How Would U.S. Banks Fare in a Negative Interest Rate Environment?*

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The effectiveness of negative interest rates as a monetary policy tool depends importantly on the response of the banking sector. This paper offers unique new insights for U.S. banks by using supervisory data to examine bank-level expectations regarding the impact of negative rates on profitability through net interest margins. The main results show that the largest U.S. banks differ significantly in how they respond to negative interest rates. The most significant channel of adverse exposure comes from the pass-through of the negative policy rate to interest rates on short-term liquid assets held on the balance sheet. At the same time, on the liability side, banks that rely more heavily on short-term wholesale funding, including financing through the repo market, may benefit through a reduction in funding costs. In the aggregate, these effects likely wash out as liquidity provision is sufficiently well diversified across the banking sector as a whole.

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1. Introduction

Since the financial crisis a number of central banks, including the European Central Bank (ECB), Danmarks Nationalbank, the

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Swedish Riksbank, the Swiss National Bank, and the Bank of Japan, have implemented negative interest rate policies with the aim of generating monetary stimulus for real economic activity.[1] In the United States, a negative interest rate policy, though never implemented, has been discussed amongst academics as well as in broad policy circles.[2] While the immediate urgency of this debate has diminished as the post-crisis expansion continues, it is still the case that the federal funds rate remains near historic lows. As such, a series of adverse shocks would likely put unconventional policy tools, including negative interest rates, back under consideration.

In principle, the transmission of monetary policy as implemented through negative interest rates can work through a number of possible transmission channels, but one that has received particular attention operates through the banking sector. The idea is that by charging a fee for holding excess reserves at the central bank, a negative interest rate policy can be used to encourage banks to substitute out of reserves and into other assets. Under a certain set of assumptions, doing so can influence the loan supply schedule such that the resulting increase in bank credit lowers the cost of capital for bank-dependent borrowers. This, in turn, has a stimulative effect on the rest of the macroeconomy. The bank lending channel of monetary policy transmission is articulated in Bernanke and Blinder (1988) and discussed more generally in Bernanke and Gertler (1995). Empirical support is provided by Bernanke and Blinder (1992), Kashyap and Stein, (1995, 2000) and Jimenez et al. (2012), among others.

[1]Bech and Malkhozov (2016) point to a desire to manage inflation and inflation expectations as a key motivation behind the ECB and the Riksbank implementing negative interest rates, while the the Swiss and Danish National Banks were motivated by a desire to mitigate appreciation pressure on their respective currencies.

[2]From an academic perspective, Goodfriend (2000) is an early contribution on the implementation of negative interest rates and Goodfriend (2017) provides a discussion of the evolution of the literature since that time. From the policy perspective, a number of prominent economists have commented on implementing negative interest rates in the United States, including Mankiw (2009), Blinder (2010), Bernanke (2016), and Kocherlakota (2016).

However, this transmission channel may be complicated by the effect of negative interest rates on bank profitability.[3] Bank profits are determined, in part, by the net interest margin—the difference between interest income and interest expenses. When the policy rate goes negative, a common concern is that banks might not be willing to pass this cost on to their deposit base. In this case, incomplete pass-through to deposit rates leads to compression of the net interest margin, which erodes bank profits. In turn, reduced profitability makes it more difficult to raise capital from retained earnings, thereby dampening monetary transmission through the bank lending channel. Kishan and Opiela (2000) and Gambacorta and Mistrulli (2004) present empirical evidence suggesting that banks' willingness to supply new loans is importantly influenced by bank capital. Even if banks do allow full pass-through to deposit rates, a negative interest rate policy can still pose complications because retail and wholesale depositors might not be willing to pay to hold deposits and may themselves substitute into other assets (i.e., cash). This potential for deposit flight can undermine financial stability by increasing liquidity risk in the banking sector.

The impact on the strength of monetary transmission, as well as on financial stability more generally, makes it clear that a more complete understanding of how bank profitability might evolve in a negative interest rate environment is an important component of the effectiveness of negative rates as a policy instrument. However, experience with negative rate episodes is limited. We can look to a short period of recent history for a subset of European and Japanese banks, but when it comes to understanding the U.S. banking system we are severely limited by lack of historical experience.

This paper is uniquely positioned to shed light on how U.S. banks view themselves as being exposed to negative interest rates. We

[3]Concerns regarding negative interest rates extend beyond bank profitability. Bernanke (2016) points to potential adverse effects on money market funds as well as legal and operational constraints on the implementation by the Federal Reserve. Hannoun (2015) raises additional concerns regarding the potential to influence risk-taking behavior via the search for yield in a low rate environment as well as the adverse impact on nonbank financial institutions which offer long-term liabilities at fixed nominal rates, such as life insurance contracts. See also McAndrews (2015) for additional discussion of the complications associated with negative interest rates.

use confidential supervisory data from the Comprehensive Capital Analysis and Review (CCAR) stress tests to empirically assess how individual banks view their own profitability—specifically through the lens of net interest margins (NIMs)—evolving in a hypothetical negative interest rate environment.[4] The data cover the 30 largest bank holding companies (BHCs) which, taken together, constitute roughly 75 percent of total assets in the U.S. banking system over five consecutive years (2014 through 2018) of stress-test vintages.

Our identification strategy exploits the fact that negative rates were introduced by the Federal Reserve as an explicit scenario design feature in the supervisory severely adverse scenario of the 2016 vintage of CCAR. This design feature allows us to isolate how individual banks view their NIMs as evolving in a negative rate environment, even after controlling for underlying macroeconomic developments and bank-specific characteristics.

The main results reveal considerable differences across the BHCs in our sample. All banks anticipate reduced profitability in response to the macroeconomic conditions that give rise to the negative rate environment in the first place. After controlling for these effects, we find that roughly one-third of the banks are exposed to lower profits through NIM compression due to negative policy rates per se. In contrast, an additional one-third project expanded NIMs as negative rates lead to lower short-term funding costs. The remaining banks in our sample do not believe that negative rates will have a material impact on profitability beyond what can be explained by the underlying macroeconomic environment.

To explain these cross-bank differences, we present a simple decomposition of the NIM and use it to highlight some potential nonlinearities that may arise as the policy rate turns negative. We examine three hypothesized channels of exposure. The *retail deposit channel* suggests that imperfect pass-through to deposit rates will amplify NIM compression. Drawing on Kashyap, Rajan, and Stein

[4]Negative interest rates can potentially affect bank profitability through a number of different channels beyond net interest margins. For example, negative rates could boost earnings through increased lending volumes or through stronger demand for capital management and investment banking services due to a low rate environment. Alternatively, negative interest rates may boost profits through asset-valuation changes. Our specific focus in this paper on net interest margins is due to data availability, as will be described in greater detail in section 3 below.

