county, we find that only digital banks see larger outflows in high-internet areas, supporting the view that digital banking, rather than unobserved bank or local characteristics, drives the heightened deposit outflows. This connects well with the implications of our model in which higher levels of digitalization result in higher sensitivity of deposits to fed fund rate shocks.

In our model, digitalization makes depositors more responsive to interest rate changes, but does not change the distribution of depositors along the circle. An alternative model could have digitalization attract a different set of depositors, who are inherently more rate-sensitive. It is important to distinguish between these two possibilities, as they have differing implications for financial stability. In the first case, digitalization increases the overall financial stability risk by increasing the number of flightier depositors. In the second case, digitalization concentrates flightier depositors in digital banks, increasing the risk to the stability of these banks but not that of the overall banking system.

To shed light on which of these two channels is driving our results, we study how county-level aggregate deposit outflows are affected by the diffusion of digital banks, measured as the proportion of digital banks operating in a county. To address concerns that digital banks may have entered markets with flightier depositors, we instrument for digital bank presence using whether the same banks operated in the county in 2009, before the rise of mobile banking. We find that counties with greater digital bank presence experience larger deposit outflows, supporting the view that digitalization increases depositor sensitivity rather than merely re-sorting them, in line with our model mechanism.

Having established that digital banks experience greater deposit walks in response to increases in the Fed funds rate, we test the second prediction of our model: that digitalization increases banks' deposit betas. Consistent with our model's prediction, we find that banks with a mobile app have higher deposit betas, ranging from 0.24 to 0.31 depending on the definition of digital, compared to 0.23 for non-digital banks, and that these differences are statistically significant and hold across the bank distribution.

Having confirmed that our model of deposits' stickiness fits the data, we use it to evaluate the impact of digitalization on banks' deposit franchise, which crucially depends on this stickiness. The model predicts conflicting effects of digitalization. The reduction in the cost of accessing and reallocating funds decreases the deposit franchise's value by undermining banks' ability to retain low-cost funding. In contrast, the decrease in the cost of servicing deposits (Koont, 2023; Hsieh and Rossi-Hansberg, 2023) increases the deposit franchise's value by increasing margins.

Our model reveals a key nonlinearity: while the duration of the deposit franchise is always negative at low Fed funds rate levels, digitalization makes it positive at higher rate levels. Consequently, the effect of monetary tightening on bank stability depends on the level of rates — stabilizing when rates are low, but destabilizing when rates are already high.

Ultimately, the net effect of digitalization on deposit franchise value is an empirical question. By combining our empirical estimates of deposit walks and betas with the model's characterization of deposit franchise value, and incorporating cost estimates from Koont (2023) and industry sources, we can assess the overall impact of digitalization.

First, we consider the level of the deposit franchise value. With marginal cost reductions of about 20% as in Koont (2023), digitalization increases the deposit franchise value only when the Fed funds rate is below 3%. If we believe industry estimates of a 60-70% eventual reduction in marginal costs, digitalization increases the value of the deposit franchise for any Fed funds rate below 6.2%. Second, we turn to the duration of the deposit franchise value, which affects the ability of banks to hedge losses on rate-sensitive assets. In non-digital banks, the duration of the deposit value franchise is always negative for plausible values of the Fed funds rates (below 10%). In digital banks, the duration turns positive at 7% if the marginal cost is still 1.5%. If the marginal cost drops to 1.2%, the duration turns positive at 6.45%. If the marginal cost drops to 0.5%, the duration turns positive at 4.35%.

Thus, as digitalization continues to advance, it may decrease or increase the value of the deposit franchise depending on the extent to which it is able to reduce marginal costs, but, in the empirically relevant range, it unambiguously increases its duration, decreasing bank stability.

Related Literature: Our work builds on a recent set of influential papers by Drechsler et al. (2017, 2021) and Drechsler et al. (2023b). In Drechsler et al. (2017), these authors show that as monetary policy tightens and interest rates increase, banks increase spreads, and deposits flow out of the banking system. They show that the limited pass-through of the Fed funds rate to deposit rates is more pronounced in more concentrated banking markets.[1] In Drechsler et al. (2021) and Drechsler et al. (2023b), they explore the implications of this finding for financial stability. In particular, they argue that maturity transformation serves as a hedge to banks' interest rate risk: "The reason is the deposit franchise, which allows banks to pay deposit rates that are low and insensitive to market interest rates. Hedging the deposit franchise requires banks to earn income that is also insensitive, that is, to lend long term at fixed rates." The key parameter is then the "deposit beta", which determines how much deposit rates, r_d, fluctuate with policy rates, as in $r_d = \beta r$, where r is the policy rate and $\beta \in (0, 1)$ is the deposit beta. As mentioned, they attribute this limited passthrough to imperfect competition among banks.[2] We show a different

[1]See also Berger and Hannan (1989), Diebold and Sharpe (1990), Hannan and Berger (1991), Neumark and Sharpe (1992) and Driscoll and Judson (2013). For an early review of the empirical literature on competition in banking, see Degryse and Ongena (2008).

[2]Hutchison (1995) is, to our knowledge, the first one to propose a formal equilibrium model of imperfect competition in deposit markets in which a constant deposit beta arises out of bank profit maximization; he also shows how this deposit beta depends on the actual number of banks present in the market. See in particular equation (35) in that

determinant of limited passthrough: technology. We also explore the corresponding financial stability implications of this channel.

The stickiness of deposits is an important source of value for banks: The ability of the bank to retain deposits at rates below those depositors could, in principle, obtain elsewhere is potentially a significant component of its equity market value, as we document below. Hutchison and Pennacchi (1996) were the first to write a model to estimate what they referred to as "a bank's monopoly rent from issuing retail deposits." More recently, Drechsler et al. (2023b, p. 9) have referred to the difference between the book and market value of deposits as the deposit franchise value of the bank. This value is, of course, directly related to the sensitivity of deposit rates to other rates available to depositors. Our paper is the first to use this framework to assess the effect of digitalization on the value of the deposit franchise. We argue that digitalization lowers this value and that this has important consequences for financial stability as it lowers the countercyclicality of the deposit franchise value: The deposit franchise value increases by less for digital-broker banks than for traditional banks when interest rates rise.

Digitalization increases the willingness of depositors to walk away when the Fed funds rate increases and banks pass through only a limited increase to their deposit rates. We build on Koont (2023), who documents that banks' digital platform adoption leads to compositional changes in funding towards less stable deposits that require higher interest rates and are more sensitive to bank risk. We follow Drechsler et al. (2021)'s empirical methodology closely and re-estimate the sensitivity of deposit rates to shocks in the Fed funds rate depending on whether banks have digital platforms and offer their customers brokerage services.

More broadly, all these findings are important because they speak to the sensitivity of bank profitability to interest rate changes and overall financial stability.[3] In particular, our work is related to Egan et al. (2017) and Jiang et al. (2023). Egan et al. (2017) explore the financial sta-

paper and the discussion around it.

[3]Samuelson (1945) is an early reference in the literature; see also Hancock (1985). Flannery (1981, 1983) finds that bank profitability have a low exposure to interest rate changes, the reason being that "large banks have effectively hedged themselves against market rate risk by assembling asset and liability portfolios with similar average maturities." English (2002) presents some international evidence consistent with this lack of exposure of bank profitability to interest rates. More recent literature explores banks' exposure, or lack thereof, to interest rate shocks using balance sheet data; see, for instance, Begenau et al. (2015), among others. Finally, another piece of literature looks at changes in bank equity valuation due to shocks in interest rates. See, for example, English et al. (2018), who use high-frequency data to assess the effect of FOMC announcements on bank stock valuation.

bility consequences of uninsured depositors' sensitivity to bank distress. Uninsured depositors are more likely to withdraw in the presence of an increase in the CDS spreads; for instance, the more sensitive uninsured depositors are to distress, the higher the interest rates that banks have to offer depositors, which lowers profitability and makes the existence of a run equilibrium more likely. Jiang et al. (2023) explore the financial stability consequences associated with the losses in the banks' hold-to-maturity portfolios. These losses are the result of the unprecedented speed of interest rate rises by the Fed throughout 2022 (see also Drechsler et al. (2023a)). If interest rate increases are small, so are the losses and a run equilibrium does not exist, whereas it does if the rate hike is large enough. Acharya et al. (2023), as Blickle et al. (2024), are concerned with the instability of deposit funding associated with the expansion and contraction of the Fed's balance sheet during QE and QT (quantitative tightening) episodes: Banks finance reserve holdings with deposits but do not shrink them when they lose them as the Fed pivots away from QE to QT. Financial market integration is another channel that can affect deposit stability. D'Amico and Alekseev (2024) study the dynamics of US financial markets integration between 1953 and 1983. They argue that the increase in nominal interest rates reduced the dispersion of lending rates across states significantly, as households substituted low paying local deposits with national instruments marketed precisely to facilitate the reallocation of funds across state lines, such as negotiable CDs.

From a modeling perspective our paper adds to a recent literature on depositor heterogeneity (Xiao, 2020; Lu et al., 2024b; Blickle et al., 2024; Egan et al., 2025). In these models there are different depositor clienteles who differ in their sensitivity to rates, which has implications for monetary policy transmission, bank stability and so on. We contribute to this literature by focusing on the effect of technology on the nature of these clienteles. In our model, digitalization affects depositors in multiple ways. First, digitalization decreases the fraction of customers locked in the current bank, for whom the cost of exploring alternative investments, such as money market funds or even other banks, is high. Second, it also affects the marginal costs of deposits, which we show has important effects on the value of the deposit franchise.

Our paper is also related to Haddad et al. (2023). These authors propose a model in which depositors face a cost when switching from one bank to another. They investigate the depositor incentives to switch even when fully insured. In their model, depositors value the stream of services banks offer in addition to the interest in deposits. Banks can still fail, which occurs when all depositors withdraw their deposits. In this case the depositor loses the present value of the stream of services associated with her deposit account. This makes her more likely to switch, and these switching incentives are more pronounced when interest rates are high. The usual complementarity obtains across depositors, which results in a run equilibrium even when depositors are fully insured: Depositors run not because that allows redemption in full ahead of others, but simply because when failure is anticipated the present value of the stream of banking services is lower, justifying bearing the costs of switching. We provide evidence that one effect of digitalization and brokerage services is to lower the cost of reallocating funds across more remunerative alternatives, either across banks or other vehicles such as mutual money market funds offering higher rates or within banks offering brokerage services. Digital-brokerage banks increase their betas, offering a higher interest rate to depositors to compensate for these lower switching costs, and in doing so lower their franchise value.

Finally, there is a small but rapidly growing literature on the effect of digitalization on banks.[4] In a contemporaneous piece Erel et al. (2023) study online banks' deposit flow sensitivity to changes in the Fed funds rate. Their focus is on banks that interact with customers mostly or entirely online, and their sample comprises seventeen banks that represent about 5% of total system deposits. They find that online banks increase interest rates significantly more than traditional banks and do not experience deposit outflows. We focus on banks that have branches and digital platforms, not online-only banks, and find that they increase rates more than banks with no digital platforms, but likely less than these online-only banks, and that, in addition, they experience greater deposit outflows than traditional banks. In subsequent work to the present piece, Benmelech et al. (2023) study the relation between branch density, bank branches divided by deposits, and deposit inflows and outflows. They show that banks with low branch density experienced larger deposit outflows during the banking crisis in the first quarter of 2023. They suggest that digital banking allows banks to grow their (uninsured) deposit base fast, but that these inflows are fickle and ready to leave at the first sign of bank trouble. We instead use a direct measure of digitalization and estimate the deposit beta, as well as the deposit outflow sensitivity of these banks, which allows us to estimate the deposit franchise value for them and study banking stability in a world of digital banking and interest rate shocks. Lu et al. (2024a) find that customers shift deposits across bank accounts more actively as payment technologies become more efficient, which provides complementary evidence in a different context to our findings that digitalization leads to a more interest-sensitive deposit base. Related to the recent banking crisis,

[4]See Stulz (2019) for a discussion of how digitalization and FinTech threaten banks' business models.

Cookson et al. (2023) document the role of social media, specifically Twitter, in fueling the bank run at SVB. In the broader literature on bank digitalization, Jiang et al. (2022) explores the effects of bank competition in the era of digital banking on financial inclusion. Haendler (2022) documents the effects of mobile banking competition on the business models of small community banks. Hong et al. (2019) show that the digitalization of asset management can lead to highly synchronized investor behavior. Curi et al. (2023) show that the digitalization of banking has been a significant factor in market valuation, especially during the Covid-19 shock. Our work is most closely related to Koont (2023), who traces out the effects of endogenous adoption of digital platforms on the industrial organization of the banking sector and the effects on financial stability through changes in banks' balance sheet composition. We focus on the effect of digitalization on the stickiness of the deposits and the value of the deposit franchise.

The rest of the paper proceeds as follows. Section 2 builds a simple model of monopolistic competition in banking to derive the effect of banks' digitalization in equilibrium. Section 3 presents the data, and Section 4 tests the empirical predictions of the model and estimates the key parameters. Section 5 uses the model and the estimated parameters to predict the level and duration of the deposit franchise level at different levels of digitalization, particularly in relation to the recent period of rate hikes that began in 2022 and led to significant banking instability. Section 6 draws some conclusions.

2 Digitalization and banking

2.1 Banks and MMFs

The economy is a cylinder of height 1 and radius ρ. Savers are uniformly distributed on the surface of the cylinder, and two banks are located at opposite edges of the cylinder (see Figure 1). Savers travel to banks along the Salop circle that goes through their location in the cylinder. Thus, the saver at location x, who lives in neighborhood $\mathcal{N}_x$, is at a distance x from Bank 1 and at a distance $\ell - x$ from bank 2 (where $\ell \equiv \pi\rho$).[5] All distances along the surface of the cylinder are measured with respect to Bank 1.

[5] A quick introduction to the standard Salop model applied to banking is Freixas and Rochet (2008, p. 68-70). Inefficient entry has been the focus of much of the literature. We abstract from this aspect to focus on the simplest model needed to analyze how digitalization impacts competition and rate-setting.

Each saver has \$1. They want to transfer this \$1 to the second period in order to consume. Banks offer services and checking accounts at an interest rate on deposits of r_i^D, with $i = 1, 2$. The utility savers derive from these services is given by $s^B - \alpha x$,[6] where α represents the costs per unit of distance of accessing traditional banking services: checking accounts, payment services, and so on. These costs are referred to in the literature as "shoe-leather" costs, a leftover of a time when people were walking to the bank branches with shoes with leather soles. s^B is the utility derived by the bank services enjoyed by a depositor who is located in the same place as a bank.

The utility of the saver when they save through a checking account in Bank 1 and 2 is then given by

$$u_1^B(x_1) = 1 + r_1^D + s^B - \alpha x \qquad \text{and} \qquad u_2^B(x_1) = 1 + r_2^D + s^B - \alpha(\ell - x_1), \tag{1}$$

respectively.

Banks want to raise deposits because they have lending opportunities elastically supplied at a rate r^L. For that, they compete for deposits offering deposit rates r_i^D. Deposits carry a marginal cost c.

There is also a competitive MMF industry that offers no banking services but offers a rate of f, the Fed funds rate. This industry is located as a line going through the middle point of the cylinder[7] and all savers bear a cost of accessing that is equal to ρ, the radius of the cylinder, which

[6] To stay as close as possible to the existing literature we present a model where rates and services are separable; the model is thus very close to the one presented by Freixas and Rochet (2008). These authors normalize $s^B = 0$; instead, we impose that $s^B > 0$, which plays a role supporting banking in the presence of competition from money market mutual funds. Indeed, if instead, we were to assume that $s^B = 0$, then a depositor who is colocated with the branches of either bank would deposit with it only if $r_i^D > f - \rho$, that is when the deposit rate is higher than the rate net of fees they can obtain in the MMF, which is counterfactual: There must be benefits of holding deposits. The literature has modeled these benefits as a preference for liquidity or some form of cash-in-advance constraint.

[7] There is a small literature that models monopolistic competition among differentiated suppliers along a Salop circle who also face the competition of an undifferentiated product supplier located at the center; see Madden and Pezzino (2011). In banking, there have been very few applications of this idea. For instance, Hemingway (2023) considers a model of deposit-taking banks competing among themselves and with a central bank offering a digital currency. He focuses on the interbank market implications of the introduction of a central bank digital currency when depositors face liquidity shocks. Nielsen and Weinrich (2023) also models shadow banks as an intermediary at the center of the Salop circle. The focus of this paper is on depositor migration to shadow banks when the costs of capital regulation are passed onto them in the form of lower deposit rates and services. More recently, Vives and Ye (2024) study competition between banks and fintechs in the lending market, where fintechs, of which there are two in their

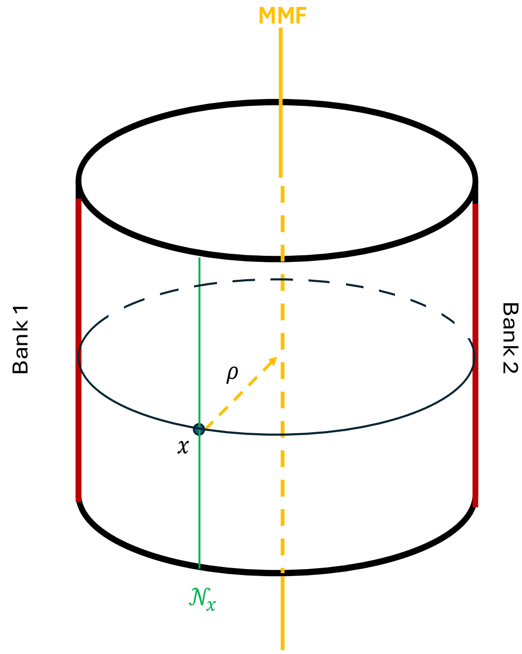


Figure 1: **The Salop cylinder**: The economy is a cylinder of height 1 and radius ρ. Savers are uniformly distributed on the surface of the cylinder and the banks are located at opposite edges of the cylinder (in red). Banks have a continuum of branches along the edge where they are located so all the agents along the a vertical line in the cylinder (in green) are at the same distance to the bank: Savers travel to the bank along the Salop circle that goes through their location in the cylinder. Thus the saver at location x, who lives in neighborhood $\mathcal{N}_x$ is at a distance x from Bank 1 and at a distance $\ell - x$ from Bank 2 (where $\ell \equiv \pi\rho$). A MMF is located as a line going through the middle point of the cylinder (in orange) and all savers bear a cost of accessing that is equal to ρ, the radius of the cylinder. In each neighborhood $\mathcal{N}_x$, there is a fraction of savers p, independent of x, who can access digital options and a fraction $1 - p$ that cannot.

represents whatever fee savers are charged to invest in the MMF.[8] Thus accessing the MMF is independent of the location of the saver: The MMF offers an undifferentiated product. The utility of saving through the MMF is given by

$$u^M = 1 + f - \rho. \tag{2}$$

model, are located at the center of the Salop circle. None of these papers is concerned with understanding deposit betas, the sensitivity of deposits to shocks in the fed funds rate, or the effect of digitalization on these magnitudes.

[8] In this our model is similar to Drechsler et al. (2017), who also consider competition with banking alternatives; see expression (6) in that paper and the discussion around it. As an aside, the model can be extended to allow for a monopolistic MMF industry.