(2002), we also examine a *liquidity-management channel* whereby exposure to negative interest rates is driven by short-term assets on the balance sheet relative to short-term liabilities. In contrast with the deposit margin channel, the liquidity-management channel relies on unimpeded pass-through to interest rates on a wide variety of short-duration assets and liabilities. Finally, we examine the *yield curve compression channel*, which suggests that as the level of the policy rate moves lower and eventually turns negative, the yield curve becomes progressively flatter, thereby amplifying NIM compression.

The decomposition is done in a way that allows a test of the empirical relevance of each channel using publicly available balance sheet data. The results suggest that U.S. banks do not face significant exposure through either the retail deposit or the yield curve compression channel. There is, however, much stronger support for exposure through liquidity-management practices. On the asset side of the balance sheet, banks with a high proportion of reserves are highly exposed to amplified NIM compression as rates turn negative. On the liability side, banks that rely more heavily on short-term wholesale funding anticipate a boost to NIMs through a reduction in funding costs in a negative rate environment.

Banks also face significant exposure through their net repo position, but this exposure differs importantly between global systemically important banks (G-SIBs) and non–G-SIBs. The more active a non–G-SIB bank is in providing liquidity to borrowers via the repo market, the larger the expected NIM compression. But, this effect is ameliorated for G-SIBs due to the fact that they have large broker-dealer subsidiaries which rely heavily on repo financing. Hence, at the holding company level, the parent G-SIB anticipates a reduction in the funding costs of their dealer-related activity which largely offsets the negative exposure faced by non–G-SIB bank holding companies.

An implication of these results is that the impact of negative rates on the U.S. banking system is largely distributional and bank-specific exposure is determined by the structure of the individual balance sheet. Some banks will experience lower profits through NIM compression, while others will see their NIMs expand. However, at the aggregate level, it is reasonable to think that these distributional effects would wash out. There is sufficient diversity in liquidity provision services across the banking sector as a whole such that, on average, the reduction in interest income from short-maturity assets is offset by lower funding costs on short-maturity liabilities.

From a policy perspective, one interpretation is that, rather than concentrating on the potential adverse consequences for the profitability of the aggregate banking sector, policymakers might be better served by placing greater emphasis on microprudential monitoring—that is, the safety and soundness of those institutions most heavily exposed to amplified losses in a negative interest rate environment. To this end, the liquidity coverage ratio (LCR)—a newly implemented regulation which encourages banks to hold a larger proportion of high-quality liquid assets on their balance sheet—could interact with a negative rate policy in an important way. The LCR is intended to reduce run risk in times of stress, but the results of this paper suggest that compliance with the LCR in a negative interest rate environment may have the unintended consequence of making it more difficult for these banks to raise capital.

We should emphasize that the results presented here are not based on *actual data*; instead, they are based on *projections* provided by the BHCs themselves *conditional on hypothetical macroeconomic scenarios*. The CCAR process is designed to ensure that the bank-provided stress-test projections are a reasonably accurate representation of how an individual bank views itself as faring in a particular macroeconomic scenario. As part of the stress-testing regime, regulators place considerable scrutiny on assessing the quality of the scenarios as well as the bank models used to produce the stress projections. In fact, at least through the 2018 stress-test vintage, banks could fail the stress tests for either quantitative or qualitative reasons, and the penalties for failure can be quite severe.[5] In addition, from an academic standpoint, there is a small body of empirical research which points favorably to the

[5]The cost of failing the stress tests is very high for the participating banks. In the past, failure has played a role in the firing of a CEO (Vikram Pandit at Citibank in 2012), has led to significant declines in the stock prices of failing banks, and has led to restrictions being placed on planned dividend payouts for shareholders.

information content of the exercises, both in the United States and the European experience.[6]

In terms of related literature, in the broadest sense, this paper builds on a wide body of existing research seeking to understand bank exposure to interest rate risk.[7] More narrowly, a few papers have empirically examined the impact of low levels of interest rates on bank profitability, but this paper is most closely related to a small but emerging body of research on negative interest rates.[8]

The theoretical literature on negative rates is limited, but two recent contributions are Rognlie (2016) and Brunnermeier and Koby (2019), both of which develop microfounded models which show that the effective lower bound for monetary policy is not necessarily zero. From an empirical perspective, a handful of studies, including Basten and Mariathasan (2018), Bottero et al. (2019), and Heider, Saidi, and Schepens (2019), use a difference-in-differences methodology to identify the affects of negative interest rates on bank behavior, mainly using European data.[9] A key point of differentiation amongst these three papers is the way in which bank exposure is measured. For example, Heider, Saidi, and Schepens (2019) rely

[6]Morgan, Peristiani, and Savino (2014), Fernandez, Igan, and Pinheiro (2017), and Flannery, Hirtle, and Kovner (2017) all present evidence arguing in favor of the information content of the U.S. stress tests, while Petrella and Resti (2013) and Camara, Pessarossi, and Philippon (2017) present evidence for the European stress tests.

[7]Flannery and James (1984) is an early paper in this literature. More recently, see Landier, Sraer, and Thesmar (2013), Begenau, Piazzesi, and Schneider (2015), and English, van den Huevel, and Zakrajsek (2018).

[8]Borio, Gambacorta, and Hofmann (2017) and Claessens, Coleman, and Donnelly (2018) find evidence of nonlinear effects of low interest rates on net interest margins. In addition, Saunders (2000), Genay and Podjasek (2014), and Busch and Memmel (2017) consider the impact of low interest rates on profitability through net interest margins.

[9]There are a couple of additional papers that study negative rates but do not use a difference-in-differences approach. Nucera et al. (2017) find evidence that market perceptions of bank-specific risk increase in a negative rate environment for institutions that rely predominately on deposit funding. Demiralp, Eisenschmidt, and Vlassopoulos (2017) measure exposure of European banks through excess liquidity and find that the way banks draw down this excess liquidity in a negative rate environment depends on their particular business model. Finally, Hong and Kondrac (2018) take a completely different approach by using stock price reactions to the Bank of Japan's unexpected announcement of its negative interest rate policy to measure exposure of Japanese banks.

on cross-bank heterogeneity in the reliance on deposit funding for identification. Basten and Mariathasan (2018) measure exposure of Swiss banks to negative rates as implemented by the Swiss National Bank using excess reserves. Finally, Bottero et al. (2019) exploit heterogeneity in the net interbank position to gauge the exposure of Italian banks to negative rates using Italian credit registry data. Each one of these papers uses its respective proxy for exposure to identify changes in bank behavior following the implementation of negative interest rates. The broad conclusion of these papers is that bank risk-taking tends to increase in a negative interest rate environment.

This paper differs from these empirical studies in two important dimensions, both of which directly relate to the use of stress-test data. First, the stress-test data are what allow this paper to focus on the exposure of U.S. banks, whereas previous studies concentrate on the actual experience of European or Japanese banks. Second, whereas previous studies identify the impact of negative rates through a single channel of exposure, an advantage of stress-test data is that they allow for many different hypothesized channels—including the ones at the heart of identification in each of the papers discussed above—in a single data set. Our results suggest U.S. banks face exposure through a variety of different channels and these channels may be importantly different from those found to be relevant for European banks. For example, the evidence here suggests the largest U.S. banks do not face significant exposure through retail deposits, whereas this has been found elsewhere to be important for European banks. Instead, U.S. banks are more concerned about direct exposure through pass-through of negative rates to short-term liquid assets held on the balance sheet. That said, the use of stress-test data also introduces some limitations. Because the structure of the balance sheet is assumed to be constant, this paper has nothing to say about how banks alter their behavior in response to negative interest rates. It cannot therefore address changes in risk-taking or portfolio rebalancing, both of which feature prominently in the analysis of the papers discussed above.

The remainder of this paper is organized as follows. The next section discusses how scenario design fits in with the broader objectives of stress testing. Section 3 describes the data and methodology. Section 4 presents the main results and section 5 examines some explanations for the heterogeneity of outcomes in our main results. Finally, section 6 concludes.

2. The Role of Scenario Analysis in Stress Testing

The Federal Reserve conducts stress tests of the largest bank holding companies in an annual exercise called the Comprehensive Capital Analysis and Review.[10] The CCAR is a supervisory exercise with both a quantitative component—to evaluate the adequacy of firms' capital buffers under a macroeconomic scenario specified by the Federal Reserve—and a qualitative component—to evaluate their capital planning processes.

The use of forward-looking scenarios is a critical component of assessing capital adequacy in CCAR. A forward-looking scenario consists of a set of variables that, taken together, detail a macroeconomic and/or financial event that forms the basis of the stress test. More specifically, a macroeconomic stress scenario consists of hypothetical paths for different macroeconomic variables (for example, gross domestic product (GDP), unemployment, etc.), various interest rates (short- and long-term Treasury rates, corporate yields, etc.) and other financial variables (equity prices, the VIX, etc.).[11] Each bank is required to project net income over a nine-quarter forward horizon conditional on the macroeconomic and financial market conditions assumed in the scenario. These net income projections, along with assumptions about dividends, share repurchases, and other capital actions, are combined to assess equity capital and regulatory capital adequacy.

All told, participating BHCs project their capital ratios under five scenarios: three are provided by the Federal Reserve, and the remaining two are provided by the banks themselves. Specifically, each participating BHC is required to develop two scenarios: a BHC baseline and a BHC severely adverse scenario. BHC-provided

[10] A detailed overview of stress testing can be found in Hirtle and Lehnert (2015).

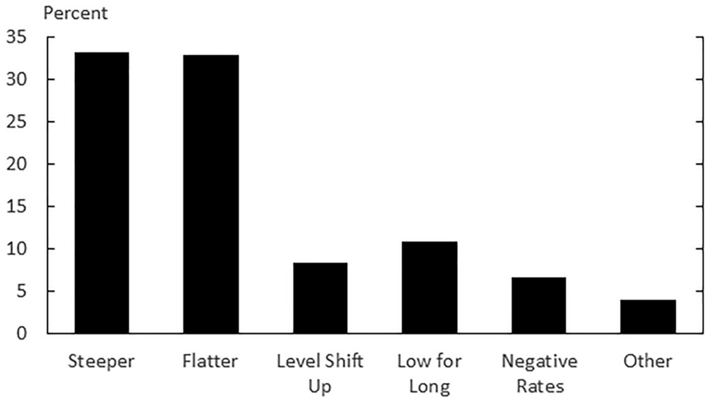
[11] The CCAR stress test also has a market shock as well as a counterparty default component for a subset of the largest participating firms. The set of variables and assumptions that comprise these aspects of the stress test are different from those underlying the macroeconomic scenarios.

scenarios are developed internally within the bank using models augmented by expert judgment and designed to comprehensively stress the bank given its unique business model and idiosyncratic risk profile. In addition, the Dodd-Frank Act calls for the Federal Reserve to evaluate participating firms under three additional scenarios: a supervisory baseline scenario; a supervisory adverse scenario; and a supervisory severely adverse scenario. All three of these supervisory scenarios are provided by the Federal Reserve, and each typically consists of a set of roughly 30 macroeconomic and financial variables accompanied by a narrative that describes how the variable paths are plausibly tied together by a common macrofinancial shock. Supervisory scenarios, as well as the underlying narrative, are made available to the public at the start of the CCAR process, typically about a month before the bank submissions are due.

This paper exploits the fact that the Federal Reserve varies the supervisory stress scenarios in response to changing macroeconomic conditions and risks. Scenario design can be motivated by a desire to stress risks seen as being particularly salient for the health of the banking sector. Alternatively, even if the risk is deemed unlikely to actually materialize, building a particular feature into a scenario can be informative in learning about exposures within the regulated banking system.

Design features introduced into scenarios in previous years include, for example, different configurations for the yield curve. In some scenarios, an adverse macroeconomic event is assumed to lead to a flatter yield curve. In others it is assumed to lead to a steepening yield curve as short rates decline while long rates either stay flat or increase. Figure 1 shows the distribution of interest rate configurations in all scenarios over the period 2014–18. Stress loss projections under different yield curve configurations reveal information to regulators about how individual BHCs view their idiosyncratic exposure to interest rate risk. Alternatively, in other instances scenarios have featured disproportionate stress playing out in certain markets in order to address potentially worrisome exposures in the banking system. For instance, the supervisory severely adverse scenario in 2015 featured a sharp widening of spreads on high-yield corporate debt, leveraged loans, or collateralized debt obligations to assess the exposure of the banking system to risky corporate lending.