2.2 Digitalization

When it comes to retail, in products or services, digitalization is about lowering the costs of access. In our framework, digitalization reduces the costs of access along two dimensions. First, it lowers access costs to traditional banking services through a lower α. Second, it lowers the costs of access to MMFs, on which more below. Finally, digitalization allows for lower marginal costs c as, for instance, less tellers are needed per branch to service depositors who can now obtain basic services through the bank's digital applications.[9]

Since the advent of the internet, banks have introduced mobile and desktop applications that facilitate access to their banking services. We refer to these applications as digital for short. Banks differ in the way they design their digital applications, making it easy for their customers to locate attractive alternative options for their funds. In addition, banks may differ in the access they give their customers to different corners of financial markets. For instance, some banks give access to brokerage services, whereas others just give access to basic banking services. There is indeed evidence of cross-sectional variation in the digital features offered by banks, judging by the reviews given by customers on the quality of their digital banking experience.[10]

In addition, there is growing evidence that depositors exhibit heterogeneity in their willingness to explore alternative investment options (Blickle et al. (2024) and Egan et al. (2025)). This heterogeneity is modeled as differential valuation for banking services (Xiao (2020)) or different degrees of "alertness" (Egan et al. (2025)). We model it as the ease of use of a digital interface. Depositors have a heterogeneous opportunity cost to explore their bank's digital options. Those with low opportunity costs look for alternatives and are ready to reallocate funds. In contrast, high-opportunity-cost depositors do not explore these alternatives and do not reallocate funds.

Given this distribution, the proportion of depositors who reallocate depends on the existence and ease of use of the digital app offered by a bank. Digitalization decreases the fraction of customers locked in the current bank, for whom the cost of exploring alternative investments is high enough to make them *consider* moving their funds away from the checking account.

Let this fraction be denoted by $p \in (0, 1)$, independent of neighborhood. A bank with a high p is one where depositors are less locked in and more actively comparing alternative investments.

[9] We thank our discussant, Thomas Philippon, for encouraging us to consider the effect of digitalization on the marginal costs of servicing deposits. We explore this effect in depth in Section 5 below.

[10] Note that we take digitalization as exogenous here. Koont (2023) studies the endogenous adoption of digital banking in a structural model of banking competition.

Alternatively, we can think of p as the probability that a depositor is attentive, as in Egan et al. (2025). The key assumption here is that good digital design reduces the lock-in and makes it easier for depositors to compare alternatives.

Banks have two possible strategies. They can compete for the marginal non-locked-in depositors or give up on those and focus on exploiting the locked-in ones. In the model, this second strategy is tantamount to a perfect first-degree price discrimination, which banks are unlikely to be able to do in practice. Therefore, both in the model and the calibration, we assume that banks cannot price discriminate and thus *always* compete for the non-locked-in depositors.

To simplify the presentation of our results, we also assume that depositors can only save through banks or MMFs, that is they cannot store their dollar "under the matress". This can be added at the cost of additional notation but for little additional economic intuition. In other terms, our assumption is that banks and MMFs are always competing for the marginal depositor who has an inelastic demand for instruments to transfer his savings from today to tomorrow.

In sum, in our framework, digitalization lowers the costs of access to traditional banking services, α, and facilitates the reallocation of funds to alternative saving vehicles such as MMFs, through a higher p. Thus, we say that a bank is "more digital' than another if it has a higher p and a lower α. In addition, recall, digitalization may lower the marginal cost, c.

2.3 Monopolistic competition between banks

Before characterizing the competition between banks and the MMF industry, it is helpful to review the standard case of monopolistic competition between banks, that is, in the absence of a MMF industry. In this case, interest rates and deposits are standard:

$$r_i^D = r^B \equiv r^L - c - \alpha\ell \quad \text{and} \quad D_i = \ell \qquad \text{for} \quad i = 1, 2 \tag{3}$$

as the marginal agent is located $\overline{x} = \frac{\ell}{2}$. In (3) we have defined r^B as the deposit rates that obtain when banks are the only alternative. Bank profits are given by $\Pi^B = \alpha\ell^2$, that is, they are increasing in the shoe-leather costs α, and the distance between banks ℓ as the higher these parameters the lower the competition among banks.

2.4 Equilibrium characterization

2.4.1 Equilibrium conditions

Return now to the cylinder economy and reintroduce the MMF industry as described in Figure 1. We consider a situation in which all agents are endowed with a checking account at date $t = 1$. At date $t = 1$ the Fed funds rate is announced and agents reoptimize their savings vehicle, staying or switching banks with their checking accounts, or potentially shifting their funds to a MMF if they are non-locked-in depositors.

Let $\overline{y}_i$ the location of the attentive depositor that is indifferent between saving through bank i or through the MMF (recall that all distances are measured with respect to Bank 1):

$$r_1^D + s^B - \alpha\overline{y}_1 = f - \rho \qquad \Rightarrow \qquad \overline{y}_1 = \alpha^{-1}\left(r_1^D + s^B - (f-\rho)\right) \tag{4}$$

$$r_2^D + s^B - \alpha\left(\ell - \overline{y}_2\right) = f - \rho \qquad \Rightarrow \qquad \overline{y}_2 = \alpha^{-1}\left(-r_2^D - s^B + (f-\rho) + \alpha\ell\right). \tag{5}$$

Instead, locked-in depositors only compare across banks and thus the indifference condition is the standard in this class of models,

$$r_1^D + s^B - \alpha\overline{x} = r_2^D + s^B - \alpha\left(\ell - \overline{x}\right) \quad \Rightarrow \quad \overline{x} = \frac{\left(r_1^D - r_2^D + \alpha\ell\right)}{2\alpha}. \tag{6}$$

Deposits are then given by

$$D_1 \equiv 2\left[p\overline{y}_1 + (1-p)\,\overline{x}\right] \qquad \text{and} \qquad D_2 \equiv 2\left[p\left(\ell - \overline{y}_2\right) + (1-p)\left(\ell - \overline{x}\right)\right], \tag{7}$$

for Bank 1 and 2, respectively. The bank's problem is then to choose r_i^D to maximize

$$\Pi\left(r_i^D\right) = \left(r^L - r_i^D - c\right) \times D_i \qquad \text{for} \quad i = 1, 2.^{11} \tag{8}$$

2.4.2 Equilibrium characterization

To build intuition on the main result of the paper, it is helpful to write the reaction function of the two banks. Maximizing (8) and rearranging

$$r_1^D = \frac{1}{2}\left(r^L - c\right) + \frac{\omega(p)}{2}\left(r_2^D - \alpha\ell\right) + \frac{1-\omega(p)}{2}\left(f - \left(s^B + \rho\right)\right) \tag{9}$$

[11] Notice that we have assumed that banks can only lend the funds raised in deposit markets. Realistically, banks can borrow in the interbank market at a rate f, the Fed funds rate. Banks, in principle can avoid the costs c_i by borrowing in the interbank markets, but these costs also capture the costs of discovering lending opportunities associated with deposits (mortgages, consumer loans, ...), thus they cannot be avoided by borrowing in interbank markets without sacrificing lending opportunities.

where

$$\omega(p) \equiv \frac{1-p}{1+p}, \tag{10}$$

and similarly for Bank 2.

The deposit rate paid by Bank 1 is a convex combination of three terms. The first is the overall surplus associated with lending, which is the lending rate net of the marginal costs associated with deposits. The second is the alternative surplus the saver could obtain if instead she banked with Bank 2. Notice that it does not depend on s^B as both banks offer the same maximum level of services. The third is the surplus associated with her savings through the MMF instead: she now earns the Fed funds rate, pays fees, ρ, and forgoes banking services s^B. Thus, the agent captures half of the overall surplus, and the other half is determined by which margin of competition is more relevant for Bank 1: Bank 2 or the MMF industry. The weight $\omega(p)$ reflects the intensity of competition with the other bank. If $p \simeq 0$, then few savers can access the MMF and thus the deposit rate is mostly set by considering competition for deposits with the other bank. Instead, if $p \simeq 1$, then the key margin of competition is with the MMF.

The model then captures neatly how competition with different financial intermediaries interacts with the distribution of clients who are alert to more attractive market opportunities, the non-locked-in depositors, versus the more traditional savers who essentially shop across different banks for banking services but are unable to take advantage of those opportunities that can be accessed though the bank's digital services.

The next Lemma describes the equilibrium rates and deposits that obtain in this model, under the assumption that the equilibrium is in the "interior". This requires the federal funds rate to be neither too high, otherwise only locked-in depositors hold deposit accounts, nor too low so that no saving takes place through the MMF. That is, $f \in \left(\underline{f}, \overline{f}\right)$ (see Appendix A.1.2 for details). Importantly, $\underline{f}$ can be negative, as it is in our calibrations below, and thus the model can be used to analyze competition and stability at the zero lower bound (ZLB).

Lemma 1 *The (symmetric) equilibrium level of deposit rates and deposits are given by*

(a) Deposit rates

$$r^D(f) = \overline{r} + \beta(p) f \tag{11}$$

where

$$\overline{r} \equiv \left(\frac{1+p}{1+3p}\right)\left[r^B + (1-\omega(p))\left(\alpha\ell - \left(s^B + \rho\right)\right)\right] \tag{12}$$

and

$$\beta\left(p\right)\equiv\frac{2p}{1+3p}\in\left(0,\frac{1}{2}\right) \tag{13}$$

and r^B *and* $\omega(p)$ *were given by* (3) *and* (10)*, respectively.*

(b) Deposits

$$D\left(f\right)=\overline{D}-\eta\left(p,\alpha\right)f \tag{14}$$

where

$$\overline{D}\equiv\left(1-p\right)\ell+2p\alpha^{-1}\left(\overline{r}+s^B+\rho\right) \tag{15}$$

and

$$\eta\left(p,\alpha\right)\equiv 2p\alpha^{-1}\left(1-\beta\left(p\right)\right)). \tag{16}$$

where, given our focus on the symmetric equilibrium, we have dropped the "i" and have emphasized the dependence of the deposit beta and outflows on the relevant digitalization parameters of the model.

Start with (11). Deposit rates are an affine function of the Fed funds rate, where the deposit beta is given in (13). Notice that when $p=0$, the deposit beta equals zero and the intercept, (12), collapses to the expression for the deposit rate when only banks compete with each other (see expression (3)).[12] Deposits are also an affine function of the Fed funds rate. Once again, it can be immediately checked that when depositors cannot access the MMF, when $p=0$, the equilibrium level of deposits for each bank is as in (3), $D_i=\ell$.

In expressions (11) and (14), $\overline{r}$ and $\overline{D}$ are the deposit rates and level of deposits, respectively, that obtain at the zero lower bound. In (12), there are three determinants of the intercept. First, there is the competitive pull of other banks, as determined by r^B and the distance between them mediated by the shoe-leather costs $\alpha\ell$. The second determinant is the competitive pull of the MMF, which is higher the lower the term $s^B+\rho$, the opportunity cost of investing in the MMF. Finally, there is the mix of depositors who are non-locked-in and thus sensitive to shocks in the Fed funds rate, p.

[12] A bit of algebra shows that the deposit rates in (11) can also be written as $r^D=(1-\beta(p))\overline{\overline{r}}+\beta(p)f$, where $\overline{\overline{r}}$ is the term in brackets in (12). Thus digitalization *increases* the sensitivity of deposit rates to money market rates and diminishes the weight in its fixed component.

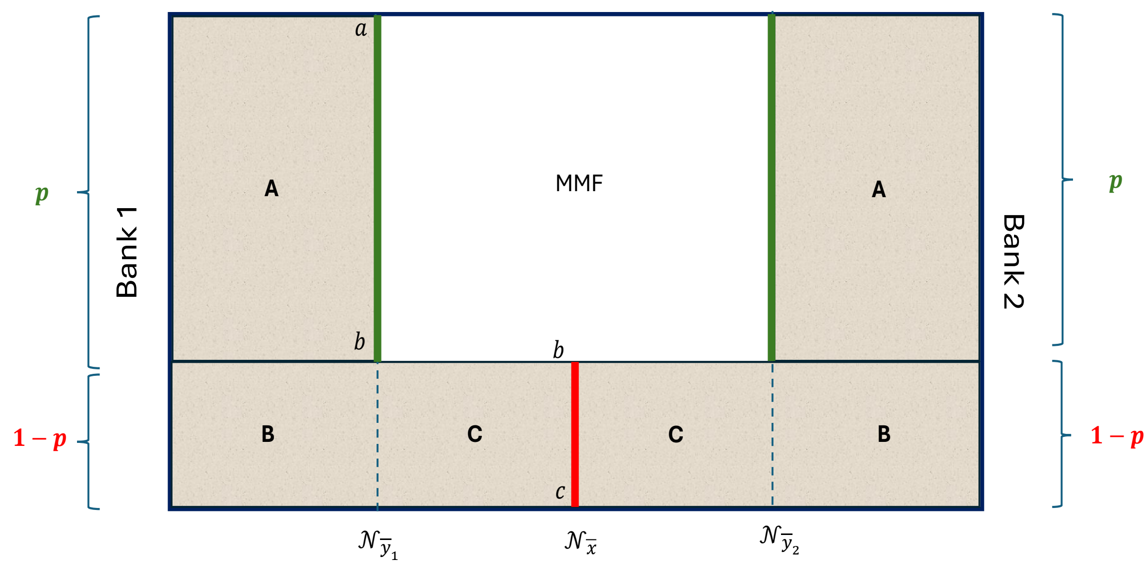


Figure 2: **Symmetric Equilibrium**: Distribution of deposits and MMF accounts in the one half of the cylinder. The set of savers on the segment $\overline{ab}$ in neighborhood $\mathcal{N}_{\overline{y}_1}$ (in green) denote the non-locked-in depositors who are indifferent between banking with bank 1 and saving through the MMF. The depositors on the segment $\overline{bc}$ in neighborhood $\mathcal{N}_{\overline{x}}$ (in red) are instead indifferent bewteen banking in bank 1 or 2.

Figure 2 shows the equilibrium distribution of deposits (in the shaded areas) and MMF accounts, where we have "cut and spread" one half of the cylinder to represent that half of the economy as a rectangle of height 1 and length $\ell \equiv \pi\rho$. Consider the case when $p \in (0, 1)$. In this case, deposits are distributed across the three shaded areas, A, B, and C, whereas MMF accounts are distributed in the unshaded areas marked MMF. Notice that the distribution of deposits and MMF accounts is symmetric, as both banks are identical.

Start with the savers in neighborhood $\mathcal{N}_{\overline{x}}$. A fraction p of the agents in that neighborhood reallocate their funds away from the banks and open MMF accounts: They are sufficiently far from either bank branches and thus obtain little in terms of bank services and thus prefer fore-going these services and carry their savings in a MMF account. Instead, a fraction $1 - p$ of the agents in neighborhood $\mathcal{N}_{\overline{x}}$ are locked in and thus unable to reallocate funds to MMF accounts. These depositors are indifferent between banking in either bank. Due to symmetry of the model, it must be that $\overline{x} = \frac{\ell}{2}$. Locked-in depositors determine the margin of competition between both

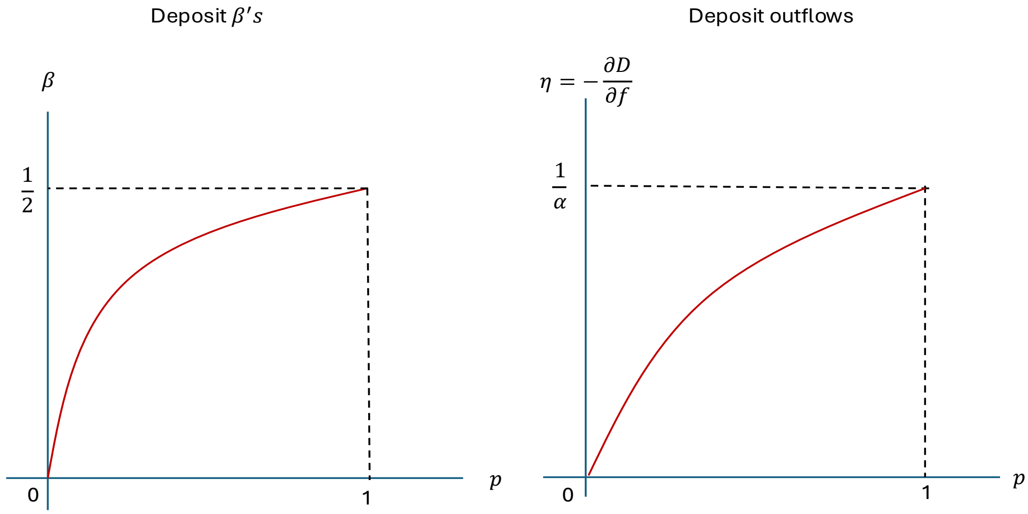


Figure 3: The effect of digitalization on the deposit beta and deposit outflow sensitivity

banks as they are indifferent between banking in one or the other. Depositors in region C will be most affected by improvements in digitalization, as increases in p result in some reallocating funds away from the checking account to the MMF account.

Consider now the agents in neighborhood $\mathcal{N}_{\overline{y}_1}$. Depositors in this neighborhood are all indifferent between saving through the bank or the MMF (see equation (4)). Depositors in the interior of regions A and B are strictly better off attached to the bank, though those in region A are flighty, and thus sensitive to shocks to the Fed funds rate, whereas those in B are not.

Bank 1 balances its two clienteles by setting deposit rates, weighting the different margins of competition for each of them, putting more weight on competition with Bank 2 if p is low (and thus the weight $\omega(p)$ is close to 1) and with the MMF industry if p is high. In particular, when $p = 1$, the margin of competition with bank 2 disappears entirely, and thus so does the area C, and in this case, only the rate and fees of the MMF industry matter when setting deposit rates.

2.4.3 Digitalization: Empirical implications

We want to understand how digitalization affects deposit betas and outflows. In our model, digitalization decreases the shoe-leather costs α of accessing traditional banking services and the proportion $1 - p$ of depositors insensitive to MMFs' competition. In addition, it may result in a reduction in marginal costs, c. The following corollary is immediate.

Corollary 2 *By increasing p and decreasing α, digitalization increases the deposit beta $\beta(p)$ and the sensitivity of deposit outflows to the Fed funds rate, $\eta(p, \alpha)$.*

As shown in Figure 3, both functions are concave in p: The effect of further digitalization on deposit betas and outflows diminishes with the initial level of digital access to alternative saving vehicles. The same is not true for the impact of the cost of accessing bank services α. the deposit beta is independent of α and the deposit outflow sensitivity η is a convex function of α.

The deposit outflow sensitivity $\eta\,(p, \alpha)$ depends on both α and p. Thus, digitalization increases deposit outflow sensitivity due to both an increase in p and a decrease in α. The reason is that as the costs of accessing banking services drop, the bank captures more depositors who are only marginally attached to the bank (the level of deposits is decreasing in α). These new depositors derive a lower level of services from the bank as they are "far' away from it, and thus are more easily lured away by MMFs when rates increase.

Finally, notice that the marginal cost, c, and thus the possible effects of digitalization on them, plays no role in either the deposit betas or outflow sensitivity. As we show below, these marginal costs play a role in the properties of the deposit franchise value (see Section 5).

Corollary 2 is the main empirical implication of our model and we proceed to test it in the sections that follow.