Figure 1. Frequency of Qualitative Yield Curve Configurations in CCAR Scenarios, 2014–18

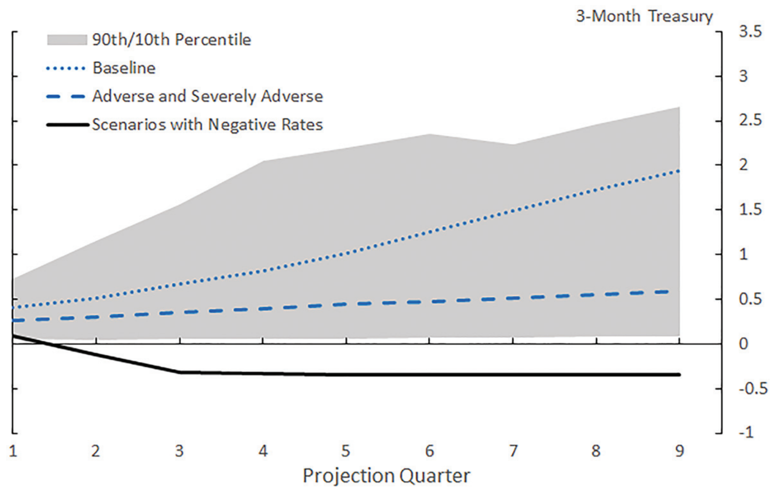


Source: Federal Reserve Y-14, author's calculations.
Notes: A steeper yield curve is one in which the spread between short and long rates is consistently larger over the projection period than it is at the jumping-off point. A flatter yield curve is one in which the spread is consistently smaller, *provided the levels of both long and short interest rates are both above 1 percent.* A level shift up in the yield curve captures a change in long and short rates that preserves the spread at the jumping-off point. "Low for Long" is a flattening at a level of interest rates below 1 percent. A negative rate scenario features the short rate falling below zero. "Other" includes everything else, including yield curve inversions and scenarios with no change.

In this paper, we focus on a design feature introduced into the 2016 supervisory severely adverse scenario at a time when sovereign bond yields around the world were turning negative. This scenario assumed a severe global recession which resulted in short-term Treasury rates falling to negative 0.5 percent shortly after the onset of the initial shock and staying at that negative level over the remainder of the nine-quarter horizon. The adjustment to negative short-term rates was assumed to proceed without additional financial market disruption.

The grey shaded region in figure 2 shows the distribution of scenario paths for the three-month Treasury rate for all but one scenario across five consecutive years of CCAR (2014 through 2018) for all participating BHCs. The solid black line plots the path of the

Figure 2. Projected Short-Term Interest Rates in CCAR Scenarios, 2014–18



Source: Federal Reserve Y-14.
Notes: The shaded area represents the distribution of short-term interest rate projections for all CCAR scenarios submitted by all participating BHCs from 2014 through 2018. The dotted line is the average for the baseline (supervisory and BHC). The dashed line is the average for the adverse and severely adverse scenarios (supervisory and BHC). The solid black line plots the negative interest rate scenario.

three-month Treasury for the 2016 supervisory severely adverse scenario (which is excluded from the distribution in the grey shaded area). The lower edge of the distribution never goes below zero, suggesting that up until the 2016 supervisory severely adverse scenario, the banks operated under the implicit assumption that the zero lower bound would a binding constraint for interest rates. In this sense, negative interest rates—and the fact that the zero lower bound might not be a binding constraint for policy—appears to have come as a surprise to the banks.

The analysis that follows centers on empirically identifying the degree to which BHCs altered their net interest margin projections, either favorably or unfavorably, in response to potential nonlinear effects of negative interest rates.

3. Methodology

3.1 Data

The analysis uses confidential supervisory data from five consecutive years (henceforth, "vintages") of CCAR stress-test exercises. A vintage consists of five different scenarios for every BHC: (i) the supervisory baseline (SB); (ii) the supervisory adverse scenario (SA); (iii) the supervisory severely adverse scenario (SSA); (iv) the BHC baseline (BHC-B); and (v) the BHC severely adverse scenario (BHC-SA). As discussed above, supervisory scenarios are designed and published by the Federal Reserve.[12] The BHC baseline is typically similar to the supervisory baseline, largely because both are based on the consensus view of economic forecasters. In contrast, banks are given explicit instructions to tailor the BHC-SA to their own risk profiles and unique vulnerabilities.[13] The motivation behind tailoring stems from the recognition of considerable diversity among the CCAR banks. Hence, a generic macroeconomic downturn as captured by the supervisory severely adverse scenario is unlikely to deliver comprehensive stress to all banks participating in the exercise. Tailoring of the bank-generated macroeconomic scenario helps alleviate this problem. To ensure compliance in scenario tailoring, the Federal Reserve has increased its scrutiny of the appropriateness of the BHC-SA through the qualitative reviews of the annual CCAR exercise. As noted in the introduction, the penalty of failure in the stress test is severe, hence banks have a strong incentive to tailor to idiosyncratic risk appropriately.

For every scenario vintage, each BHC is required to provide a nine-quarter projection for its NIM conditional on the

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[12]The SB is based on surveys of economic forecasters and is chosen to be representative of economic outcomes under normal conditions. The SA is typically a moderate downturn, potentially coupled with some other feature that sets it apart from the SSA. Finally, the SSA is characterized by a severe recession in the United States which propagates globally and is coupled with large declines in asset prices and increases in risk premiums.

[13]The preamble to the Capital Plan Rule (see 77 Fed. Reg. 74631, 74636 (December 1, 2011)) states that "the bank holding company-designed stress scenario should reflect an individual company's unique vulnerabilities to factors that affect its firm-wide activities and risk exposures, including macroeconomic, market-wide, and firm-specific events."

underlying macroeconomic environment that defines the scenario. In what follows let $i \in [1, I]$ index bank; let $j \in [SB, SA, SSA, BHC\text{-}B, BHC\text{-}SA]$ index scenario; and, let $k \in [2014, 2015, 2016, 2017, 2018]$ index CCAR vintage. Finally, let t index time over the nine-quarter projection period for each bank scenario vintage.