3 Data and Definitions

Digital Banks. We consider three measures of *Digital* banks. Our data on banks' digital platforms comes from Koont (2023), who constructs a data set related to the introduction of digital banking platforms for the universe of US banks. Specifically, our measures of digital presence are based on the release dates of banks' earliest mobile applications on either the Apple or Android App Store.

For our first two measures, in order to focus our analysis on banks with significant usage of digital platforms, we leverage information on the number of reviews that these applications have received on the iTunes app store up to 2022, and we take a higher number of reviews to correlate with significant use of the digital platform. Our first classification is binary, $\text{Digital}^B_{b,t}$ in which we define a bank to be digital in a given year t if it has a mobile banking application in year t, and the app has at least 300 reviews through 2022. This measure is attractive in that it provides a simple classification, however it misses banks with fewer than 300 application reviews, and may correlate with bank size due to a lack of normalization of the review count. Accordingly, our second classification is continuous, $\text{Digital}^C_{b,t}$, in which we define the digital services offered by a bank in a given year t to be,

$$\text{Digital}^C_{b,t} = \frac{\text{Number of mobile application reviews up to 2022}}{\text{Average number of deposit accounts 2010 –2022}}, \tag{17}$$

if the bank has a mobile banking app in year t. We winsorize this measure at 1% and normalize it to range from 0 to 1 across the sample for interpretability. For both of these reviews-based measures, time-variation comes from the timing of banks' mobile application release, as the number of reviews that a banks' application receives is always taken as the stock of reviews through 2022.

While our first two measures are likely to capture banks that have significant usage of digital platforms, there is a concern that banks may choose whether or not to offer digital services in response to depositor rate sensitivity as the Fed funds rate changes. In order to rule out this possibility, we consider a third measure that utilizes bank digitalization *prior* to the Fed Funds rate increases during the past decade. Specifically, our third measure of *Digital* banks is a binary measure that defines a bank to be digital in a given year t if it has a mobile banking application in year t, and this application was released prior to the beginning of 2016.

Appendix Figure A.3 documents in Panel A the proportion and in Panel B the number of banks that are classified to be digital according to our three measures during our sample period, from 2010 to 2022. The proportion of digital banks increases throughout the time period across all definitions, reflecting that more banks have adopted digital platforms throughout the past decade. Table 1 Panel A provides summary statistics related to these classifications for the universe of commercial banks in 2022, and Table 1 Panel B repeats the analysis focusing only on banks with between \$1 and \$250 billion in asset size. The summary statistics reveal that digital banks across all three measures tend to be larger in terms of asset size than the average bank and that there is variation in the number of banks classified as digital across the three measures.[13] Although our

[13]For instance, at the beginning of our sample in 2010, JP Morgan Chase Bank was digital by all three of our classifications as it released its digital platform by the beginning of 2010 and had thousands of reviews by 2022. In contrast, US Bank was not digital by any of our three classifications, as it released its digital platform by the beginning of 2012. By end of our sample in 2022, Silicon Valley Bank was digital by all three of our classifications,

three measures capture different samples of digital banks, we ultimately find that our empirical findings are not sensitive to the choice of measure. This suggests that any differential outcomes are not easily explained by differences in bank scale, concurrent technology adoption decisions by banks, or noise in the application review data.

Brokers. In addition to identifying digital banks, we categorize banks depending on whether or not they have a brokerage. In order to do so, we collect banks' income in fees and commissions from securities brokerage from the FFIEC Consolidated Reports of Condition and Income, generally referred to as Bank Call Reports. These regulatory filings provide quarterly bank-level information for every U.S. commercial bank. We find that 8% of banks report non-zero brokerage income in 2022. Throughout the paper, we define a bank to be a *Broker* if it reports non-zero brokerage income. Table 1 panel A tabulates the number of banks that are brokers and that are digital in 2022, and Table 1 panel B repeats the tabulation focusing only on banks with between \$1 and \$250 billion in asset size.

Traditional Banks. For simplicity, we refer to the relevant untreated group as "traditional banks," meaning either non-digital or non-digital-broker banks depending on the specification.

Bank Deposits. We construct various categories of bank deposits, as following. First, we consider bank-level deposits, which we take to be the sum of savings deposits, demand deposits, and time deposits from banks' Call Reports. Second, we consider bank-level estimated insured deposits from the FDIC SDI. Finally, at the bank-branch level, we obtain deposit quantities from the FDIC Survey of Deposits (SOD).

Additional Data Sources. We collect additional bank balance sheet quantities from banks' Call Reports. For our within-bank analysis, we obtain annual branch locations from the FDIC Survey of Deposits. We collect the proportion of households in a county who have internet subscrip-

as it released its digital platform by the beginning of 2012 and had 378 reviews by 2022; Citizens Alliance Bank (a community bank serving Minnesota and Montana) was digital only according to our continuous classification, as it released its digital platform by the beginning of 2017 and had 27 reviews by 2022; and Union County Savings Bank (a community bank serving New Jersey) was not digital according to any of our classifications, as it had not yet released digital banking by 2022.

tions from the 2019 Census American Community Survey, using the 5-year estimates. For our aggregate county-level analysis, we obtain annual county-level median income from the Census Small Area Income and Poverty Estimates (SAIPE). We obtain annual county-level number of establishments, employees, and payroll from the Census County Business Patterns (CBP). Aggregate time-series data on nominal commercial bank deposits, GDP, and the effective Fed funds rate come from Federal Reserve Economic Data (FRED). Throughout the paper, we refer to the effective federal funds rate as the "Fed funds" rate.

4 Digitalization increases deposit outflows and betas

The stability of deposits plays a central role in the banking literature. Other than for their payment needs, depositors may withdraw funds either because they are concerned about the health of the bank and they are uninsured (what is generally referred to in the literature as a "bank run"), or because they hope to obtain a remuneration for their funds higher than that paid by their bank. We focus on this second source of deposit sensitivity, which we will refer to as "bank walk." It is this less-than-perfect sensitivity that generates the deposit franchise value.

As our model in Section 2 highlights, digitalization alters this sensitivity: it increases both deposit betas and the severity of the deposit outflows when the Fed increases rates. Now, we will empirically test these predictions: in Section 4.1 for deposit outflows, and in Section 4.2 for deposit betas.

4.1 Deposit outflows

4.1.1 Bank-level panel regressions

Our model implies that the magnitude of deposit outflows will be greater for digital banks. In order to empirically test this prediction, we first estimate a panel regression of the form,

$$\begin{aligned} \frac{\mathrm{Y}_{b,t}-\mathrm{Y}_{b,t-1}}{\mathrm{Y}_{b,t-1}} &= \alpha_b+\beta_1\,\Delta FFR_{t,t-1}+\beta_2\,\Delta FFR_{t,t-1}\times \text{Digital}_{b,t}+\beta_3\,\Delta FFR_{t,t-1}\times \text{Broker}_{b,t} \\ &+ \beta_4\,\Delta FFR_{t,t-1}\times \text{Digital}_{b,t}\times \text{Broker}_{b,t}+\beta_5\,\text{Digital}_{b,t}+\beta_6\,\text{Broker}_{b,t} \qquad (18) \\ &+ \text{Controls}_{b,t}+\varepsilon_{b,t} \end{aligned}$$

where $\mathrm{Y}_{b,t}$ is the outcome variable of interest in each specification. We consider the universe of U.S. banks annually between 2010 and 2022. The main explanatory variables are $\Delta FFR_{t,t-1}$, the difference in the Fed funds rate between years $t-1$ and year t, in percentage points, interacted with the corresponding indicator variables. $\text{Digital}_{b,t}$ is a variable that tracks bank b's digital classification in year t, and we consider both our binary and continuous measures in turn. $\text{Broker}_{b,t}$ is an indicator variable that takes the value one if bank b has a brokerage in year t. We include in the specification the level terms of $\text{Digital}_{b,t}$ and $\text{Broker}_{b,t}$ to capture the average effects of these characteristics on banks' deposit growth. In $\text{Controls}_{b,t}$ we also include the log assets of the bank (lagged one period) and its interaction with differences of the Fed funds rate. Finally, we include a bank fixed effect, α_b, to absorb out time invariant bank characteristics such as the average size of each bank.

Tables 2 and 3 reports the estimates using the binary and continuous classification, respectively, of banks' digital services. We consider two deposit categories: in both tables, columns (1) and (2) consider all deposits, and columns (3) and (4) consider insured deposits, as defined in Section 3.

Beginning with our binary classification of digital banks, Table 2 column (1) reports that a 100bps increase in the Fed funds rate decreases the rate of growth of deposits in a digital bank by 2.5%, compared to 1.7% for traditional banks. This specification includes level controls for Digital and Broker, which enter positively and negatively, respectively: Digitalization increases the rate of growth of deposits in the cross-section, whereas the existence of a brokerage decreases them, presumably because of the reallocation away from deposits and into brokerage accounts when that option is available. Thus, digitalization helps banks grow their deposits faster, but renders them more sensitive to interest rate shocks, highlighting the double edged sword nature of digitalization for banking stability.[14] In column (2), we find that the results are robust to the inclusion of size effects (as measured by the Lag Log Assets) even when interacting with the shocks to the Fed funds rate.

In columns (3) and (4) of Table 2, we next consider the growth of insured deposits. We find that a 100bps increase in the Fed funds rate reduces the growth of insured deposits in a digital bank by 1.9%, compared to 1.4% for traditional banks, a difference which is statistically significant at the 1% level. In column (4), when we additionally include size controls, the reduction in growth becomes 4.1% for digital banks relative to 3.4% for traditional banks. The level controls for Digital and Broker remain strongly significant throughout both specifications.

[14] We thank our discussant, Marianne Farboodi, for encouraging us to highlight this specification and suggesting this interpretation.

In Table 3, we report the same regressions but now using the continuous digital classification defined in expression (17). We find that the results remain very similar. Throughout specifications and definitions of deposits, a positive shock to the Fed funds rate results in an additional drop in the rate of growth of deposits for digital banks relative to traditional banks. For instance, in column 1, we find that a 100bps positive increase in the Fed funds rate results in a 3.9% slowdown in the growth of all deposits for digital banks, relative to 1.7% for traditional banks. As before, the slowdown in deposit growth is robust to the inclusion of size controls.

With the continuous measure of digital banks, we find that the slowdown in deposit growth is even stronger for digital banks that additionally offer brokerage services, our "digital-broker" banks. For instance, in column 1, we find that digital-broker banks see an additional 3.6% slowdown in the growth of all deposits, resulting in an overall slowdown of 7.5% ($= 3.9 + 3.6$) in the growth of all deposits for these banks, relative to the 1.7% at traditional banks.

We consider several additional specifications in the Appendix. In Appendix Table A.1 we show the robustness of our results to including a year fixed effect, alleviating worries that the results may be driven by differences in bank behavior during the latter part of the sample when digitalization is more prevalent. In Appendix Table A.2, we show that the results remain consistent when we use our 2016 measure of digitalization instead, prior to the first rate hike in our sample, which rules out the possibility that banks may be altering their digitalization decision in response to changes in the Fed funds rate in a way that correlates with their depositor behavior. Finally, in Appendix Tables A.3 and A.4, we examine whether the deposit outflows can be driven by differential M&A activity of digital banks during Fed funds rate changes. For instance, we may worry that traditional banks disproportionately engage in acquisitions during periods of Fed funds rate increases, which could explain why these banks exhibit less pronounced deposit outflows. In order to determine whether this type of activity could be driving the results, we take a conservative approach and re-analyze banks' deposit flows while excluding from the regressions any year in which the bank has any M&A or sales activity. We find that our results remain consistent, suggesting that our findings are not driven by banks' differential M&A or sales activity which correlates with changes in the Fed funds rate.

In sum, the bank-level evidence supports the first empirical prediction of our model: Digital banks see heightened deposit outflows in response to increases in the Fed funds rate, above and beyond the deposit outflows that traditional banks experience.

4.1.2 Within-bank-year panel regression

While the bank-level evidence goes some way towards testing our model predictions, the fact that a bank has a digital platform or offers its clients brokerage services may correlate with other characteristics that make deposits behave differently in response to changes in the Fed funds rate. To provide evidence that our observed effects operate through digitalization, we next estimate the following within-bank regression,

$$\frac{\mathrm{D}_{b,c,t} - \mathrm{D}_{b,c,t-1}}{\mathrm{D}_{b,c,t-1}} = \alpha_{b,t} \quad + \quad \gamma \, \Delta FFR_{t,t-1} \times \mathrm{Internet}_c \\ \quad + \quad \beta \, \Delta FFR_{t,t-1} \times \mathrm{Internet}_c \times \mathrm{Digital}_{b,t} + \varepsilon_{b,c,t}. \tag{19}$$

The dependent variable is the deposit growth of bank b in county c across year t. Bank b's deposits in a given county c are calculated as the sum of all deposits accruing to branches of bank b within the county c. We estimate this bank-county-year panel between 2010 and 2022. The inclusion of a bank-year fixed effect $\alpha_{b,t}$ restricts variation to be across different counties that a bank operates in when it faces a shock to the Fed funds rate, where the "treatment intensity" is determined by each county's internet usage, $\mathrm{Internet}_c$. The main explanatory variable now is thus $\Delta FFR_{t,t-1} \times \mathrm{Internet}_c \times \mathrm{Digital}_{b,t}$, which is the difference in the Fed funds rate in percentage points, interacted with the county-level proportion of households that have internet subscriptions, and additionally by a variable which tracks whether the bank offers digital services. Specifically, $\mathrm{Internet}_c$ is a variable that ranges from 0 to 1, and $\mathrm{Digital}_{b,t}$ is the binary or continuous classification of digital in turn, as defined in Section 3.

Table 4 Columns (1) and (4) report the results for the binary and continuous classification of digital banks, respectively. We find that for a given 100 bps increase in the Fed funds rate, banks with digital platforms face more pronounced outflows in markets with high internet usage. For a 10% increase in county-level internet usage, digital banks' deposit growth is 1.4% lower according to the binary classification or 2.5% lower according to the continuous classification.

In general, counties with high internet usage may differ in deposit flows than those with low internet usage. This granular specification allows us to consider a specification with a county fixed effect α_c, absorbing out average differences across counties,

$$\frac{\mathrm{D}_{b,c,t} - \mathrm{D}_{b,c,t-1}}{\mathrm{D}_{b,c,t-1}} = \alpha_{b,t} + \alpha_c + \gamma \, \Delta FFR_{t,t-1} \times \mathrm{Internet}_c \\ + \quad \beta \Delta FFR_{t,t-1} \times \mathrm{Internet}_c \times \mathrm{Digital}_{b,t} + \varepsilon_{b,c,t}. \tag{20}$$

Table 4 Columns (2) and (5) reports the results for the binary and continuous classification of digital banks, respectively, and the results remain very similar. We find that for a given 100 bps increase in the Fed funds rate, banks with digital platforms face more pronounced outflows in markets with high internet usage, even after controlling for county-level differences. For a 10% increase in county-level internet usage, digital banks' deposit growth is 1.3% lower according to the binary classification, or 2.3% lower according to the continuous classification.

Finally, for the most restrictive specification in this setting we can further include county-year α_{ct} and bank-county α_{bc} fixed effects. The county-year fixed effect α_{ct} takes out the county-level average effect in a given year and looking at variation across types of banks, depending on whether or not they are digital. The county-bank fixed effect α_{bc} controls for persistent differences in banks' deposit growth across counties. Effectively, we look within-county at differential outflows for digital and non-digital banks as the Fed funds rate changes.

$$\frac{\mathrm{D}_{b,c,t} - \mathrm{D}_{b,c,t-1}}{\mathrm{D}_{b,c,t-1}} = \alpha_{b,t} + \alpha_{c,t} + \alpha_{b,c} + \beta_1\ \Delta FFR_{t,t-1} \times \text{Internet}_c \times \text{Digital}_{b,t} + \varepsilon_{b,c,t}. \tag{21}$$

Table 4 Columns (3) and (6) report the results for the binary and continuous classification of digital banks, respectively. Even with this most stringent specification, we find that for a given 100 bps increase in the Fed funds rate, banks with digital platforms face more pronounced outflows in markets with high internet usage. For a 10% increase in county-level internet usage, their differential deposit growth is 0.8% lower according to the binary classification, after controlling for the average yearly growth rate of each county with the county-year fixed effect, and persistent differences in banks' deposit growth across counties with the bank-county fixed effect. The magnitude of the estimate for the continuous digital classification is 1.7%, but is marginally insignificant. In Appendix Table A.6, we repeat the analysis for our measure of digitalization by 2016 and find that the results remain strong and consistent.

Notice that this analysis allows us to address two key identification concerns. First, a worry may be that depositors of digital banks are flighty for a reason orthogonal to the existence of a digital platform. By comparing the local deposits of banks within the same county, we can tighten our identification by comparing depositors that are more homogeneous and face a similar economic environment. Relative to our bank-level analysis, we can rule out that digital banks' depositors react differently to monetary policy shocks due to living in disparate regions of the country.

Second, the bank-year and county-year fixed effects together control for time-varying differences in banks' investment opportunities and overall depositor clientele. For instance, it may be that the investment opportunities of banks with digital platforms deteriorate when the Fed funds rate increases by more than the investment opportunities of banks with no digital platform. As a result, banks with digital platforms may underwrite a lower amount of loans and create fewer deposits. However, deposits are fungible across counties and can be invested at the bank level. Thus, this alternative story does not explain why digital banks would suffer larger deposit outflows in counties with greater internet usage. If local loan growth varies across counties, leading to differential deposit growth, it should not vary differently for digital banks relative to non-digital banks within the same county.

An identification challenge to these results can arise only if the deposit sensitivity to the Federal fund rate is affected by a county-level variable (like average level of wealth) through a channel independent from the digitalization one but correlated with our digital measure. We regard this possibility as unlikely.

In sum, we find that banks' deposit outflows are more pronounced in markets with higher internet usage, but that this is only the case for digital banks. Thus, through the inclusion of bank-year and county-year fixed effects, we are able to identify that digital platforms do indeed lead to greater deposit outflows in response to changes in the Fed funds rate, consistent with the first empirical prediction of our model. This finding supports the interpretation that it is digital banking that has led banks' deposits to become more sensitive to shocks in the Fed funds rate rather than some unobserved characteristics of these digital banks. This connects well with the implications of our model. In effect, our empirical strategy is akin to varying the degree of digitalization, which in our model is the result of increasing the share of non-locked-in depositors p and lowering shoe leather costs α. As predicted by the model, digitalization results in larger deposit outflow sensitivity.

4.1.3 County-level panel regression

Thus far, we have shown that digital banks experience greater deposit outflows in response to increases in the Fed funds rate. This may arise through two channels: flightier depositors prefer digital banks or digital banks make depositors flightier by reducing the costs of moving deposits around. While both channels have implications for financial stability, it is particularly important to determine whether digitalization is simply leading to a reallocation of depositors or if it changes depositors' behavior.

The time-series trend in Appendix Figure A.2 suggests that the behavior of deposits has been changing in recent decades, becoming more sensitive to changes in the Fed funds rate. However, it is difficult to link this time-series trend to one particular channel, such as digitalization. Moreover, teasing out whether differential deposit outflows are due to re-sorting or changes in deposit behavior is challenging, given the lack of data on deposit account level information in the U.S. banking sector. However, county-level deposit data can provide some evidence on whether the observed differential behavior of digital deposits has aggregate implications beyond simply re-sorting depositors. In particular, we assess next how positive shocks to the Fed funds rate increase county-level aggregate deposit outflows, depending on the digitalization of local banks.