For each scenario vintage, bank i submits a nine-quarter horizon NIM projection, where each quarterly observation is denoted $\widetilde{NIM}_{i,j,k,t}$. The BHC-provided projection is derived from models—statistical, judgmental, or otherwise—that are internal to the bank. While we do not observe these models, we do observe the underlying macroeconomic data (which are submitted to the Federal Reserve as a requirement of CCAR) upon which the BHC's projection is conditioned. This information is critical because it allows us to construct a *model-based projection* for bank i's NIM, denoted $\widehat{NIM}_{i,j,k,t}$, which can be used to purge the *BHC-provided projection* of its dependence on macroeconomic and bank-specific factors.[14]

We do this in three steps. The first step is to estimate individually for every bank in our sample the following empirical model:

$$\begin{aligned} NIM_{i,t} = \beta_0^i + \beta_1^i NIM_{i,t-1} + \beta_2^i 3MT_{t-1} + \beta_3^i SPREAD_{t-1} \\ + \beta_4^i \Delta GDP_t + \beta_{\mathbf{5}}^{\mathbf{i}} \mathbf{X}_{i,t-1} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $NIM_{i,t}$ is the net interest margin for bank i; $3MT_{t-l}$ is the three-month Treasury rate; $SPREAD_{t-l}$ is the spread between the 10-year and three-month Treasury; ΔGDP_t is quarterly GDP growth; and $\mathbf{X}_{i,t}$ is a vector of bank-specific controls found in the literature to be important in explaining bank NIMs. Specifically, following Claessens, Coleman, and Donnelly (2018), $\mathbf{X}_{i,t}$ includes total securities over total assets, deposits over total liabilities, and total equity capital over total assets. The model is estimated using quarterly data over the period 1996:Q4 to 2017:Q4, implying a maximum of 84 quarterly observations for each bank (excluding one lag)

[14]In our notation, a $\widehat{hat}$ denotes a model-based projection estimated specifically for bank i, whereas a $\widetilde{tilde}$ denotes a projection taken from a BHC-provided scenario vintage. So, to be clear, $\widehat{NIM}$ is a model-based projection, the construction of which is described on the next page. In contrast, $\widetilde{NIM}$ is an observable projection provided by the bank in its CCAR submission.

to get a set of eight bank-specific estimated coefficients conditioned on the general macroeconomy (captured by interest rates and output growth, which is obviously common to all banks) as well as bank-specific characteristics and bank i's own historic NIM data.

Macro data are taken from the Federal Reserve Economic Data (FRED) database maintained by the Federal Reserve Bank of St. Louis, and the bank-specific historic NIMs are obtained from the Call Report data, merger-adjusted and aggregated up to the bank holding company level. Summary statistics for all the data are presented in table A.1 in the supplementary appendix (available at http://www.ijcb.org), and the model output on a bank-by-bank basis is presented in table B.1.

Once we have these bank-specific coefficients, the second step is to use the bank-specific estimated model along with the bank-provided paths for the macrovariables in a given scenario vintage ($\widetilde{3MT}_{i,j,k,t}, \widetilde{SPREAD}_{i,j,k,t}$, and $\Delta\widetilde{GDP}_{i,j,k,t}$) to project the model-based NIM path, $\widehat{NIM}_{i,j,k,t}$. In generating this conditional model-based projection, we assume that bank's balance sheet stays constant, so that $\mathbf{X}_{i,t}$ is held constant at the last observed value over the entire projection period.[15]

The final step is to construct the difference between the model-based and the BHC-provided projections:

$$\xi_{i,j,k,t} = \widetilde{NIM}_{i,j,k,t} - \widehat{NIM}_{i,j,k,t}. \tag{2}$$

The model-based projection, $\widehat{NIM}_{i,j,k,t}$, as well as the BHC-provided projection, $\widetilde{NIM}_{i,j,k,t}$, both internalize the same underlying macroeconomic environment and, at least to some degree, the same broad bank-specific characteristics. Thus, the difference between the two should be purged of these effects. However, this does not necessarily mean that $E[\xi_{i,j,k,t}] = 0$. One reason is that bank i might have an understanding of how its particular business model might amplify or dampen the impact of a given macroeconomic environment on its net interest margins in a way that is not

[15] As discussed in the introduction, this assumption is consistent with the implementation of the stress tests. It also necessarily precludes using these data to address portfolio rebalancing or changes in risk-taking behavior as is commonly the focus of other empirical papers studying negative interest rates.

easy to quantify through the simple linear empirical model as given by equation (1) above. For example, if $\xi_{i,j,k,t} > 0$ the bank projection is more optimistic with regard to how its NIMs will evolve in a particular macroeconomic environment relative to what the simple linear model would predict. The opposite is true if $\xi_{i,j,k,t} < 0$.

The analysis that follows builds on this in the sense that negative interest rates have a potentially nonlinear effect on NIMs that will not be captured in our simple linear model-based projection. In contrast, the banks themselves understand the nuances of their own business model and balance sheet exposures and, as such, the BHC-provided projections should internalize these nonlinear effects. In other words, the identification relies on the fact that the banks themselves are better equipped to forecast their own NIMs relative to our simple statistical model. This crucial difference suggests that we can identify the impact of negative interest rates on NIMs by using the qualitative feature of negative interest rates as a scenario design element to explain systematic projection differences for a given bank across different scenario-vintages.

3.2 Empirical Model

The final step of the analysis centers on the following regression, which tests the sensitivity of the earnings of bank i to potential nonlinear effects of negative interest rates:

$$\xi_{i,j,k,t} = \alpha_i + \beta_i Z_{i,j,k,t} + \gamma_i D_{k=2016} + \epsilon_{i,j,k,t}, \tag{3}$$

where $Z_{i,j,k,t}$ is an indicator function that takes on the value of one if negative short-term interest rates are a qualitative feature of the given bank scenario-vintage in quarter t and zero otherwise. Negative rates feature prominently in the 2016 vintage, so to ensure that $Z_{i,j,k,t}$ is not inadvertently capturing a vintage-specific effect, we include $D_{k=2016}$, which is an indictor that takes on the value of one if the scenario is from the 2016 vintage. The equation also allows for bank-specific fixed effects, α_i, to control for time-invariant differences in the NIM projections for a given bank. Finally, $\epsilon_{i,j,k,t}$ is an error term.

Our main results focus on the parameter of interest, β_i, which gauges how bank i views its profitability being influenced through the impact of negative interest rates on its NIM. Specifically, we are interested in whether or not the scenario design feature of negative interest rates leads bank i to adjust its internal NIM projection beyond that which can already be explained through our linear model conditional on the general macroeconomic environment and bank-specific characteristics.

If we find that β_i is not statistically different from zero, then bank i does not have a strong view on how negative rates affect profitability. On the other hand, if we find $\beta_i \neq 0$, this suggests bank i has some internal view on potential nonlinear effects not picked up by the linear model. Conditional on finding evidence of nonlinearities, we remain agonistic at this point in the paper on whether the effects are expected to be positive or negative for the profitability of a given bank. We will return to this question later in the paper in section 5.

The model is estimated using ordinary least squares with robust standard errors clustered at the bank scenario-vintage level. The final data set is an unbalanced panel that includes 30 banks. All told, there are 4,986 total observations.[16] As shown in figure 1, negative interest rates feature in 7.5 percent of the sample, or 378 total observations.