Specifically, we calculate the proportion of digital banks that operate in the county according to either our binary or continuous classification. Bank presence in a county though is endogenous: digital banks may enter certain counties exactly because of differential depositor behavior. In order to account for this, we use historical bank presence prior to the adoption of mobile banking services, using the branches that banks had in 2009 to determine bank presence in each county. The set of banks present in a given county is thus the set of banks that operated at least one branch in the county in 2009. The proportion of banks that are digital in a given county in year t, Proportion $\text{Digital}_{c,t}$, then ranges from 0 to 1 and is the proportion of banks among this set that are digital in year t, according to either our binary or continuous specification. We consider the following annual county-level specification from 2010 through 2022,

$$\begin{aligned}\frac{\mathrm{D}_{c,t}-\mathrm{D}_{c,t-1}}{\mathrm{D}_{c,t-1}} = \alpha_t + \alpha_c \quad &+ \quad \beta \; \Delta FFR_{t,t-1} \times \text{Proportion Digital}_{c,t} \\ &+ \quad \gamma \; \text{Proportion Digital}_{c,t} + \text{Controls}_{c,t} + \varepsilon_{c,t}, \end{aligned} \tag{22}$$

where the outcome variable is the annual county-level deposit growth. We include year and county fixed effects, absorbing out the overall effect of changes in the Fed funds rate as well as time-invariant differences across counties. Finally, we include a variety of time-varying demographic characteristics at the county-level in the controls.

The results are reported in Table 5. Columns (1) through (4) consider our binary classification of digital banks, whereas columns (5) through (8) consider our continuous classification. We find that β is consistently negative and is significant in 7 out of 8 specifications, ranging from between -.008 to -.045. Appendix Table A.7 shows that the results remain consistent with our measure of digitalization by 2016. These findings show that county-level aggregate deposit outflows are larger when there are a higher proportion of digital banks present. This heightened aggregate deposit outflow at the county level strongly suggests that the differential deposit outflows of digital banks are not all due to re-sorting among depositors.

4.2 Deposit betas

So far, we have shown empirical evidence in support of our first model prediction: that the magnitude of deposit outflows in response to increases in the Fed funds rate will be greater for digital banks. In Tables 2 and 3, we document that digital banks experience greater deposit outflows in the cross-section of banks, in Table 4, we show that within-bank, digital banks face greater deposit outflows in counties with greater internet usage in the presence of increases in the Fed funds rate, and in Table 5 we document that digitalization has an effect on the aggregate county-level deposit growth.

Our model also generates an empirical prediction for the behavior of banks' deposit rates: Digitalization increases deposit betas or the sensitivity of banks' deposit rates to changes in the Fed funds rate. We turn to testing this prediction next. Drechsler et al. (2021) suggest an estimation technique for what they refer to as banks' deposit beta.[15] Specifically they suggest the following specification

$$\Delta \textit{Deposit Expense}_{b,t} = \alpha_b + \alpha_t + \sum_{\tau=0}^{3} \beta_{b,\tau}^{\text{Dep}} \Delta FFR_{t-\tau} + \varepsilon_{b,t}, \tag{23}$$

where *Deposit Expense*$_{bt}$ is the change in bank b's deposit expenses scaled by bank b's deposits. They define the bank-specific deposit beta as $\sum_{\tau=0}^{3} \beta_{b,\tau}^{\text{Exp}}$ "to capture the cumulative effect of Fed funds rate changes over a full year".[16] In this section we follow the convention in Drechsler et al.

[15] In Appendix Table A.8, we calculate average deposit and interest expense betas in our full sample of banks. Notably, deposit betas overall are lower over the past decade; however, our results demonstrate that digital banks face elevated betas relative to the average bank during this period. The lower average betas are consistent with the fact that our sample period is dominated by the ZLB, during which the noise-to-signal ratio in deposit expenses is much higher because the signal is near zero—leading to a downward bias in estimated coefficients. See also Kang-Landsberg et al. (2023), who also calculate the cumulative change in deposit rates relative to the cumulative change in the Fed funds rate over several tightening cycles. Additionally, we consider the general beta for all interest expenses in Table A.9 and find similar results.

[16] See Drechsler et al. (2021, p. 1112) equation (9) and the discussion around it.

(2023b) of reporting the Fed funds rate, FFR, in decimal points so that .01 is 1 percentage point.

First, we adapt this methodology to estimate a single average deposit beta for each category of bank we consider, such as traditional and digital banks, rather than bank-specific betas. In order to do so, we estimate the following regression specification,

$$\Delta \mathit{IntExp}_{b,t} = \alpha_b + \alpha_t + \sum_{\tau=0}^{3} \beta_\tau^{\text{Exp}} \Delta FFR_{t-\tau} + \sum_{\tau=0}^{3} \beta_\tau^{\text{Digi Exp}} \Delta FFR_{t-\tau} \times \text{Bank Type}_{b,t} \tag{24}$$
$$+ \gamma \text{ Bank Type}_{b,t} + \varepsilon_{b,t},$$

where Bank Type$_{b,t}$ varies depending on whether we are estimating differential betas for digital banks or digital-broker banks. When estimating differential betas for digital banks, Bank Type$_{b,t}$ is simply equal to the digital classification (either binary or continuous). When estimating differential betas for digital-broker banks, Bank Type$_{b,t}$ is equal to the product of our digital classification and our broker indicator variable. We calculate the differential deposit betas to be the sum of statistically significant coefficients $\sum_{\tau=0}^{3} \beta_{b,\tau}^{\text{Exp}} + \beta_{b,\tau}^{\text{Digi Exp}}$, whereas the deposit beta for banks not of the given bank type remains the sum of statistically significant coefficients $\sum_{\tau=0}^{3} \beta_{b,\tau}^{\text{Exp}}$.

Table 6 reports the results for digital and digital-broker banks, using both the binary and continuous classification of digital. In columns (1) and (2), we consider the differential deposit beta of digital banks using the binary and continuous classification of digital in turn. We find that the deposit beta for digital banks is significantly higher than that of non-digital banks, between 0.24 and 0.31 relative to 0.23. In columns (3) and (4), we consider the differential deposit beta of digital-broker banks for the binary and continuous classification of digital in turn. Again, we find that the interest expense beta for digital brokers is significantly higher, between 0.25 and 0.30, compared to an average beta of 0.23. The F-statistic associated with a test of statistical difference across these betas is reported at the bottom of the tables, and we find that these differences are significant across all specifications. Appendix Table A.10 repeats the analysis using our digital by 2016 measure, and finds that the results remain consistent.

Estimating an average beta for digital (or digital-broker) banks allows us to isolate the average differential sensitivity of deposit rates for each category of bank. However, it is also of interest to explore the dispersion of betas in the cross-section of banks. Accordingly we next estimate bank-level deposit betas following Drechsler et al. (2021), and report the distribution of deposit and interest expense betas in Appendix Tables A.11 and A.12. We report betas separately for banks that are classified to be digital or not in 2022, according to each of our two binary measures of digitalization. Since it is infeasible to estimate time-varying bank-specific betas, the betas are an average of the banks' betas throughout the time period from 2010 to 2022, however we still find that banks which are classified to be digital in 2022 have higher average deposit betas across the distribution of banks, for both of our binary measures of digitalization. Moreover, we find that there is significant variation in deposit betas in the cross-section of banks for both digital and non-digital banks, with a standard deviation that is roughly half the mean beta for each group, reflecting the heterogeneous nature of the U.S. banking sector.

In sum, the empirical evidence is consistent with the predictions of the model in Corollary 2: Digital banks experience larger outflows in the presence of positive shocks in the Fed funds rate but also adjust deposit rates more than traditional banks.

5 Digital banking and the deposit franchise value

The deposit franchise is the component of a bank's value generated by a bank's ability to pay a rate on deposits below the Fed funds rate. We follow the current literature and define the deposit franchise value as the present value of the spread that the bank earns on deposits net of costs of servicing those deposits, that is,

$$DF(f) \equiv \text{PV}\left[\left(f - r^D - c\right) D\right]. \tag{25}$$

Drechsler et al. (2021) and DeMarzo et al. (2024) have emphasized the importance for bank stability of the sign of the duration of this deposit franchise: If the value of the deposit franchise increases with interest rates, then this increase will offset the losses banks experience in their loan and securities portfolios, improving bank stability in the process.[17] While the magnitude and the duration of the deposit franchise's value are crucial for bank stability, they are not directly observable.[18] To further complicate things, the duration of the deposit franchise's value is not independent of the source of the friction that generates this value. Our model allows for endogenizing these frictions in the duration calculation. For this reason, in this section, we will first

[17] Drechsler et al. (2021) and Drechsler et al. (2023b) argue in this sense. Metrick (2024) applies this idea to the case of Silicon Valley Bank.

[18] DeMarzo et al. (2024) for an attempt to estimate it indirectly.

derive some theoretical results on the sign of the duration of the deposit franchise value, then calibrate these results with the estimates obtained in Section 4, and finally discuss the implications for bank stability.

5.1 Theory

Using (11) to substitute r^D in (25), we can write the deposit franchise value as

$$DF\left(f\right) = \left[\left(1 - \beta\left(p\right)\right) - \left(\frac{\overline{r} + c}{f}\right)\right] D(f). \tag{26}$$

There are two elements to the deposit franchise value. The first one, the term in $1 - \beta\left(p\right)$, captures what DeMarzo et al. (2024) refer to as the floating component of the deposit franchise, as it is valued at par. It is immune to shocks in the Fed funds rate. The second component is the value of a perpetuity paying a coupon $\overline{r} + c$. The value of that perpetuity, on which the bank has a short position, is the fixed component of the deposit franchise value.

By differentiating (26) with respect to f, we obtain that the duration is determined by

$$-\frac{\partial DF}{\partial f} = -\left(\frac{\overline{r} + c}{f^2}\right) D + \left[\left(1 - \beta\left(p\right)\right) - \left(\frac{\overline{r} + c}{f}\right)\right] \eta\left(\alpha, p\right), \tag{27}$$

where the expressions for $\overline{r}$, $\beta\left(p\right)$ and $\eta\left(\alpha, p\right)$ are all given in Lemma 1. Substituting for D, given in (14), and rearranging, we obtain

$$-\frac{\partial DF}{\partial f} = -\left(\frac{\overline{r} + c}{f^2}\right) \overline{D} + \left(1 - \beta\left(p\right)\right) \eta\left(\alpha, p\right), \tag{28}$$

where $\overline{D}$, was given in (15).

There are two terms in (28). The first term captures the effect of higher rates on the deposit franchise value on account of the fact that the bank has a short position on a perpetuity. If $\overline{r} + c > 0$, the deposit franchise increases in value when rates increase and thus results in a *negative* duration effect. Notice that it is scaled by the level of deposits at the zero lower bound, $\overline{D}$.

The second is the term associated with the drop in value of the deposit franchise when the bank experiences deposit outflows in the presence of positive shocks in the Fed funds. This effect in turn induces a *positive* duration. This term depends on both the equilibrium response of deposit rates to shocks in the Fed funds rate, $\beta\left(p\right)$, and the extent to which savers switch away from deposits to MMF accounts when that happens, $\eta\left(\alpha, p\right)$.

The sign of the duration of the deposit franchise value is then ambiguous whenever $\overline{r}+c>0$. Notice though that when $\overline{r}+c\approx 0$, then the the first term in expression (28) approaches zero, and thus sign of the duration of the deposit franchise is always positive and equal to $(1-\beta(p))\,\eta(\alpha,p)$. It is immediate to show that this term is increasing in p and decreasing in α. Thus, when $\overline{r}+c\approx 0$, the duration of the deposit franchise is positive and higher for digital banks. Digitalization then increases bank instability: In the presence of increases in the Fed funds rate, the value of the deposit franchise goes down by more for digital than for traditional, brick-and-mortar banks.

In what follows, and as in the literature, we focus on the case

$$\overline{r}+c>0, \tag{29}$$

which is also the empirically plausible case.[19] The following lemma offers a complete characterization of the duration of the deposit franchise value in our model and the impact of digitalization on it. Recall that, as discussed in Section 2.4.2 (and more formally in Appendix A.1.2), $\overline{f}$ is the maximum admissible rate: Below that rate, some non-locked-in agents hold deposit accounts.

Lemma 3 *(Characterization of the deposit franchise value) Assume* (29) *holds, then*

(a) The deposit franchise value is strictly concave in the rate, f.

(b) There exists a $f_0\in\left(0,\overline{f}\right)$, such that $DF(f)<0$ for $f<f_0$ and $DF(f)\geq 0$ for $f\in\left[f_0,\overline{f}\right]$

(c) For a degree of digitalization p sufficiently close to one, the deposit franchise value reaches a strict maximum at $f^{*}\in\left(f_0,\overline{f}\right)$.

(d) When $\overline{r}+c\approx 0$, the duration of the deposit franchise is positive and higher for digital banks.

Figure 4 shows the characterization of the deposit franchise value in Lemma 3 for a "high" and "low" values of p. Notice first, that when the rate f is below f_0, which depends on the parameters of the model (see expression (40) in the Appendix) and thus is different for traditional and digital banks, the value of the deposit franchise is negative. We have plotted the value of the

[19]Note that for $\overline{r}+c\leq 0$, $\overline{r}\leq -c$. In any model that yields deposit rates as an affine function of the fed funds rate, the intercept, $\overline{r}$, is the deposit rate at the zero lower bound. Thus, we would require the deposit rate at the ZLB to be -1.5% (if $c=.015$, for example), which we did not observe in the recent period of low rates.

deposit franchise for a low value of p (low digitalization) as being above the value of the deposit franchise for high values of p, but this does not necessarily need to be the case when all the effects of digitalization are taken into account. We calibrate the deposit franchise value below to assess to what extent the shapes in Figure 4 obtain in the range of empirically plausible parameters, which they do.

To understand the behavior of the value of the deposit franchise for different degrees of digitalization, let's consider first the case in which p is low. In this case, most agents are locked-in and thus insensitive to positive shocks in the Fed funds rate. As a result, depositors do not flee if a bank does not increase deposit rates when the Fed funds rate rises and the value of the deposit franchise continues to increase with f. In the limiting case in which $p = 0$, when banks face no competition from the MMF, the deposit franchise value is given by

$$DF(f) = \left(1 - \frac{r^B + c}{f}\right)\ell,$$

where recall r^B was the deposit rates when there are only locked-in agents and it was given by (3). In this case, the deposit franchise has a negative duration and is a source of banking stability in the presence of monetary tightening for any level of f.

Instead, when p is high, most bank customers are sensitive to positive shocks in the Fed funds rate. These sensitive customers will walk away if the bank does not increase deposit rates when the Fed funds rate rises, with two negative effects on the value of the deposit franchise. First, the bank has to increase rates more to reduce the magnitude of the walk. But, second, it will not raise them enough so as prevent deposit outflows completely. The higher the Fed funds rate, the more intense this walk is. Lemma 3 (c) shows that whenever $f > f^*$, duration is positive and the value of the deposit franchise declines with additional positive shocks to the Fed funds rate. In effect, in the presence of positive shocks to the Fed funds rate, the bank trades-off the benefit of retaining the marginal non-locked-in depositor with a higher deposit rate against the costs of giving all inframarginal deposits (which includes inframarginal non-locked-in agents and locked in ones) those higher rates. In sum, then, this deposit walk explains why, when digitalization is advanced enough and p is close to one, the deposit franchise value has positive duration for $f \in \left(f^*, \overline{f}\right]$. That is, the second term in (28) dominates the first.

Notice that letting some deposit walk is profit maximizing: Both $\beta(p)$ and $\eta(\alpha, p)$ are the result of the bank's optimal response to competition from other banks and the MMF industry. Moreover, as shown in Corollary 2, both β and η are increasing in p, so in principle the effect

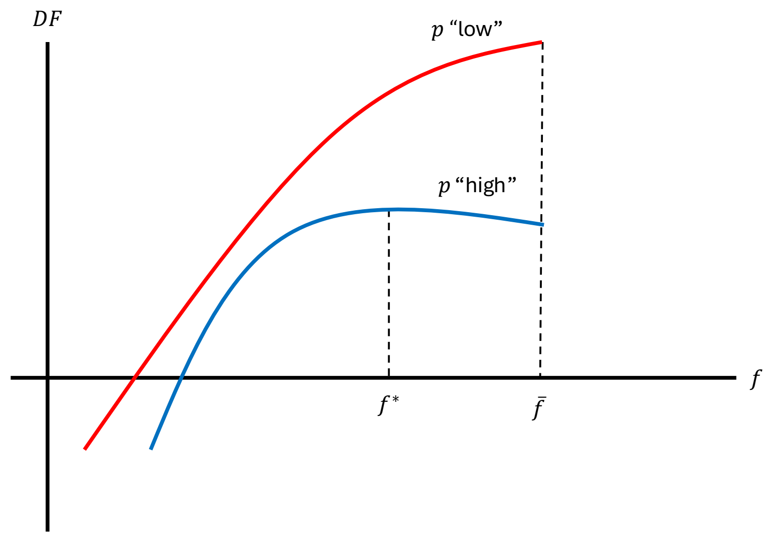


Figure 4: **Digitalization and the deposit franchise value**: Lemma 3. The value of the deposit franchise as a function of the Fed funds rate f when the extent of digitalization is low (p close to 0; in red) and high (p close to 1; in blue). $\overline{f}$ is the maximum admissible rate (see section A.1.2) and f^* is the maximum of the deposit franchise value when p is close to 1.

of an increase in p on $(1-\beta(p))\,\eta\,(\alpha, p)$ is ambiguous. It is immediate to show though that this term is in fact increasing in the extent of digitalization: Banks do make deposit rates more sensitive to the Fed funds rate, and thus the drop in $1-\beta(p)$, but the increase in $\eta\,(\alpha, p)$ more than compensates for that drop, inducing a positive duration when the Fed funds rate is high enough.

It is useful to relate our results to those in the literature to highlight our contribution better. Drechsler et al. (2021, p. 1108) consider a model in which, by assumption, $\overline{r} = 0$ and thus $\overline{r} + c = c$. They go on to assume in Drechsler et al. (2023b, p. 12-13) that this first term in (28) dominates the second and thus that the value of the deposit franchise has negative duration. In contrast, DeMarzo et al. (2024, p. 12) assume a functional form for the deposit rate as in (11) (they denote $\overline{r}$ by $-\alpha^D$). They correctly argue that the duration is not just determined by c, but by $\overline{r} + c$, which can potentially be negative, leading to a deposit franchise value with positive duration even in the absence of any bank walk.

So far, the literature has focused on bank runs and has largely ignored bank walks, i.e., decreases in the level of deposits caused by an increase in the federal funds rate.[20] We show that this is crucial to understanding the sign of the duration of the deposit franchise, particularly as digitalization becomes more prevalent. When the Fed funds rate increases, banks lose some deposits (the term $\eta(\alpha, p)$ in equation (28), which reduces the value of the deposit franchise). For low enough f, the first term in (28) clearly dominates and the duration is clearly negative. If f is sufficiently high, however, the second term can dominate.