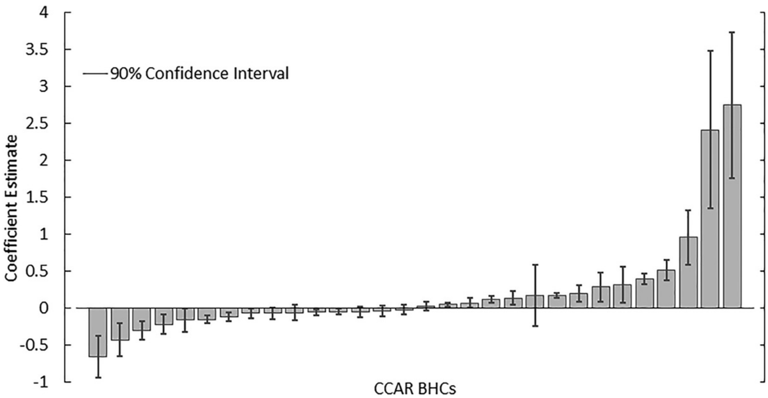
4. Main Results

The main results are presented in figure 3, which presents the estimated coefficient, $\widehat{\beta}_i$, for each bank along with 90 percent confidence intervals. The results are shown for a total of 30 banks, increasing in the magnitude of the point estimate going from left to right.

Starting on the left, 10 banks have coefficient estimates that are negative and statistically significant. These banks believe that negative interest rates would lead to a compression of their NIM above and beyond what would otherwise be explained by the underlying macroeconomic environment, even taking into account bank-level

[16] If the panel were balanced, we would have 6,750 observations (that is, 30 banks, five vintages, five scenarios per vintage, with each scenario having nine quarterly observations). The unbalanced nature of the panel reflects that fact that the number of banks participating in each CCAR vintage has changed over time. The peak occurred in 2016 when 33 BHCs participated. But even in that year some data had to be dropped from firms that only became BHCs recently and, hence, had no record of historic NIMs data with which to derive a model-based estimate for $\widehat{NIM}$.

Figure 3. Estimated Effect of Negative Interest Rates on NIM Projections for CCAR BHCs



Source: Author's calculations.
Notes: Each bar represents the coefficient estimate for β_i from equation (3) for a given CCAR BHC. The whiskers around each coefficient estimate show the 90 percent confidence interval based on cluster-robust standard errors.

controls. The point estimates range from −0.07 to −0.65, implying that the NIM is permanently lower over the nine-quarter projection period by between 7 and 65 basis points. On the far right, there are 12 banks that have coefficients that are positive and statistically significant. These banks anticipate improved profitability through an expansion in the NIM by between 5 and 275 basis points. Finally, the remaining roughly one-third of banks in the middle of the figure all have coefficients that are not statistically different from zero. Our interpretation is that these banks do not have strong views on how negative rates might affect their profitability.

There are two ways to give some economic context. First, as in Genay and Podjasek (2014), it is informative to express the estimated coefficient for each bank as a ratio of the volatility of that bank's historic NIMs data. This gives a sense of the size of the negative rate shock relative to typical quarter-to-quarter variation in the data. To preserve anonymity of the banks in the sample, the results in table 1 are reported as averaged across banks that fall within one of three bins depending on whether negative rates increase, decrease, or have no impact on NIMs.

Table 1. Economic Significance

	Estimated Coefficient	Estimated Coefficient Relative to Volatility of Historic NIMs	Observations
NIM Compression	−0.25	−0.55	8
NIM Expansion	0.66	0.78	13
No Effect	−0.03	−0.07	9

Source: Federal Reserve Y-14, author's calculations.

For the 13 banks that anticipate that negative rates will lead to higher NIMs, the average estimate, shown in the first column, is 66 basis points. When expressed relative to historic NIM volatility, the resulting ratio averages 0.78 across the 13 banks. This means that, on average, these banks expect negative rates to result in a positive shock that is in line with just under a one-standard-deviation shock, given the historical distribution of their respective NIMs data. Moreover, the shock is anticipated to persist over all nine quarters of the scenario horizon. Viewed in this light, the overall effect is economically sizable. Similarly, the average coefficient estimate for the nine banks that anticipate NIM compression is −25 basis points and the average ratio of the point estimate to observed volatility is 0.55—somewhat smaller, but still sizable.

An alternative way of gauging the economic effect is to compare the results found here with those found elsewhere the literature. No other papers study the effect of negative interest rates on NIMs, so we do not have a direct comparison, but there are a handful of papers that report empirical estimates of the impact of movements in short-term interest rates.[17] Here, the estimates typically fall on the order of tens of basis points, with Borio, Gambacorta, and Hofmann (2017) finding the largest effects—as much as 50 basis points over a year time frame when monetary tightening brings the interest rate from 0 percent to 1 percent. Another point of reference is Claessens,

[17]See Genay and Podjasek (2014), Altavilla, Boucinha, and Peydró (2017), Borio, Gambacorta, and Hofmann (2017), Busch and Memmel (2017), and Claessens, Coleman, and Donnelly (2018).

Coleman, and Donnelly (2018), which finds that "low-for-long" interest rates imply an initial decline of up to 20 basis points in the NIM, with the effect growing by 10 basis points for every additional year of "low for long." Compared with these estimates (which, admittedly, are for a different type of shock, but are nonetheless informative as a benchmark), the findings presented here are sizable.

4.1 Robustness

The results are based on a bank-specific NIMs model motivated by Claessens, Coleman, and Donnelly (2018). Other studies have found additional macroeconomic and financial variables, beyond those already included in equation (1), that also have explanatory power for net interest margins. We test the sensitivity of the results presented above to the inclusion of these other variables by reestimating the bank-specific NIMs model while controlling for the unemployment rate, the level of the VIX, changes in residential home prices, changes in commercial real estate prices, and changes in stock prices as measured by the S&P 500. For each alternative specification of equation (1), a new model-based NIM prediction, $\widehat{NIM}_{i,j,k,t}$, is generated and used to recalculate $\xi_{i,j,k,t} = \widetilde{NIM}_{i,j,k,t} - \widehat{NIM}_{i,j,k,t}$. This new measure of $\xi_{i,j,k,t}$ is then used to reestimate equation (3) and we can compare the output with the main results presented in figure 1.

We find that introducing these additional variables to the bank-specific NIM model makes very little difference. For this reason, we do not present the results in the main text and instead put them in table C.1 in the online appendix.