To reiterate, our contribution is twofold. First, we show that when one takes into account the effect of the Fed funds rate on the level of deposits, the sign of the duration of the deposit franchise value switches from negative to positive for high values of the Fed funds rate whenever digitalization is high. Second, as we show below, for realistic values of the parameters, digitalization can increase the value of the deposit franchise, but it also increases its duration. As a result, in an environment with high levels of the Fed funds rate, further increases in rates decrease the deposit franchise value of digital banks, adding to financial instability.

Finally, it is perhaps helpful to reiterate the point made by DeMarzo et al. (2024, equation (4)) in what concerns the duration of the bank's franchise value:

$$FV(f) \equiv PV\left[\left(r^L - r^D(f) - c\right) D(f)\right].^{21} \tag{30}$$

They emphasize that what is key to assess the solvency of a bank as an ongoing enterprise in the presence of shocks to the Fed funds rate, is the duration of the total franchise value (deposit franchise plus loan franchise), rather than that of the *deposit* franchise value. In our framework, and using the results in Lemma 1:

$$-\frac{\partial FV}{\partial f} = \beta(p)\eta(\alpha, p) + \left(\frac{r^L - c - \overline{r}}{f^2}\right)\overline{D} > 0. \tag{31}$$

In our framework, as in theirs, a bank's total franchise value always exhibits positive duration.

5.2 A simple calibration

Lemma 3 shows that the sign of the duration of the deposit franchise depends on the extent of digitalization. Are those results empirically relevant? What do our estimates imply? In particular,

[20] The focus of the literature is on *runs*, the destruction of the deposit franchise value that follows from depositors withdrawing deposits on account of solvency concerns. Instead, we emphasize the "walk" channel, the reallocation that occurs even without any solvency concerns.

[21] Recall that in our framework the size of the balance sheet is determined by the level of deposits.

what do they imply for the period of interest rate hikes that started in March of 2022?

We parameterize our model as follows. First, as mentioned, we want to focus our calibration in the period in which rates went from about 25bps to about 5.5%, which covers the range covered by the Fed funds rate between early 2022 and 2025. During this period the bank prime rate was as high as 8.5% so we set $r^L = .085$.[22] As for ρ, the rates by funds such as Vanguard and Schwab charge are between 12bps and 30bps. For instance, in July 2025, the effective Fed funds rate was 4.33% and the rate Schwab Treasury Obligations Money Fund was 4.02%, a spread of 31bps. We take the midpoint of about 20bps and thus set $\rho = .002$. This implies a size of the economy of $2\ell \approx .013$, given that the height of the cylinder is one.

Finally, to determine the marginal cost of deposit before digitalization, we resort to a 2010 FDIC study on the cost structure of banks. It estimates that the average noninterest expense to average asset ratio in the period 2002-2007 was 3.12%, while in the period 2008-2009, it was 2.95%.[23] This represents the cost of both servicing deposits and making loans. Thus, we allocate half of that cost to servicing deposits. Finally, we assume that marginal and average costs are the same, thus we set the marginal cost of servicing deposits at 1.5%.

Koont (2023) estimates that digitalization has thus far decreased the marginal cost of servicing deposits for the average bank by 20%. Industry reports on fully online banks suggest that digitalization will reduce marginal costs by even more in the future, potentially reaching 60–70%. For example, in its S1 filing, Chime Financial, an online bank, states, "The average annual cost-to-serve a retail deposit customer is an estimated three times higher for the three largest incumbent banks and five times higher for mid-sized and regional banks when compared to Chime."[24]

Obtaining estimates for the digitalization parameters, p and α is more challenging. It is here where our model is most helpful. Specifically, we use the estimates of deposit sensitivity outflows and betas from column (1) of Table 3 and column (2) of Table 6 for both digital and traditional banks and then use the expressions in Lemma 1 for $\beta(p)$ and $\eta(\alpha, p)$ to obtain estimates of p and α. For instance, the estimates for the deposit beta for the digital and traditional bank, using the continuous classification, are given by

$$\widehat{\beta}^{dig.} = .306 \qquad \text{and} \qquad \widehat{\beta}^{trad.} = .226. \tag{32}$$

[22] In the model all the rates are in decimal points as we normalize the savings of each of the depositors to \$1.

[23] Robert E. Basinger, "Highlights from the 2010 Summary of Deposits", FDIC Quarterly 41 2010, Volume 4 (4).

[24] Form S-1, Chime Financial, Inc., p.85

Using the expression (13), we can then calculate the values of p for the traditional and digital banking system, which are

$$\widehat{p}^{dig.} = .28 \qquad \text{and} \qquad \widehat{p}^{trad} = .17. \tag{33}$$

To estimate η we use our estimates for deposit outflow sensitivity, which are .039 and .017 for digital and traditional banks respectively. We can then use expression (16) in Lemma 1 to obtain an estimate of α,[25] which are

$$\widehat{\alpha}^{dig.} = 16.02 \qquad \text{and} \qquad \widehat{\alpha}^{trad} = 24.78. \tag{34}$$

Finally, we need estimates for s^B. We do so by setting $\overline{r} = 0$ in (11). Notice that in any model that yields deposit rates as an affine function of the fed funds rate, the intercept, $\overline{r}$, is the deposit rate at the zero lower bound. During the ZLB period, deposit rates were zero or very close to zero, hence $\overline{r} = 0$ is a reasonable assumption.

Using expression (12), we can back out s^B, which is $.0518$ or 5.2%. Recall that the interpretation of s^B is the additional interest rate an investor who is colocated with the bank would be willing to forego to remain a depositor and obtain bank services.[26]

Before we use this calibration to derive estimates of the deposit franchise value and its duration, it is helpful to assess whether the model delivers some realistic magnitudes concerning

[25] A subtletly here is that our regressions are run using changes in the Fed funds rate in percentages, whereas the right interpretation of the rates is in decimal points. Indeed in our model,

$$\frac{D(f') - D(f)}{D(f)} = -\eta(p, \alpha)\left(\frac{f' - f}{D(f)}\right)$$

whereas we run a regression of the form

$$\frac{D(f') - D(f)}{D(f)} = \text{constant} + \gamma(f' - f) \times 100 + \text{controls} + \text{error term}$$

and thus

$$\eta(p, \alpha) = -\gamma \times D(f) \times 100.$$

Notice that in order to obtain our estimate of η we need to scale the parameters by the level of deposits at a bank, which we do by multiplying our estimates by $\ell = \pi\rho$.

[26] We derive this number using the parameters obtained from the digital banks. This introduces a slight inconsistency when plugging in this number for traditional banks. The estimate of s^B from traditional banks is too low to be plausible. To see this notice that from (12), $s^B = r^B + (1 - \omega(p))(\alpha\ell - \rho)$, as recall that we have assumed that $\overline{r} = 0$. When α is large, as is the case for traditional banks, competition for deposits is very weak and thus the rate when only banks compete against each other, r^B, is in turn very low and this pushes s^B below 0.

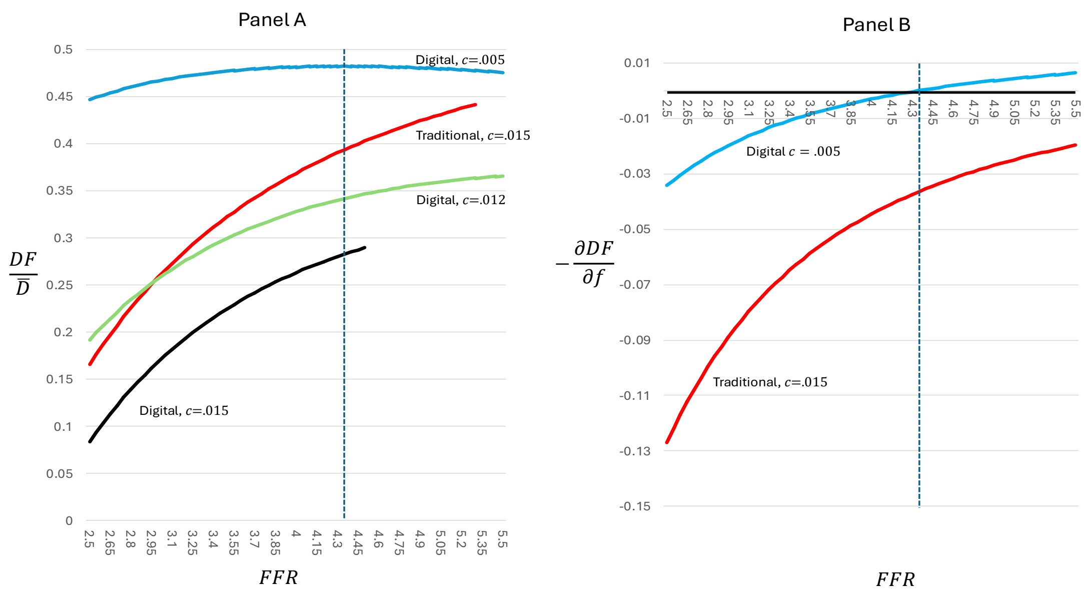


Figure 5: Panel A: The deposit franchise value for traditional and digital banks, normalized by the maximum volume of deposits $\overline{D}$ (see (15)) as a function of the rate f (in %). To obtain these plots we set $r^L = .085$, $\rho = .002$, $\overline{r} = 0$, and $s^B = .0518$. For digital banks we take $p^{dig.} = .28$ and $\alpha^{dig} = 16.02$. For traditional banks $p^{trad} = .17$ and $\alpha^{trad} = 24.78$. The estimates for these digitalization parameters are derived from our estimates of deposit outflow sensitivity and betas. We plot the deposit franchise value of digital banks under three different assumptions of the marginal cost of deposits, $c = \{.005, 0.012, 015\}$. The vertical dotted line denotes the maximum value of the deposit franchise value for digital banks, when $c = .015$, which is at $f = 4.34\%$. The value of $DF/\overline{D}$ for digital and traditional banks when $c = .015$ does not go beyond 4.5% and 5.3% as beyond those values of the Fed funds rate the conditions of Lemma 1 are not met (see Appendix for details). Panel B: Duration for digital and traditional banks when $c = 0.005$ and $c = .015$, respectively.

the variation in deposits in the presence of changes in rates. We focus on the most recent tightening period, which started in March of 2022 and peaked in August of 2023. This period is of interest because mobile and desktop banking were well-established banking features by then. In February of 2022, the month before the Federal Reserve started tightening in the post-pandemic period, demand deposits stood at about \$16.5tr. The effective Fed funds rate at that point was 8bps.[27] The tightening cycle took the effective federal funds rate to 5.33% in August of 2023. By then, demand deposits had dropped to \$14.3tr, a drop of more than two trillion dollars or 13.6% of their initial level. In our model, a similar rate increase generates a drop of 20.1% in the level of deposits for digital banks and 9.4% for traditional banks, which brackets nicely the observed drop in the data.[28]

5.3 Implications for the Duration of the Deposit Franchise's Value

Let's turn to the quantitative implications of our model for the deposit franchise value. Figure 5 Panel A plots the deposit franchise value for digital and traditional banks as a function of the effective Fed funds rate, which is our proxy for f. Given the uncertainty surrounding the drop in the marginal cost of deposits associated with digitalization, we plot the deposit franchise value for $c = \{.005, .012, .015\}$ for digital banks, and leave the marginal cost for traditional banks at $c = .015$. Finally, to give a sense of the magnitude of the value of the deposit franchise we normalize it by the maximum level of deposits, $\overline{D}$, for both traditional and digital banks, $\overline{D}$ (see equation (15)), which are given by $\overline{D}^{trad} = .0059$ and $\overline{D}^{dig} = .0064$, respectively. We plot these values starting at a rate of $f = 2.5\%$ to emphasize the non-linearity associated with the deposit franchise value.

First, notice that, if we keep the marginal cost of deposit constant, the deposit franchise's value is lower for digital banks than for traditional banks: Digitalization, by lowering the deposit betas and increasing the deposit outflow sensitivity, lowers the value of the deposit franchise.

[27] To construct the demand deposit series, we take from Fred, the Federal Reserve Bank of St. Louis data service, the series "Deposits, All Commercial Banks" and subtract from it the sum of "Large Time Deposits, All Commercial Banks," and "Small-Denomination Time Deposits: Total." The rate is the effective Fed funds rate as downloaded from Fred.

[28] We take the marginal cost of deposits for both banks to be $c = .005$; the model drop in deposits for digital and traditional banks is not very sensitive to the specific assumption on the marginal cost of deposits. For instance, if we instead assume that $c = .015$, the drop in deposits for digital banks is 23% and 10% for traditional banks.

Intuitively, as digitalization lowers the marginal cost of deposits, the deposit franchise value of digital banks increases, but the effect is subtle. For instance, when $c = .012$, in line with Koont (2023) estimates, the normalized deposit franchise value of digital banks is above that of traditional banks for $f < 3\%$ and below it for Federal funds rate above that level. The reason for this switch in the relative ranking is straightforward. When rates are low, the discounted value of the marginal costs (which is lower for digital banks) looms large in the deposit franchise value. As a result, the larger magnitudes of both β and η in digital banks become second-order (see expression (26)). Instead, the marginal costs are more heavily discounted as the Federal funds rate increases. As a result, the deposit franchise value becomes dominated by the deposit betas and outflow sensitivity, which are lower for traditional banks.

Second, the normalized level of the deposit franchise value is very high. Estimates of the deposit franchise value range in the single, high, digit percentage domain.[29] As Drechsler et al. (2023b) shows, formula (25) overestimates the deposit franchise value because it ignores any deposit attrition. If we assume (as Drechsler et al. (2023b)) a 10% annual attrition rate of deposits, then the deposit franchise value for a traditional bank with a marginal cost of 1.5% is 16% when the Fed funds rate is 4%. At the same Fed funds rate level, the deposit franchise value for a digital bank with a marginal cost of 1.5% is 12%. If the digital bank has a marginal cost of 1.2%, the deposit franchise value for a digital bank is 15%, and if it has a marginal cost of 0.5%, the deposit franchise value for a digital bank is 20%. Thus, if it can deliver on the promised cost reduction, digitalization will increase the deposit franchise value at common levels of the Fed funds rate. At the current level of cost reduction, however, digitalization slightly decreases the deposit franchise value.

Figure 5 Panel B, shows the duration of the deposit franchise value for our favorite parametric specification, which features a marginal cost of deposits of $c = .005$ for digital banks and of $c = .015$ for traditional banks. The duration is negative for traditional banks through the range of recently observed levels of the Fed funds rate. Instead in the case of digital banks, it switches signs and becomes positive when the Fed funds rate crosses 4.34%.

In sum, for this parameterization, digitalization results in higher deposit franchise values. The reason is that the improvement in marginal costs, from $c = .015$ to $c = .005$, is enough

[29]For instance, the May 2025 Financial Stability Report from the European Central Bank estimates the median value of the deposit franchise value for the banks in the Eurosystem at 10% of the value of the deposit. See ECB (2025, May, page 52, Chart A).

to compensate the increase in deposit betas and outflow sensitivity associated with digitalization. Nevertheless, digitalization increases the duration of the deposit franchise value relative to that of traditional banks. If the level of the fed funds rate is low, further increases in rates result in much higher values of the deposit franchise for traditional banks than for digital banks. That is, exiting the zero lower bound, bank recapitalization through an increase in rates is more pronounced for traditional than for digital banks. When rates are high, further increases can in fact *lower* the value of the deposit franchise for digital banks, adding to financial instability. Thus digitalization makes the deposit franchise value less of a hedge against fluctuations in the fed funds rate.[30]

6 Conclusions

Historically, the franchise value of deposits played an important role in banks' stability. Yet, the literature has been ambivalent on the source of the friction that generates this value. Without being specific on the source of this friction, we cannot address the fundamental question of how digitalization affects bank stability.

In this paper, we build a simple model that captures the two main frictions behind the value of the deposit franchise: product differentiation and depositors' inertia. The model with these two features allows us to analyze how digitalization changes the nature of competition and, hence, the value of the deposit franchise. We show that this model fits well the rise in deposit rates and the outflows of deposits that occurred during the 2022-2023 tightening cycle.

We compute the magnitude and duration of the deposit franchise's value based on the parameters estimated during this period and how digitalization affects them. These two variables, crucial for bank stability, are not directly observable. Hence, we regard the ability to pin them down through the lens of our model as the main contribution of the paper.

We find that digitalization has ambiguous effects on the value of the deposit franchise, depending on the magnitude of the reduction in the marginal cost. Still, digitalization unambiguously increases its duration, decreasing bank stability.

Our paper has two main limitations. The first is that we keep the decision to digitize as exogenous. Since this decision is sunk by the time the Fed decided to raise interest rates, we

[30]It is immediate to calculate the duration of the franchise value, as given in (31), for our calibrated parameters. The duration is positive and higher for digital banks. Thus, digitalization makes the franchise value of banks more sensitive to shocks in the Fed funds rate.

do not regard it as a major shortcoming for the exercise at hand. The reader interested in this endogenization is referred to Koont (2023).

Second, ours is a static model. In a dynamic model, the present value of the deposit franchise today is the discounted expected value of the deposit franchise in future states of the world. A contribution of our model is to show that this value is non-monotonic. This is particularly important since the Fed funds rate is not a martingale, but a mean-reverting process. Thus, when the Fed funds rate is high, investors will expect the Fed funds rate to drop in the future. In a dynamic model, the rise in Fed funds rate, specially starting from a high level, will have three effects. First, it will yield an increase in the spread between the Fed funds rate and the deposit rate; this will have a positive effect on the value of the deposit franchise. Second, a deposit walk which will reduce the value of the deposit franchise. Third, an expectation of future drops in the FFR, which most likely will lead to a drop in the deposit franchise. Our model brings the second term into the picture, but not the third as our model is static. Only a dynamic model of deposits, along the lines of Bolton et al. (2025), would be able to address this issue.

References

Acharya, Viral V, Rahul S Chauhan, Raghuram Rajan, and Sascha Steffen, "Liquidity Dependence and the Waxing and Waning of Central Bank Balance Sheets," Technical Report, National Bureau of Economic Research 2023.

Altavilla, Carlo, Lorenzo Burlon, Mariassunta Giannetti, and Sarah Holton, "Is there a zero lower bound? The effects of negative policy rates on banks and firms," *Journal of Financial Economics*, 2022, *144* (3), 885–907.

Basten, Christoph and Mike Mariathasan, "How banks respond to negative interest rates: Evidence from the Swiss exemption threshold," Technical Report, CESifo Working Paper 2018.

Begenau, Juliane, Monika Piazzesi, and Martin Schneider, "Banks' risk exposures," Technical Report, National Bureau of Economic Research 2015.

Benmelech, Efraim, Jun Yang, and Michal Zator, "Bank branch density and bank runs," Technical Report, National Bureau of Economic Research 2023.

Berger, Allen N and Timothy H Hannan, "The price-concentration relationship in banking," *The Review of Economics and Statistics*, 1989, pp. 291–299.

Blickle, Kristian, Jian Li, Xu Lu, and Yiming Ma, "The Dynamics of Deposit Flightiness and its Impact on Financial Stability," *Available at SSRN*, 2024.

Bolton, Patrick, Ye Li, Neng Wang, and Jinqiang Yang, "Dynamic Banking and the Value of Deposits," *The Journal of Finance*, 2025.