Another robustness test tries to further isolate the effect of negative interest rates by controlling for alternative interest rate configurations. Using the estimate for $\xi_{i,j,k,t}$ from the baseline model, we reestimate equation (3) introducing a dummy variable to control for a so-called "low-for-long" interest rate configuration interpreted as a scenario in which the yield curve flattens out with both short- and long-term interest rates settling in at under 1 percent for the duration of the projection. This dummy variable should help isolate how negative interest rates are different from a "low-for-long" configuration, which accounts for roughly 10 percent of the sample (see figure 1). The results are robust to controlling for "low-for-long" scenarios, further emphasizing the special nature of negative interest rates. Additionally, we also control for either a steeper yield curve or a higher, flatter yield curve. Neither make much of a difference.

Finally, we examine whether or not regulatory ratios affect the NIMs projections for different banks. For example, banks with low regulatory capital ratios may have an incentive to report higher NIMs paths in the stress-test submissions. To address this, we use the baseline estimate for $\xi_{i,j,k,t}$ and reestimate equation (3) controlling for, separately, the common equity tier 1 (CET1) capital ratio, the leverage ratio, and high-quality liquid assets (HQLA) as a fraction of total assets. The results, reported in table C.1 in the online appendix, are robust to controlling for either regulatory capital or liquidity ratios.

5. What Explains the Cross-Bank Differences?

The results reveal considerable heterogeneity in bank-specific exposure to negative interest rates. This section presents a simple decomposition of the net interest margin to help explain these cross-bank differences using publicly available balance sheet data.

5.1 Potential Nonlinearities in NIMs Associated with Negative Rates

The definition of net interest margin is given by

$$NIM = \frac{Interest\ Income - Interest\ Expense}{Interest\ Earning\ Assets}.$$

For simplicity, assume that banks hold only two types of assets.[18] Short-duration assets, denoted A^s, deliver a gross return R^s, and long-duration assets, A^l, deliver a return $R^l \geq R^s$. Total interest income can be expressed as $R^s A^s + R^l A^l$. On the liability side of the

[18]By assuming a simplified balance sheet, this approach abstracts from some important aspects of the duration mix of interest-bearing products and the way interest rates on these products are linked to market rates. Busch and Memmel (2017) show this is important for how the level of interest rates affects NIMs using data on German banks.

balance sheet, assume that banks fund themselves through deposits or other sources of short-term funding, denoted L^s, and long-term liabilities, denoted L^l. The deposit rate paid by the bank is given by R^d. For simplicity, assume that the cost of funding for long-term liabilities is similar to the return on long-term assets and, hence, is also given by R^l. Total interest expenses can be expressed as $R^d L^s + R^l L^l$. Finally, total interest-earning assets are given by $A^s + A^l$ and total interest-bearing liabilities are $L^s + L^l$.

Define the share of long-duration assets in total interest earning assets, $\chi = \frac{A^l}{A^s + A^l}$, which is a measure of the duration sensitivity of interest-earning income. Similarly, define $\eta = \frac{L^l}{L^s + L^l}$ as a measure of the duration sensitivity of interest expenses. Finally, let $\lambda = \frac{L^s + L^l}{A^s + A^l}$ denote total interest-bearing liabilities as a share of total interest-earning assets.

With these share definitions, we can rewrite the net interest margin as

$$NIM = R^s - \lambda R^d + \chi(R^l - R^s) - \lambda\eta(R^l - R^d).$$

Written this way, the net interest margin is made up of three components. The first, $R^s - \lambda R^d$, captures the idea that, all else equal, net interest margins are higher as the short-term lending rate exceeds the short-term cost of funding. The second term, $\chi(R^l - R^s)$, captures the idea that it is profitable for the bank to engage in maturity transformation as the returns on long-term assets exceed those on short-term assets. Finally, the third term, $-\lambda\eta(R^l - R^d)$, highlights the fact that short-term funding is cheap relative to long-term funding.

To address potential nonlinearities associated with negative rates, we need to make some additional assumptions about both the policy rate itself and how the policy rate is passed through to interest rates on assets and liabilities on the bank balance sheet.

The *unconstrained policy rate*, denoted $\hat{R}(\epsilon)$, is assumed to fluctuate around a target level, $\bar{R}$, in response to an underlying shock, ϵ. The shock takes a value of $\epsilon > 0$ with probability 1/2, or, alternatively, a value of $-\epsilon$ with probability 1/2. The unconstrained policy rate fluctuates around its target as follows:

$$\hat{R}(\epsilon) = \begin{cases} \bar{R} + \epsilon & with\ probability\ \ 1/2 \\ \bar{R} - \epsilon & with\ probability\ \ 1/2. \end{cases}$$

For simplicity, assume the target rate is sufficiently low so we just consider the case of $\bar{R} = 0$. In this low interest rate environment, a bank forming expectations of the policy response to an underlying shock must take into account not only the realization of the shock but also whether or not the zero lower bound (ZLB) is expected to bind for monetary policy. If banks anticipate that the ZLB is a binding constraint, the *actual policy* rate will be given by $R^*(\epsilon) = max(0, \hat{R}(\epsilon))$. In contrast, if banks believe the monetary authority is willing to implement negative interest rates, the actual policy rate is unconstrained, so that $R^*(\epsilon) = \hat{R}(\epsilon)$. The motivation for including expectations over whether or not the ZLB is a binding constraint for policy comes from figure 1. In all of the CCAR scenarios over the three years from 2014 to 2016, the lower end of the distribution of short-term interest rate projections was always bounded below by zero. The exception is the 2016 SSA as well as a few instances of the 2016 BHC-SA scenarios.[19] The interpretation is that negative interest rates came as a surprise to these banks and therefore the surprise itself may explain the nonlinear results found in section 4.

The next set of assumptions relate the policy rate to interest rates on short-duration assets and short-duration liabilities held by the bank. The interest rate on short-duration assets is assumed to be a fixed markup, $\mu > 1$, over the policy rate, so that $R^s = \mu R^*(\epsilon)$. In contrast, the interest rate paid on short-duration liabilities is given by

$$R^d = \Omega R^*(\epsilon) \text{ where } \Omega = \begin{cases} 1 & if\ \ R^*(\epsilon) \geq 0 \\ \omega & if\ \ R^*(\epsilon) < 0. \end{cases}$$

[19]The banks observe the supervisory scenarios roughly a month prior to submitting their CCAR submissions. Hence, it is reasonable to think that banks were surprised after observing the supervisory scenarios when they were released publicly and this surprise informed the construction of the BHC scenario for that same vintage.