Cookson, J. Anthony, Corbin Fox, Javier Gil-Bazo, Juan Felipe Imbet, and Cristoph Schiller, "Social Media as a Bank Run Catalyst," *Available at SSRN*, 2023.

Curi, Claudia, Ana Lozano-Vivas, and Maurizio Murgia, "Does Digital Finance Matter? Evidence from the impact of COVID-19 shock on bank stocks," *Working Paper*, 2023.

D'Amico, Leonardo and Maxim Alekseev, "Financial Integration and Growth in the American Mid-Century," *Harvard University, Working Paper*, 2024.

Degryse, Hans and Steven Ongena, "Competition and regulation in the banking sector: A review of the empirical evidence on the sources of bank rents," *Handbook of financial intermediation and banking*, 2008, *2008*, 483–554.

DeMarzo, Peter M, Arvind Krishnamurthy, and Stefan Nagel, "Interest rate risk in banking," Technical Report, National Bureau of Economic Research 2024.

Diebold, Francis X and Steven A Sharpe, "Post-deregulation bank-deposit-rate pricing: The multivariate dynamics," *Journal of Business & Economic Statistics*, 1990, *8* (3), 281–291.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, "The deposits channel of monetary policy," *The Quarterly Journal of Economics*, 2017, *132* (4), 1819–1876.

_ , _ , and _ , "Banking on deposits: Maturity transformation without interest rate risk," *The Journal of Finance*, 2021, *76* (3), 1091–1143.

_ , _ , and _ , "Why do banks invest in MBS?," 2023.

_ , _ , _ , and Olivier Wang, "Banking on Uninsured Deposits," Technical Report, National Bureau of Economic Research 2023.

Driscoll, John C and Ruth Judson, "Sticky Deposit Rates," *Federal Reserve Board*, 2013.

ECB, "Financial Stability Report, May 2025," *European Central Bank*, 2025, May.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos, "Deposit competition and financial fragility: Evidence from the us banking sector," *American Economic Review*, 2017, *107* (1), 169–216.

_ , Ali Hortacsu, Nathan Kaplan, Adi Sunderam, and Vincent Yao, "Sleepy Deposits," *Available at SSRN*, 2025.

Eggertsson, Gauti B, Ragnar E Juelsrud, Lawrence H Summers, and Ella Getz Wold, "Negative nominal interest rates and the bank lending channel," *Review of Economic Studies*, 2024, *91* (4), 2201–2275.

English, William B, "Interest rate risk and bank net interest margins," *BIS Quarterly Review*, 2002, *10* (1), 67–82.

— , **Skander J Van den Heuvel, and Egon Zakrajšek**, "Interest rate risk and bank equity valuations," *Journal of Monetary Economics*, 2018, *98*, 80–97.

Erel, Isil, Jack Liebersohn, Constantine Yannelis, and Samuel Earnest, "Monetary Policy Transmission Through Online Banks," *Fisher College of Business Working Paper*, 2023, (2023-03), 015.

Flannery, Mark J, "Market interest rates and commercial bank profitability: An empirical investigation," *The Journal of Finance*, 1981, *36* (5), 1085–1101.

— , "Interest rates and bank profitability: Additional evidence," *Journal of Money, Credit and Banking*, 1983, *15* (3), 355–362.

Freixas, Xavier and Jean-Charles Rochet, *Microeconomics of banking*, MIT press, 2008.

Haddad, Valentin, Barney Hartman-Glaser, and Tyler Muir, "Bank fragility when depositors are the asset," *Available at SSRN 4412256*, 2023.

Haendler, Charlotte, "Keeping Up in the Digital Era: How Mobile Technology Is Reshaping the Banking Sector," *Available at SSRN 4287985*, 2022.

Hancock, Diana, "Bank profitability, interest rates, and monetary policy," *Journal of Money, Credit and Banking*, 1985, *17* (2), 189–202.

Hannan, Timothy H and Allen N Berger, "The rigidity of prices: Evidence from the banking industry," *American Economic Review*, 1991, *81* (4), 938–945.

Hanson, Samuel G, Andrei Shleifer, Jeremy C Stein, and Robert W Vishny, "Banks as patient fixed-income investors," *Journal of Financial Economics*, 2015, *117* (3), 449–469.

Heider, Florian, Farzad Saidi, and Glenn Schepens, "Life below zero: Bank lending under negative policy rates," *The Review of Financial Studies*, 2019, *32* (10), 3728–3761.

Hemingway, Benjamin, "The impact of central bank digital currency on bank deposits and the interbank market," Technical Report, Bank of Lithuania 2023.

Hong, Claire Yurong, Xiaomeng Lu, and Jun Pan, "FinTech platforms and mutual fund distribution," Technical Report, National Bureau of Economic Research 2019.

Hsieh, Chang-Tai and Esteban Rossi-Hansberg, "The industrial revolution in services," *Journal of Political Economy Macroeconomics*, 2023, *1* (1), 3–42.

Hutchison, David E, "Retail bank deposit pricing: An intertemporal asset pricing approach," *Journal of Money, Credit and Banking*, 1995, *27* (1), 217–231.

_ and George G Pennacchi, "Measuring rents and interest rate risk in imperfect financial markets: The case of retail bank deposits," *Journal of Financial and Quantitative Analysis*, 1996, *31* (3), 399–417.

Jiang, Erica Xuewei, Gloria Yang Yu, and Jinyuan Zhang, "Bank Competition amid Digital Disruption: Implications for Financial Inclusion," *Available at SSRN 4178420*, 2022.

_ , Gregor Matvos, Tomasz Piskorski, and Amit Seru, "Monetary Tightening and US Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?," Technical Report, National Bureau of Economic Research 2023.

Kang-Landsberg, Alena, Stephen Luck, and Matthew Plosser, "Deposit Betas: Up, Up, and Away?," Technical Report, Federal Reserve Bank of New York, Liberty Street Economics 2023.

Kashyap, Anil K, Raghuram Rajan, and Jeremy C Stein, "Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking," *The Journal of finance*, 2002, *57* (1), 33–73.

Koont, Naz, "The Digital Banking Revolution: Effects on Competition and Stability," *Available at SSRN 4624751*, 2023.

Lu, Xu, Yang Song, and Yao Zeng, "The Making of an Alert Depositor: How Payment and Interest Drive Deposit Dynamics," *University of Washington, Working Paper*, 2024.

_ , _ , and _ , "Tracing the Impact of Payment Convenience on Deposits: Evidence from Depositor Activeness," *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper, The Wharton School Research Paper*, 2024.

Madden, Paul and Mario Pezzino, "Oligopoly on a Salop circle with centre," *The BE Journal of Economic Analysis & Policy*, 2011, *11* (1).

Metrick, Andrew, "The failure of silicon valley bank and the panic of 2023," *Journal of Economic Perspectives*, 2024, *38* (1), 133–152.

Neumark, David and Steven A Sharpe, "Market structure and the nature of price rigidity: evidence from the market for consumer deposits," *The Quarterly Journal of Economics*, 1992, *107* (2), 657–680.

Nielsen, Carsten Krabbe and Gerd Weinrich, "Bank regulation and market structure," *International Journal of Industrial Organization*, 2023, *88*, 102944.

Repullo, Rafael, "The Deposits Channel of Monetary Policy: A Critical Review," Technical Report, CEMFI 2025.

Sá, Ana Isabel and José Jorge, "Does the deposits channel work under a low interest rate environment?," *Economic Letters*, 2019, *185* (1), 1–5.

Samuelson, Paul A, "The effect of interest rate increases on the banking system," *The American Economic Review*, 1945, *35* (1), 16–27.

Stulz, René M, "Fintech, bigtech, and the future of banks," *Journal of Applied Corporate Finance*, 2019, *31* (4), 86–97.

Ulate, Mauricio, "Going Negative at the Zero Lower Bound," *American Economic Review*, 2021, *111* (1), 1–40.

_ **and Olivia Lofton**, "How Do Low and Negative Interest Rates Affect Banks?," *FRBSF Economic Letter*, 2021, p. 23.

Vives, Xavier and Zhiqiang Ye, "Fintech Entry, Lending Market Competition, and Welfare," Technical Report, IESE Business School 2024.

Xiao, Kairong, "Monetary transmission through shadow banks," *The Review of Financial Studies*, 2020, *33* (6), 2379–2420.

Tables

Table 1: Summary Statistics

Panel A: Digital Platforms in 2022 for All Banks

	Number	Mean	Assets	Int Exp	NIM
Banks	4,756		4.97	0.40	3.13
Digital Banks (Binary)	908	0.19	21.43	0.37	3.18
Digital Banks (Continuous)	3,626	0.07	6.16	0.39	3.19
Digital Banks (By 2016)	2,641	0.56	8.27	0.37	3.18
Brokers	398	0.08	42.87	0.36	2.99
Digital Brokers (Binary)	233	0.05	67.12	0.34	3.01
Digital Brokers (Continuous)	357	0.01	46.41	0.35	3.00
Digital Brokers (By 2016)	354	0.07	46.56	0.35	3.00

Panel B: Digital Platforms in 2022 for Banks With Assets Between $1 Billion and $250 Billion

	Number	Mean	Assets	Int Exp	NIM
Banks	973		9.64	0.43	3.19
Digital Banks (Binary)	505	0.52	13.41	0.39	3.21
Digital Banks (Continuous)	852	0.10	10.09	0.42	3.20
Digital Banks (By 2016)	827	0.85	10.05	0.40	3.14
Brokers	299	0.31	17.66	0.35	3.00
Digital Brokers (Binary)	205	0.21	22.00	0.32	3.02
Digital Brokers (Continuous)	276	0.04	18.44	0.34	3.01
Digital Brokers (By 2016)	277	0.28	18.07	0.34	3.01

Panel A tabulates the number of digital banks and brokers in 2022, and panel B repeats the tabulation focusing only on banks with between $1 and $250 billion in asset size, where bank classifications are described in the main text. In both panels, the sample mean of the digital or digital-broker classifications are reported in the "Mean" column. Assets are reported in billions of dollars. Int Exp is calculated as interest expenses on deposits scaled by deposits and multiplied by 100. NIM is calculated as the difference in interest income from assets minus interest expense, scaled by assets. Data on digital platforms come from Koont (2023), and bank balance sheet information come from Call Reports.

Table 2: Deposit Volumes with Binary *Digital* Classification

	All Deposits (Non-brokered)		Insured Deposits	
	(1)	(2)	(3)	(4)
Δ FFR	-0.017***	0.006	-0.014***	-0.034***
	(0.001)	(0.006)	(0.001)	(0.006)
Δ FFR × Digital	-0.008***	-0.005***	-0.005***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.001)
Δ FFR × Broker	-0.002	0.001	0.008***	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Δ FFR × Digital × Broker	-0.003	-0.003	-0.005	-0.005
	(0.004)	(0.004)	(0.004)	(0.004)
Digital	0.037***	0.042***	0.028***	0.034***
	(0.004)	(0.004)	(0.004)	(0.004)
Broker	-0.031***	-0.034***	-0.028***	-0.030***
	(0.003)	(0.003)	(0.003)	(0.003)
Lag Log Assets		-0.014***		-0.015***
		(0.004)		(0.004)
Δ FFR × Lag Log Assets		-0.002***		0.002***
		(0.000)		(0.000)
F Digital	30.75	11.51	14.80	27.02
F Digital-Broker	25.51	5.72	0.54	6.86
Bank FE	Yes	Yes	Yes	Yes
Observations	68999	68999	69058	69058
R2	0.25	0.25	0.22	0.22

This table reports the slope estimates from an annual bank-level panel regression of proportional changes in various measures of deposits on differences in the Fed funds rate, Δ FFR, interacted with indicator variables for whether a bank has a digital platform, Digital, and offers brokerage services, Broker. This table uses the binary digital classification as described in the main text. The sample period is from 2010 through 2022. In columns (1) and (2) Deposits are defined as the sum of savings deposits, time deposits, and demand deposits. Columns (3) and (4) considers banks' estimated insured deposits as reported to the FDIC SDI. All specifications include bank and year fixed effects, as well as indicator variables for Digital and Broker banks. Columns (2) and (4) additionally include controls for banks' lagged log assets and an interaction term of lagged log assets with Δ FFR. Standard errors are clustered by bank and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively. F-stats corresponding to tests of significantly different deposit outflows for digital and digital-broker banks are reported.

Table 3: Deposit Volumes with Continuous *Digital* Classification

	All Deposits (Non-brokered)		Insured Deposits	
	(1)	(2)	(3)	(4)
Δ FFR	-0.017***	0.006	-0.014***	-0.030***
	(0.001)	(0.006)	(0.001)	(0.005)
Δ FFR × Digital	-0.022***	-0.017***	-0.013**	-0.017***
	(0.007)	(0.007)	(0.006)	(0.006)
Δ FFR × Broker	-0.002	0.002	0.007***	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Δ FFR × Digital × Broker	-0.036**	-0.033**	-0.031**	-0.034**
	(0.016)	(0.016)	(0.015)	(0.015)
Digital	0.224***	0.263***	0.174***	0.213***
	(0.015)	(0.016)	(0.014)	(0.015)
Broker	-0.028***	-0.033***	-0.026***	-0.029***
	(0.003)	(0.003)	(0.003)	(0.003)
Lag Log Assets		-0.022***		-0.020***
		(0.004)		(0.004)
Δ FFR × Lag Log Assets		-0.002***		0.001***
		(0.000)		(0.000)
F Digital	10.81	6.72	5.03	8.79
F Digital-Broker	20.77	12.62	9.55	14.08
Bank FE	Yes	Yes	Yes	Yes
Observations	68999	68999	69058	69058
R2	0.25	0.25	0.22	0.22

This table reports the slope estimates from an annual bank-level panel regression of proportional changes in various measures of deposits on differences in the Fed funds rate, Δ FFR, interacted with indicator variables for whether a bank has a digital platform, Digital, and offers brokerage services, Broker. This table uses the continuous digital classification as described in the main text. The sample period is from 2010 through 2022. In columns (1) and (2) Deposits are defined as the sum of savings deposits, time deposits, and demand deposits. Columns (3) and (4) considers banks' estimated insured deposits as reported to the FDIC SDI. All specifications include bank and year fixed effects, as well as indicator variables for Digital and Broker banks. Columns (2) and (4) additionally include controls for banks' lagged log assets and an interaction term of lagged log assets with Δ FFR. Standard errors are clustered by bank and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively. F-stats corresponding to tests of significantly different deposit outflows for digital and digital-broker banks are reported.

Table 4: Digital Banks Experience Greater Outflows in Counties with High Internet Usage

	Binary			Continuous		
	(1)	(2)	(3)	(4)	(5)	(6)
Δ FFR $\times$ HH Internet Prop.	0.062*	-0.014		0.003	-0.069***	
	(0.034)	(0.031)		(0.028)	(0.026)	
Digital $\times$ Δ FFR $\times$ HH Internet Prop	-0.143***	-0.131***	-0.075*	-0.250**	-0.225*	-0.174
	(0.040)	(0.038)	(0.039)	(0.123)	(0.119)	(0.113)
Bank-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	No	No	Yes	No
Bank-County FE	No	No	Yes	No	No	Yes
County-Year FE	No	No	Yes	No	No	Yes
Observations	287119	287114	280469	287119	287114	280469
R2	0.24	0.26	0.50	0.24	0.26	0.50

This table reports the slope estimates from an annual bank-county-level panel regression of proportional changes in deposits on differences in the Fed funds rate, Δ FFR, interacted with the county-level proportion of households that have internet subscriptions, HH Internet Prop, and with a variable tracking whether the bank offers digital services, Digital. HH Internet Prop ranges from 0 to 1 and is retrieved from the 2019 Census ACS. Results for both binary and continuous classifications of Digital are presented, where the construction of each is as described in the main text. The sample period is from 2010 through 2022. The outcome variable is proportional changes in a bank's deposits in a given county for a given year, where deposits are calculated as the sum of all deposits accruing to branches of the bank in that county, retrieved from the FDIC SOD. Standard errors are clustered by county-year and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: Aggregate County Deposit Outflows Increasing in Digital Bank Presence

	Binary				Continuous			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Proportion Digital × Δ FFR	-0.011***	-0.011***	-0.008***	-0.002	-0.045***	-0.045***	-0.025***	-0.014**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.007)	(0.007)
Proportion Digital	0.010***	0.019***	0.018***	0.017***	0.041***	0.044***	0.044***	0.043***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.005)	(0.010)	(0.011)	(0.011)
Median Income			0.048***	0.051***			0.048***	0.052***
			(0.007)	(0.007)			(0.007)	(0.007)
Payroll			0.011**	0.013**			0.010*	0.012**
			(0.005)	(0.005)			(0.005)	(0.005)
Establishments			0.018**	0.018**			0.020***	0.020***
			(0.007)	(0.007)			(0.007)	(0.007)
Employees			0.025***	0.022***			0.027***	0.024***
			(0.007)	(0.007)			(0.007)	(0.007)
Median Income × Δ FFR				0.008***				0.008***
				(0.003)				(0.003)
Payroll × Δ FFR				-0.010***				-0.010***
				(0.003)				(0.003)
Establishments × Δ FFR				-0.008***				-0.008***
				(0.002)				(0.002)
Employees × Δ FFR				0.014***				0.014***
				(0.004)				(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	41082	41075	39739	39739	41082	41075	39739	39739
R2	0.24	0.32	0.34	0.34	0.24	0.32	0.34	0.34

This table reports the slope estimates from an annual county-level panel regression of proportional changes in deposits on differences in the Fed funds rate, Δ FFR, interacted with the county-level proportion of banks that are digital, according to the binary or continuous classification, where the construction of this county-level variable is as described in the main text. Columns (3) and (4) additionally control for several time varying county-level characteristics, which come from the Census SAIFE and CBP. 2022 values for CBP variables are imputed to be equal to 2021 values due to data availability. Median Income, Payroll, Establishments, and Employees are all logged. The sample period is from 2010 through 2022. Standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Banks' Deposit Betas

	Digital 2010-2022		Digital Broker 2010-2022	
	(1)	(2)	(3)	(4)
	Binary	Continuous	Binary	Continuous
Δf_t	0.078***	0.076***	0.080***	0.080***
	(0.001)	(0.001)	(0.001)	(0.001)
Δf_{t-1}	0.014***	0.014***	0.014***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)
Δf_{t-2}	0.024***	0.025***	0.024***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)
Δf_{t-3}	0.113***	0.111***	0.113***	0.113***
	(0.002)	(0.002)	(0.002)	(0.002)
$\Delta f_t \times$ Bank Type	0.015***	0.067***	0.019***	0.080***
	(0.002)	(0.008)	(0.002)	(0.011)
$\Delta f_{t-1} \times$ Bank Type	0.002	-0.001	0.011***	0.049***
	(0.002)	(0.010)	(0.003)	(0.012)
$\Delta f_{t-2} \times$ Bank Type	-0.001	-0.016*	0.004	0.025**
	(0.002)	(0.010)	(0.003)	(0.011)
$\Delta f_{t-3} \times$ Bank Type	-0.002	0.029*	-0.014***	-0.086***
	(0.003)	(0.016)	(0.004)	(0.019)
Bank Type	-0.000***	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Beta	0.229	0.226	0.231	0.231
Beta for Bank Type	0.244	0.306	0.247	0.299
F Statistic	31.52	37.91	33.26	19.96
Observations	297696	297696	297696	297696
R2	0.25	0.25	0.25	0.25

This table reports the slope estimates from an quarterly bank-level panel regression of changes in deposit interest expenses divided by deposits on contemporaneous and lagged changes in the Fed funds rate, Δ FFR, along with indicator variables and interaction terms for digital and digital-broker banks (denoted as "Bank Type") as well as the level term of these variables. Results for both binary and continuous classifications of Digital are presented, where the construction of each is as described in the main text. All specifications include a bank fixed effect. Heteroskedasticity-robust standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively. F-statistics associated with a test of statistical significance for the difference between the betas of traditional banks and digital or digital-broker banks are reported.

Appendix A.1 Proofs and parameter restrictions

A.1.1 Proofs

Proof of Lemma 1: (a) Impose $r_1^D = r_2^D$ in the "reaction function" (9) to obtain after rearranging:

$$r^D = \frac{1}{2}\left(\frac{r^L - c}{1-\frac{\omega}{2}}\right) - \frac{1}{2}\left(\frac{\omega\alpha\ell + (1-\omega)\left(s^B+\rho\right)}{1-\frac{\omega}{2}}\right) + \frac{1}{2}\left(\frac{1-\omega}{1-\frac{\omega}{2}}\right)f, \tag{35}$$

where ω was given in (10). Define

$$\beta(p) \equiv \frac{1}{2}\left(\frac{1-\omega}{1-\frac{\omega}{2}}\right) = \frac{2p}{1+3p}, \tag{36}$$

and the intercept

$$\overline{r} \equiv \frac{1}{2}\left(\frac{1}{1-\frac{\omega}{2}}\right)\left[\left(r^L - c\right) - \left(\omega\alpha\ell + (1-\omega)\left(s^B+\rho\right)\right)\right]. \tag{37}$$

Notice that

$$\frac{1}{1-\frac{\omega}{2}} = 2\left(\frac{1+p}{1+3p}\right).$$

Add and subtract $\alpha\ell$ inside the bracket in (37), use the definition of r^B in (3), and the expression follows.

(b) As for deposits, first notice that, from (6), in a symmetric equilibrium

$$\overline{x} = \frac{\ell}{2}. \tag{38}$$

Given (38) we can substitute in (7) to obtain

$$D = 2\left[(1-p)\frac{\ell}{2} + p\alpha^{-1}\left(r^D + s^B + \rho\right) - f\right]. \tag{39}$$

Expression (14) s follows immediately when substituting $r^D = \overline{r} + \beta(p) f$ in (39) and rearranging. □

Proof of Corollary 2: This follows immediately from differentiation. In particular notice that

$$\frac{\partial\eta}{\partial p} \propto \frac{1+3p^2+2p}{(1+3p)^2} > 0 \qquad \text{and} \qquad \frac{\partial\eta}{\partial\alpha} = -\frac{2p}{\alpha^2}\left(1-\beta(p)\right) < 0,$$

and similarly for $\beta(p)$. □

Proof of Lemma 3: (a) This follows from differentiation of (28) (with the appropriate sign):

$$\frac{\partial^2 DF}{\partial f^2} = -\left(\frac{\overline{r}+c}{f^3}\right)\overline{D} < 0.$$

(b) Trivially f_0 is defined as the value of the Fed funds rate for which the value of the deposit franchise is equal to 0, that is

$$f_0 = \frac{\overline{r}+c}{(1-\beta(p))}, \tag{40}$$

which is positive given (29). Notice that, trivially, and given that $D(f) > (1-p)\,\ell \geq 0$, with equality if and only if $p = 1$, as $f < \overline{f}$, $DF(f) > 0$ for $f > f_0$ and $DF(f) \leq 0$ for $f \leq f_0$. Moreover, it can be shown with a little bit of algebra tat

$$\left.\frac{\partial DF}{\partial f}\right|_{f=f_0} = \frac{(1-\beta(p))^2}{\overline{r}+c}\left((1-p)\,\ell + 2p\alpha^{-1}\left(s^B+\rho-c\right)\right) > 0,$$

given (A3) below.

(c) From (28) the deposit franchise value achieves a maximum, f^* at

$$f^* = \left[\frac{(\overline{r}+c)\,\overline{D}}{(1-\beta(p))\,\eta(\alpha,p)}\right]^{\frac{1}{2}}, \tag{41}$$

which again relies on (29). When $p = 1$,

$$\beta(1) = \frac{1}{2} \qquad \text{and} \qquad \eta(\alpha,1) = \alpha^{-1}. \tag{42}$$

In addition

$$\overline{r}(p=1) = \frac{1}{2}\left(r^L - c - \left(s^B+\rho\right)\right) \qquad \text{and} \qquad \overline{D}\,(p=1) = \alpha^{-1}\left(r^L - c + \left(s^B+\rho\right)\right) \tag{43}$$

We drop the "$p = 1$" to lighten the notation in what follows. Substituting then (42) and (43) in (41) yields

$$f^{*2} = \left(r^L - c + \left(s^B+\rho\right)\right)\left(r^L + c - \left(s^B+\rho\right)\right). \tag{44}$$

The upper bound of the Fed funds rate is given by (see below (A1))

$$\overline{f} = r^L - c + \left(s^B+\rho\right) \tag{45}$$

Thus we can combine (45) with (44) which yields,

$$f^{*2} = \overline{f}\left(r^L + c - \left(s^B+\rho\right)\right) = \overline{f}^2\left[\frac{r^L - \left(\left(s^B+\rho\right)-c\right)}{r^L + \left(\left(s^B+\rho\right)-c\right)}\right]. \tag{46}$$

By assumption (A3) below $s^B + \rho > c$ and thus it follows that $f^* < \overline{f}$.

As for $f^* > f_0$, first recall that f_0 is defined as the value of the Fed funds rate for which the value of the deposit franchise is equal to 0 (see expression (40)), which at $p = 1$ is

$$f_0 = r^L + c - \left(s^B+\rho\right). \tag{47}$$

Notice then that, a long similar lines as above,

$$f^{*2} = f_0^2\left[\frac{r^L + \left(\left(s^B+\rho\right)-c\right)}{r^L - \left(\left(s^B+\rho\right)-c\right)}\right], \tag{48}$$

which again by assumption (A3) implies that $f^* \in \left(f_0, \overline{f}\right)$.

(d) The statement on the positive duration follows trivially by inspection of (28). As for the statement on the effect of digitalization, notice that

$$\frac{\partial}{\partial p}\left[(1-\beta(p))\,\eta\left(\alpha,p\right)\right]=\frac{2\alpha^{-1}\left(1-\beta(p)\right)\left(1+2p+3p^{2}\right)}{\left(1+3p\right)^{2}}>0 \tag{49}$$

and

$$\frac{\partial}{\partial \alpha}\left[(1-\beta(p))\,\eta\left(\alpha,p\right)\right]=-2p\alpha^{-2}\left(1-\beta(p)\right)^{2}<0, \tag{50}$$

so that increase in p and a drop in α increases the duration of the deposit franchise value. $\square$

A.1.2 Parameter restrictions

The characterization of the equilibrium in Lemma 1 requires three assumptions so that interest rates and deposits are in the "interior".[31] Specifically, we want to guarantee that the equilibrium satisfies that $r^{D}\geq 0$ and $D\left(f\right)\in\left(\left(1-p\right)\ell,\ell\right)$, which assures that both banks and MMFs are active and that deposit rates are positive, in line with empirical observations (see Figure A.1 Panel A, for the European case).[32] To achieve this we impose that the Fed funds rate is neither too high, nor too low, so that deposit rates remain positive, though not necessarily above Fed funds rate, and deposits are in the desired range. The essence of the parameter restrictions can be grasped by looking at Figure A.1 Panel B.[33] First, we assume that the Fed funds rate f is not so high, that attentive depositors who are colocated with the bank branches would not want to save through the bank, which guarantees that $D>\left(1-p\right)\ell$:

$$f\leq\overline{f}\qquad\text{where}\qquad\overline{f}=\frac{\overline{r}+s^{B}+\rho}{1-\beta}. \tag{A1}$$

Thus, in Figure 5, the normalized value of the deposit franchise for digital and traditional banks when $c=.015$ is plotted up to $\overline{f}$.

Second, if the Fed funds rate is instead too low, all agents would potentially prefer to save through the bank, and capture s^{B}, rather than pay the cost ρ and obtain very low rates. In fact, agent may want to short the MMF and open checking accounts in order to capture $s^{B}+\rho$! To avoid this[34] we assume that

$$f\geq\underline{f}'\qquad\text{where}\qquad\underline{f}'=\overline{f}-\frac{1}{2}\left(\frac{\alpha\ell}{1-\beta}\right). \tag{51}$$

[31] Salop circle models obtain closed-form solutions by imposing linearity and thus require assumptions to obtain realistic equilibrium quantities and prices; see, for example Vives and Ye (2024, p. 11-12).

[32] Recall that we have assumed in addition that savers cannot hold cash, that is, that they are forced to save either through bank or MMF accounts. This can be added without any gain in terms of the intuition, but at an additional notational costs.

[33] This figure should be contrasted with Ulate and Lofton (2021, Figure 1), from which we draw inspiration. There are differences though. First, these authors implicitly assume a "β" of one, as they draw deposits rates to be parallel to policy rates. Second, and more realistically, they assume a lending rate, which is increasing in the policy rate, whereas it is flat in our case.

[34] Repullo (2025) has recently studied the model of Drechsler et al. (2017) imposing the constraint that the deposit rate cannot fall below zero and that agents cannot borrow at the Fed funds rate (see his Proposition 3 and the discussion around it). In our model there is an additional degree of freedom that allows us to obtain monotone

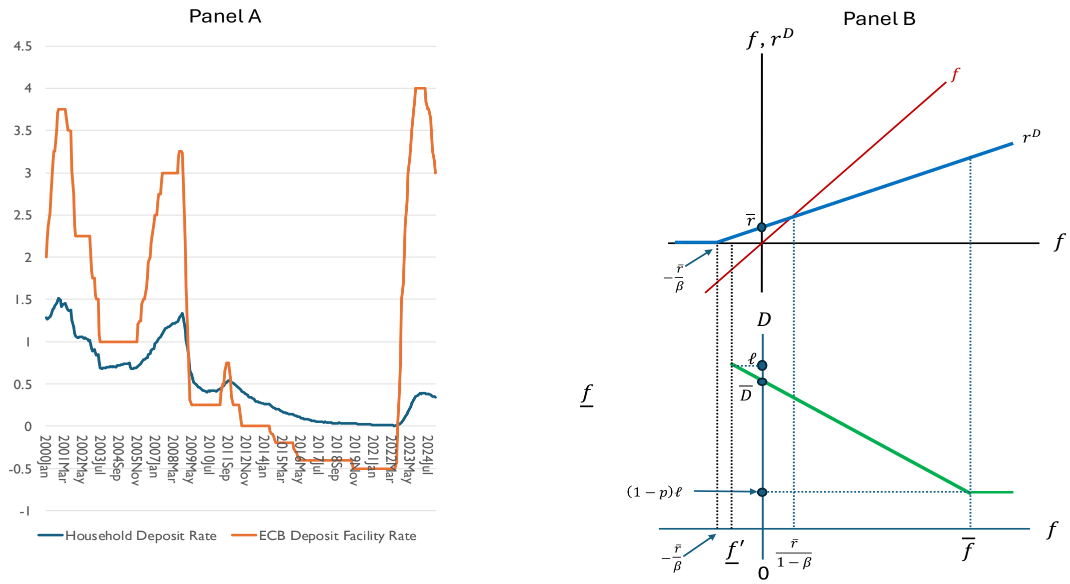


Figure A.1: Panel A: Euro area household overnight deposit rates and ECB Deposit Facility Rate for the Euro Area; Percent, Monthly. Data source: ECB data portal, MFI Interest Rate Statistics - MIR and Fred. Panel B: Parameter restrictions in the model.

This guarantees that the $D(f) \leq \ell$, with equality if and only if $f = \underline{f}'$.

Notice that when α is high enough $\underline{f}' < 0$, which is also the case in most of our calibrations.[35] In addition, we want to guarantee that $r^D \geq 0$, which trivially requires that

$$f \geq -\frac{\overline{r}}{\beta}. \tag{52}$$

whenever $\beta > 0$. To make sure then that $r^D \geq 0$ and $D \leq \ell$ it is enough to choose

$$\underline{f} = \max\left\{\underline{f}', -\frac{\overline{r}}{\beta}\right\}, \tag{53}$$

which in Figure A.1 Panel B, for example, is given by $\underline{f}'$. In our calibration, and given that at the ZLB, deposit rates

behavior of rates and deposits as a function of the Fed funds rate, namely the *dis*utility depositors in neighborhood $\mathcal{N}_{\frac{\ell}{2}}$ of banking, which is determined by $\frac{\alpha\ell}{2}$. We use this extra degree of freedom in our model relative to that of Drechsler et al. (2017) to obtain monotone behavior in rates and deposits as a function of the Fed funds rate. See also Sá and Jorge (2019).

[35]For instance, for the calibrations for the cases in Figure 5, when $c = .015$, $\underline{f} = -.060$, or minus 6%, for traditional banks and $\underline{f}' = -.027$, or minus 2.7% for digital banks. For a digital bank with $c = .012$, the marginal cost of digital banks in Koont (2023), $\underline{f}' = -.017$, or minus 1.7%, and only for $c = .005$ is the $\underline{f}' = .005$, or .5%, a bit above the ZLB.

were always non-negative, we set $\overline{r} = 0$ and thus we simply consider the Fed funds rate in the domain

$$f \in \left[0, \overline{f}\right]. \tag{A2}$$

But to reiterate, our model can accommodate situations in which, at least to an extent, f can fall below the deposit rate and even below zero, as it did in the Euro Area, Sweden, Switzerland, Denmark and Japan, while deposit rates remain positive (see Figure A.1 Panels A and B):[36]

$$r^D \begin{cases} \geq f & \text{if} \quad f \in \left[0, \frac{\overline{r}}{1-\beta}\right) \\ < f & \text{if} \quad f \in \left(\frac{\overline{r}}{1-\beta}, \frac{\overline{r}+s^B+\rho}{1-\beta}\right] \end{cases}$$

Finally, we assume that

$$s^B > c - \rho. \tag{A3}$$

That is, even when deposit rates are very low, there is social surplus associated with the existence of banks as deposit taking institutions: The value of banking services is greater than the marginal costs of deposits net of the marginal costs of saving through the MMF. Notice that this assumption combined with (29) implies that $\overline{f} > 0$.

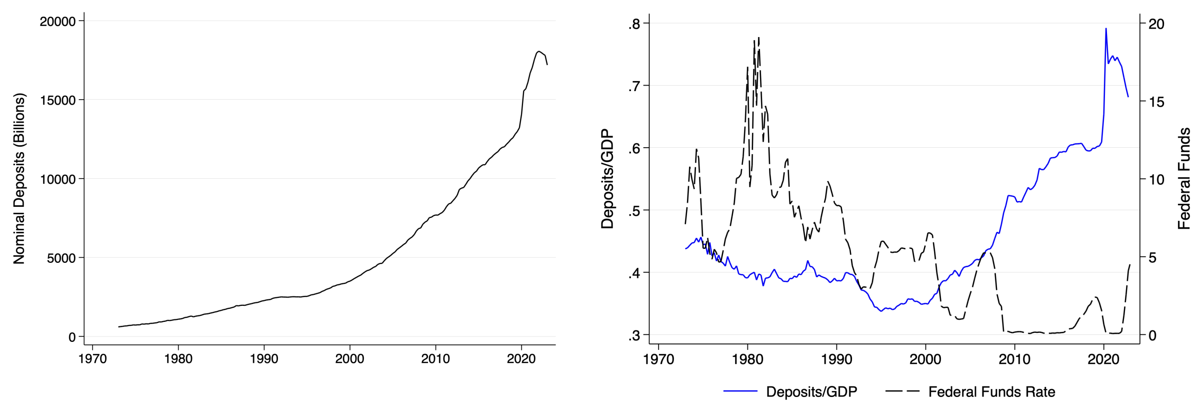
[36]More broadly, there is a literature documenting the behavior of deposit rates at the zero lower bound. Roughly the finding is that deposit rates can be negative or not depending on whether deposits are held by households or firms. Altavilla et al. (2022) for instance, find that banks were able "charge negative rates on a significant portion of their deposits, especially if they have sound balance sheets," for corporations. They go on to argue that a zero lower bound may be operational for households, as it is easier for them to hold cash, but that firms rely on banks to conduct their payments. There are several papers that confirm this. For instance, Eggertsson et al. (2024) document the existence in Sweden of a deposit rate lower bound for households (which they term DLB) and argue for the economic importance of this constraint for policy purposes; Heider et al. (2019), using the ECB data, show that negative policy rates do not transmit to lower deposit rates for Eurozone households as banks are reluctant to transmit those rates to them; they study the implications of this fact for bank credit policies; Basten and Mariathasan (2018) find similar evidence for Switzerland. Ulate (2021) documents evidence of zero lower bounds for bank deposit rates in a cross section of 19 countries/regions, five of which set negative nominal rates (the Euro Area, Sweden, Switzerland, Denmark, and Japan) or very low rates (United States, United Kingdom, Canada, Norway, and Australia). He focuses on policy effectiveness when deposit rates are at the zero lower bound.

Appendix A.2 Additional Figures and Tables

Figure A.2: Time-Series Trends

Panel A: Nominal Deposits

Panel B: Deposit Elasticity

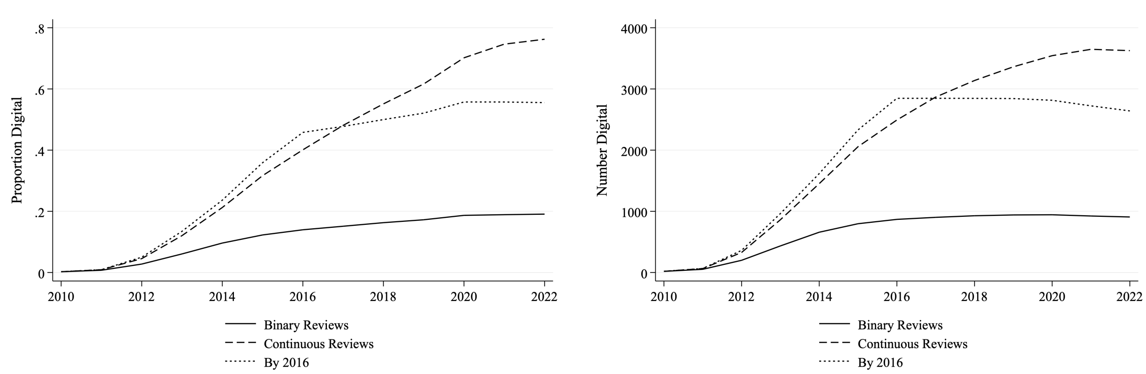


Panel A plots the nominal level of bank deposits, in Billions of dollars, between the first quarter of 1973 and the first quarter of 2023. Panel B plots the ratio of nominal deposits to nominal GDP between the same period, overlayed with the level of the Fed funds rate. All aggregate variables are retrieved from Fred.

Figure A.3: Digital Banks

Panel A

Panel B



Panel A plots the proportion and Panel B the number of banks that are classified to be digital according to our three measures during our sample period, from 2010 to 2022.

Table A.1: Deposit Volumes Robustness to Year Fixed Effects

	Binary		Continuous	
	(1)	(2)	(3)	(4)
	All (Non-brokered)	Insured	All (Non-brokered)	Insured
Δ FFR × Digital	-0.005***	-0.003**	-0.010	-0.003
	(0.001)	(0.001)	(0.007)	(0.006)
Δ FFR × Broker	-0.005**	0.004	-0.004*	0.005*
	(0.003)	(0.003)	(0.002)	(0.003)
Δ FFR × Digital × Broker	-0.001	-0.003	-0.029*	-0.024
	(0.004)	(0.004)	(0.016)	(0.015)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	68999	69058	68999	69058
R2	0.29	0.28	0.29	0.28

This table reports the slope estimates from an annual bank-level panel regression of proportional changes in All and Insured deposits on differences in the Fed funds rate, Δ FFR, interacted with indicator variables for whether a bank has a digital platform, Digital, and offers brokerage services, Broker. Results for both binary and continuous classifications of Digital are presented, where the construction of each is as described in the main text. The sample period is from 2010 through 2022. In columns (1) and (3) Deposits are defined as the sum of savings deposits, time deposits, and demand deposits. Columns (2) and (4) consider banks' estimated insured deposits as reported to the FDIC SDI. All specifications include bank and year fixed effects. Standard errors are clustered by bank and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Deposit Volumes Robustness to Digital by 2016

	All Deposits (Non-brokered)		Insured Deposits	
	(1)	(2)	(3)	(4)
Δ FFR	-0.016***	0.002	-0.013***	-0.036***
	(0.001)	(0.006)	(0.001)	(0.006)
Δ FFR $\times$ Digital	-0.006***	-0.005***	-0.004***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Δ FFR $\times$ Broker	-0.003	0.001	0.011*	0.008
	(0.005)	(0.005)	(0.006)	(0.006)
Δ FFR $\times$ Digital $\times$ Broker	-0.003	-0.003	-0.008	-0.009
	(0.005)	(0.005)	(0.006)	(0.006)
Digital	0.038***	0.046***	0.029***	0.038***
	(0.002)	(0.002)	(0.002)	(0.002)
Broker	-0.026***	-0.030***	-0.024***	-0.027***
	(0.003)	(0.003)	(0.003)	(0.003)
Lag Log Assets		-0.025***		-0.024***
		(0.004)		(0.004)
Δ FFR $\times$ Lag Log Assets		-0.001***		0.002***
		(0.001)		(0.000)
F Digital	32.25	15.40	15.92	32.62
F Digital-Broker	33.52	9.82	0.20	7.66
Bank FE	Yes	Yes	Yes	Yes
Observations	68999	68999	69058	69058
R2	0.25	0.25	0.22	0.23

This table reports the slope estimates from an annual bank-level panel regression of proportional changes in All and Insured deposits on differences in the Fed funds rate, Δ FFR, interacted with indicator variables for whether a bank has a digital platform, Digital, and offers brokerage services, Broker. Banks are defined to be digital according to our classification that requires banks to have adopted digital platforms by 2016, as described in the main text. The sample period is from 2010 through 2022. In columns (1) and (3) Deposits are defined as the sum of savings deposits, time deposits, and demand deposits. Columns (2) and (4) consider banks' estimated insured deposits as reported to the FDIC SDI. All specifications include bank and year fixed effects. Standard errors are clustered by bank and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Deposit Volumes Robustness to M&A: Binary

	All Deposits (Non-brokered)		Insured Deposits	
	(1)	(2)	(3)	(4)
Δ FFR	-0.016***	0.004	-0.013***	-0.037***
	(0.001)	(0.006)	(0.001)	(0.006)
Δ FFR $\times$ Digital	-0.008***	-0.005***	-0.005***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.001)
Δ FFR $\times$ Broker	-0.004	-0.001	0.007**	0.004
	(0.002)	(0.003)	(0.003)	(0.003)
Δ FFR $\times$ Digital $\times$ Broker	-0.002	-0.001	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)
Digital	0.044***	0.034***	0.036***	0.027***
	(0.003)	(0.003)	(0.003)	(0.003)
Broker	-0.041***	-0.037***	-0.039***	-0.034***
	(0.002)	(0.002)	(0.002)	(0.002)
Lag Log Assets		0.026***		0.025***
		(0.004)		(0.004)
Δ FFR $\times$ Lag Log Assets		-0.002***		0.002***
		(0.000)		(0.000)
F Digital	33.04	10.85	17.23	27.72
F Digital-Broker	26.96	6.66	0.82	8.45
Bank FE	Yes	Yes	Yes	Yes
Observations	66061	66061	66120	66120
R2	0.26	0.26	0.24	0.24

This table reports the slope estimates from an annual bank-level panel regression of proportional changes in All and Insured deposits on differences in the Fed funds rate, Δ FFR, interacted with indicator variables for whether a bank has a digital platform, Digital, and offers brokerage services, Broker. Results for the binary classification of Digital is presented, where the construction is as described in the main text. The sample period is from 2010 through 2022, and excludes any bank-year observations in which a bank has any M&A or sales activity. In columns (1) and (3) Deposits are defined as the sum of savings deposits, time deposits, and demand deposits. Columns (2) and (4) consider banks' estimated insured deposits as reported to the FDIC SDI. All specifications include bank and year fixed effects. Standard errors are clustered by bank and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4: Deposit Volumes Robustness to M&A: Continuous

	All Deposits (Non-brokered)		Insured Deposits	
	(1)	(2)	(3)	(4)
Δ FFR	-0.017***	0.004	-0.014***	-0.033***
	(0.001)	(0.006)	(0.001)	(0.005)
Δ FFR $\times$ Digital	-0.024***	-0.019***	-0.016***	-0.019***
	(0.007)	(0.007)	(0.006)	(0.006)
Δ FFR $\times$ Broker	-0.003	0.000	0.007***	0.003
	(0.002)	(0.002)	(0.003)	(0.003)
Δ FFR $\times$ Digital $\times$ Broker	-0.030*	-0.026*	-0.027*	-0.029**
	(0.016)	(0.016)	(0.014)	(0.014)
Digital	0.252***	0.215***	0.204***	0.168***
	(0.014)	(0.015)	(0.014)	(0.014)
Broker	-0.038***	-0.036***	-0.037***	-0.033***
	(0.002)	(0.002)	(0.002)	(0.002)
Lag Log Assets		0.019***		0.020***
		(0.004)		(0.004)
Δ FFR $\times$ Lag Log Assets		-0.002***		0.001***
		(0.000)		(0.000)
F Digital	13.52	7.70	7.65	10.77
F Digital-Broker	19.86	10.84	9.43	13.41
Bank FE	Yes	Yes	Yes	Yes
Observations	66061	66061	66120	66120
R2	0.26	0.27	0.24	0.25

This table reports the slope estimates from an annual bank-level panel regression of proportional changes in All and Insured deposits on differences in the Fed funds rate, Δ FFR, interacted with indicator variables for whether a bank has a digital platform, Digital, and offers brokerage services, Broker. Results for the continuous classification of Digital is presented, where the construction is as described in the main text. The sample period is from 2010 through 2022, and excludes any bank-year observations in which a bank has any M&A or sales activity. In columns (1) and (3) Deposits are defined as the sum of savings deposits, time deposits, and demand deposits. Columns (2) and (4) consider banks' estimated insured deposits as reported to the FDIC SDI. All specifications include bank and year fixed effects. Standard errors are clustered by bank and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5: Banks' Deposit Interest Expense and NIM

	Interest Expense			NIM		
	(1)	(2)	(3)	(4)	(5)	(6)
	Binary	Continuous	Digital by 2016	Binary	Continuous	Digital by 2016
Δ FFR $\times$ Digital	0.046***	0.189***	0.032***	0.001	0.004	-0.006***
	(0.005)	(0.023)	(0.004)	(0.002)	(0.009)	(0.001)
Δ FFR $\times$ Broker	0.091***	0.100***	0.111***	0.006**	0.006**	0.009
	(0.010)	(0.010)	(0.020)	(0.003)	(0.003)	(0.007)
Δ FFR $\times$ Digital $\times$ Broker	0.016	0.076	-0.005	0.000	0.005	0.000
	(0.015)	(0.060)	(0.021)	(0.004)	(0.017)	(0.007)
Digital	-0.008	-0.026	-0.010***	-0.003	-0.016	-0.002
	(0.005)	(0.021)	(0.003)	(0.002)	(0.011)	(0.002)
Broker	-0.021***	-0.023***	-0.023***	0.002	0.002	0.001
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
F Digital	70.39	69.72	72.47	0.21	0.22	22.63
F Digital-Broker	236.25	52.18	291.06	9.43	1.37	1.48
Observations	68701	68701	68701	69789	69789	69789
R2	0.60	0.60	0.60	0.20	0.20	0.20

This table reports the slope estimates from an annual bank-level panel regression of proportional changes in Interest Expense and NIM on differences in the Fed funds rate, Δ FFR, interacted with indicator variables for whether a bank has a digital platform, Digital, and offers brokerage services, Broker. Results for all three classifications of Digital are presented, where the construction of each is as described in the main text. Int Exp is calculated as interest expenses on deposits scaled by deposits and multiplied by 100. NIM is calculated as the difference in interest income from assets minus interest expense, scaled by assets. The sample period is from 2010 through 2022. All specifications include bank and year fixed effects. Standard errors are clustered by bank and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.6: Within-Bank: Robustness to Digital by 2016

	(1)	(2)	(3)
Δ FFR $\times$ HH Internet Prop.	0.083	-0.009	
	(0.058)	(0.054)	
Digital $\times$ Δ FFR $\times$ HH Internet Prop	-0.134**	-0.106*	-0.134**
	(0.060)	(0.058)	(0.059)
Bank-Year FE	Yes	Yes	Yes
County FE	No	Yes	No
Bank-County FE	No	No	Yes
County-Year FE	No	No	Yes
Observations	287119	287114	280469
R2	0.24	0.26	0.50

This table reports the slope estimates from an annual bank-county-level panel regression of proportional changes in deposits on differences in the Fed funds rate, Δ FFR, interacted with the county-level proportion of households that have internet subscriptions, HH Internet Prop, and with a variable tracking whether the bank offers digital services, Digital. HH Internet Prop ranges from 0 to 1 and is retrieved from the 2019 Census ACS. Banks are defined to be digital according to our classification that requires banks to have adopted digital platforms by 2016, as described in the main text. The sample period is from 2010 through 2022. The outcome variable is proportional changes in a bank's deposits in a given county for a given year, where deposits are calculated as the sum of all deposits accruing to branches of the bank in that county, retrieved from the FDIC SOD. Standard errors are clustered by county-year and reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.7: Aggregate County Deposit Outflows: Robustness to Digital by 2016

	(1)	(2)	(3)	(4)
Proportion Digital × Δ FFR	-0.011***	-0.011***	-0.008***	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Proportion Digital	0.006***	0.003	0.003	0.003
	(0.001)	(0.002)	(0.002)	(0.002)
Median Income			0.049***	0.052***
			(0.007)	(0.007)
Payroll			0.010*	0.012**
			(0.005)	(0.005)
Establishments			0.021***	0.020***
			(0.007)	(0.007)
Employees			0.027***	0.024***
			(0.007)	(0.007)
Median Income × Δ FFR				0.008***
				(0.003)
Payroll × Δ FFR				-0.011***
				(0.003)
Establishments × Δ FFR				-0.008***
				(0.002)
Employees × Δ FFR				0.014***
				(0.004)
Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes
Observations	41082	41075	39739	39739
R2	0.24	0.32	0.34	0.34

This table reports the slope estimates from an annual county-level panel regression of proportional changes in deposits on differences in the Fed funds rate, Δ FFR, interacted with the county-level proportion of banks that are digital, according to the classification that requires banks to have adopted digital platforms by 2016, as described in the main text. Columns (3) and (4) additionally control for several time varying county-level characteristics, which come from the Census SAIFE and CBP. 2022 values for CBP variables are imputed to be equal to 2021 values due to data availability. Median Income, Payroll, Establishments, and Employees are all logged. The sample period is from 2010 through 2022. Standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.8: Average Bank Betas

	1983-2017		2010-2022	
	(1)	(2)	(3)	(4)
	Deposit Beta	Interest Expense Beta	Deposit Beta	Interest Expense Beta
Δf_t	0.113***	0.089***	0.081***	0.050***
	(0.001)	(0.001)	(0.001)	(0.002)
Δf_{t-1}	0.161***	0.161***	0.014***	0.090***
	(0.001)	(0.001)	(0.001)	(0.002)
Δf_{t-2}	0.010***	0.005***	0.024***	0.082***
	(0.001)	(0.001)	(0.001)	(0.002)
Δf_{t-3}	0.047***	0.040***	0.113***	-0.054***
	(0.001)	(0.001)	(0.002)	(0.003)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Beta	0.331	0.295	0.232	0.168
Observations	1232446	1225700	301929	251036
R2	0.24	0.41	0.25	0.29

This table reports the slope estimates from an quarterly bank-level panel regression of average bank betas calculated over 1983-2017 in columns (1) and (2), and over 2010-2022 for columns (3) and (4). Columns (1) and (3) calculate banks' deposit beta, where the outcome variable is changes in deposit interest expenses divided by deposits, and columns (2) and (4) calculate banks' interest expense beta, where the outcome variable is changes in interest expenses divided by assets. The betas are calculated as the sum of the coefficients on the contemporaneous and lagged differences in the Fed funds rate, Δ FFR. All specifications include bank and year fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.9: Banks' Interest Expense Betas

	Digital 2010-2022		Digital Broker 2010-2022	
	(1)	(2)	(3)	(4)
	Binary	Continuous	Binary	Continuous
Δf_t	0.045***	0.044***	0.047***	0.047***
	(0.002)	(0.002)	(0.002)	(0.002)
Δf_{t-1}	0.089***	0.090***	0.090***	0.090***
	(0.002)	(0.002)	(0.002)	(0.002)
Δf_{t-2}	0.085***	0.085***	0.084***	0.084***
	(0.003)	(0.003)	(0.002)	(0.002)
Δf_{t-3}	-0.056***	-0.057***	-0.053***	-0.054***
	(0.003)	(0.003)	(0.003)	(0.003)
$\Delta f_t \times$ Bank Type	0.031***	0.119***	0.045***	0.196***
	(0.004)	(0.017)	(0.005)	(0.023)
$\Delta f_{t-1} \times$ Bank Type	0.006	-0.002	0.018***	0.060**
	(0.005)	(0.022)	(0.006)	(0.027)
$\Delta f_{t-2} \times$ Bank Type	-0.020***	-0.055**	-0.026***	-0.113***
	(0.006)	(0.023)	(0.007)	(0.029)
$\Delta f_{t-3} \times$ Bank Type	0.017***	0.077***	0.009	0.051**
	(0.005)	(0.020)	(0.006)	(0.025)
Bank Type	-0.000***	-0.000	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Bank FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Beta	0.163	0.162	0.168	0.167
Beta for Bank Type	0.191	0.303	0.205	0.361
F Statistic	66.75	53.84	67.29	61.17
Observations	247402	247402	247402	247402
R2	0.30	0.30	0.30	0.30

This table reports the slope estimates from an quarterly bank-level panel regression of changes in interest expenses divided by assets on contemporaneous and lagged changes in the Fed funds rate, Δ FFR, along with indicator variables and interaction terms for digital and digital-broker banks (denoted as "Bank Type") as well as the level term of these variables. Results for both binary and continuous classifications of Digital are presented, where the construction of each is as described in the main text. All specifications include bank and year fixed effects. Heteroskedasticity-robust standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively. F-statistics associated with a test of statistical significance for the difference between the betas of traditional banks and digital or digital-broker banks are reported.

Table A.10: Banks' Deposit and Interest Expense Betas: Robustness to Digital by 2016

	Deposit Beta	Interest Expense Beta
Δf_t	0.072***	0.036***
	(0.001)	(0.003)
Δf_{t-1}	0.018***	0.090***
	(0.001)	(0.003)
Δf_{t-2}	0.025***	0.092***
	(0.002)	(0.003)
Δf_{t-3}	0.108***	-0.072***
	(0.002)	(0.004)
$\Delta f_t \times$ Bank Type	0.015***	0.026***
	(0.001)	(0.003)
$\Delta f_{t-1} \times$ Bank Type	-0.006***	0.001
	(0.002)	(0.004)
$\Delta f_{t-2} \times$ Bank Type	-0.001	-0.020***
	(0.002)	(0.004)
$\Delta f_{t-3} \times$ Bank Type	0.009***	0.040***
	(0.003)	(0.004)
Bank Type	-0.000***	-0.000**
	(0.000)	(0.000)
Bank FE	Yes	Yes
Year FE	Yes	Yes
Beta	0.223	0.146
Beta for Bank Type	0.241	0.192
F Statistic	53.76	163.59
Observations	297696	247402
R2	0.25	0.30

Column (1) reports the slope estimates from an quarterly bank-level panel regression of changes in deposit interest expenses divided by deposits on contemporaneous and lagged changes in the Fed funds rate, Δ FFR, along with indicator variables and interaction terms for digital and digital-broker banks (denoted as "Bank Type") as well as the level term of these variables, from 2010 through 2022. Column (2) repeats the exercise where the outcome variable is now changes in interest expenses divided by assets. Digital is defined according to our classification requiring banks to have adopted digital platforms by 2016, as described in the main text. All specifications include a bank and year fixed effect. Heteroskedasticity-robust standard errors are reported in parentheses. One, two, and three stars indicate statistical significance at the 10%, 5%, and 1% level, respectively. F-statistics associated with a test of statistical significance for the difference between the betas of traditional banks and digital banks are reported.

Table A.11: Banks' Deposit Betas: Distribution

	Mean	S.D.	p25	p50	p75	Count
Digital (Binary Reviews Measure)						
Digital Deposit Beta	0.241	0.113	0.166	0.234	0.305	907
Traditional Deposit Beta	0.230	0.125	0.141	0.212	0.301	3739
Digital by 2016						
Digital Deposit Beta	0.237	0.112	0.160	0.227	0.303	2639
Traditional Deposit Beta	0.225	0.135	0.127	0.203	0.298	2007

This table reports the distribution of banks' deposit betas separately for banks that are classified to be digital or not in 2022, according to our two binary measures of digitalization, as defined in the main text. The betas are an average of the banks' betas throughout the time period from 2010 to 2022.

Table A.12: Banks' Interest Expense Betas: Distribution

	Mean	S.D.	p25	p50	p75	Count
Digital (Binary Reviews Measure)						
Digital Interest Expense Beta	0.194	0.141	0.100	0.194	0.283	907
Traditional Interest Expense Beta	0.170	0.163	0.055	0.163	0.269	3782
Digital by 2016						
Digital Interest Expense Beta	0.190	0.146	0.087	0.187	0.279	2639
Traditional Interest Expense Beta	0.157	0.174	0.035	0.147	0.262	2050

This table reports the distribution of banks' interest expense betas separately for banks that are classified to be digital or not in 2022, according to our two binary measures of digitalization, as defined in the main text. The betas are an average of the banks' betas throughout the time period from 2010 to 2022.