In this expression, $\omega \in (0,1)$ captures the possibility of imperfect pass-through from the policy rate into interest rates on short-duration liabilities, including the retail deposit rate. If $\omega = 1$, as is assumed when interest rates are positive, pass-through is complete and the policy rate flows through one-for-one into the interest paid on short-term liabilities. However, when the policy rate turns negative, values of $\omega < 1$ allow for incomplete pass-through. For example, in the case of retail deposit rates, a bank might not want to pass on the cost of holding deposits on to its customer base out of concern of deposit flight—that is, depositors may look to move their funds elsewhere to avoid paying the fee or they may simply hold cash instead. In the extreme, $\omega = 0$ sets a floor such that $R^d = 0$ when $R^*(\epsilon) < 0$.

Finally, moving up the yield curve, we assume long-term interest rates are a function of short-term rates, so that $R^l = \phi(R^*(\epsilon))$, where $\phi(R^*(\epsilon))$ is a sufficiently general function that captures a wide variety of alternative assumptions regarding the response of the yield curve to a decline in short rates. For example, $\phi(R^*) = \bar{\phi}R^*$ where $\bar{\phi} \geq 1$ implies that the yield curve shifts down in parallel as short-term rates decline. Alternatively, $\phi(R^*)$ could be parameterized to have properties that imply that short-term interest rates are an increasing proportion of long rates as the level of the policy rate declines (and potentially turns negative). This has the implication that the yield curve becomes progressively flatter as the level of the policy rate declines. Claessens, Coleman, and Donnelly (2018) find that such a relationship is important for describing NIMs in a low interest rate environment.

Substituting these interest rate assumptions into the expression for NIMs and rearranging yields

$$NIM = \left[(1-\chi)\mu - (1-\eta)\lambda\Omega\right] R^*(\epsilon) + (\chi - \lambda\eta)\phi(R^*(\epsilon)).$$

This expression allows us to highlight three potential sources of nonlinearities associated with negative interest rates, each operating through three distinct channels described below.

5.1.1 The Retail Deposit Channel

According to this channel of exposure, what differentiates an interest rate cut into negative territory from a similar cut at a low, but ultimately positive, level of interest rates is the idea that banks want to avoid passing negative interest rates through to their deposit base and they are willing to change their behavior in order to do this. In other words, it is the change in behavior of the banks that makes negative interest rates special from the perspective of net interest margins.

We can isolate the retail deposit channel by assuming that $\phi(R^*) = \bar{\phi}R^*$, so that long-term interest rates on assets and liabilities move one-for-one with the policy rate. Under this assumption, the expected change in the NIM with respect to the underlying shock becomes

$$\frac{\partial NIM}{\partial \epsilon} = \left[(1-\chi)\mu - (1-\eta)\lambda\Omega + (\chi - \lambda\eta)\bar{\phi}\right] E[\partial R^*(\epsilon)/\partial \epsilon].$$

As the policy rate moves into negative territory, the shift in the degree of pass-through that banks chose to allow introduces a nonlinearity as $\Omega = 1$ changes to $\Omega = \omega < 1$. With incomplete pass-through, the decline in the policy rate does not fully translate into lower deposit funding costs. All else equal, this should compress NIMs relative to the alternative of complete pass-through.

This channel is summarized with the following hypothesis:

HYPOTHESIS 1. *If banks are hesitant to let negative rates flow through to their deposit base, imperfect pass-through implies additional nonlinear NIM compression as the policy rate moves below zero.*

To test this hypothesis, we can proxy for the strength of the deposit margin channel using balance sheet data to measure the share of retail deposits in total interest-bearing liabilities, $(1-\eta)\lambda$. A bank that has greater dependence on retail deposit funding likely values its deposit base more relative to a bank that can easily substitute into other funding short-term sources. As a result, these banks should be more reluctant to pass negative rates through to deposit rates and, hence, more likely to suffer NIM compression in a negative rate environment.

5.1.2 The Liquidity-Management Channel

In contrast to the retail deposit channel, exposure through the liquidity-management channel assumes that pass-through to interest rates on short-duration assets and liabilities is not impeded and, as a result, generates potential gains and losses depending on a given banks' liquidity-management practice. An important aspect of the identification of this channel stems from the fact that the violation of the zero lower bound comes as a surprise.[20] In other words, what makes a cut into negative territory special is the fact that it reveals that a constraint on monetary policy that was previously thought to be binding, in fact, no longer binds.

To understand the importance of the ZLB in identifying this channel of exposure, consider that when the policy rate is positive, $R^*(\epsilon) \geq 0$, our assumptions on pass-through imply $\Omega = 1$. As long as the bank believes that the ZLB is a binding constraint, we have $E[R^*(\epsilon)|ZLB] = \frac{1}{2}\epsilon$. These expectations reflect the fact that the policy rate is assumed to respond only asymmetrically to shocks. This asymmetry carries over to the expected evolution of the NIM as the ZLB effectively dampens anticipated losses (gains) on interest income (expenses) from short-duration assets (liabilities) in the event of an adverse shock. However, if the monetary authority pushes the policy rate into negative territory, this insulating effect no longer applies. In this case, we have $E[R^*(\epsilon)|No\ ZLB] = 0$, and because $E[R^*(\epsilon)|No\ ZLB] \leq E[R^*(\epsilon)|ZLB]$, any bank with a large share of short-duration assets will suffer amplified NIM compression through losses on interest income. In contrast, a bank with a large share of short-duration liabilities will experience an unanticipated expansion of its NIM through a reduction in funding costs. Hence, it is the liquidity-management practice (short-term assets relative to short-term liabilities on the balance sheet) that determines the response of NIMs when the movement of the policy rate into negative territory comes as a surprise.

This leads to the following testable hypothesis:

Hypothesis 2. *When the policy rate unexpectedly moves into negative territory, relaxing the zero lower bound amplifies exposure via unanticipated pass-through to short-term interest rates.*

[20] Hong and Kondrac (2018) also use the surprise announcement of a negative interest policy to identify the exposure of Japanese banks to negative interest rates.

We can proxy for the strength of this channel of exposure using balance sheet data to measure the share of short-duration assets in total interest-earning assets, $(1-\chi)\mu$, and the share of short-duration interest-bearing liabilities in total interest-bearing liabilities, $(1-\eta)\lambda$. Banks that have a large exposure to short-duration assets will suffer amplified NIM compression as the policy rate turns negative. The opposite is true of banks that have a large exposure to short-duration liabilities.

5.1.3 The Yield Curve Compression Channel

The yield curve compression channel captures the idea that the yield curve becomes progressively flatter as the level of short-term interest rates decline.

This exposure channel can be highlighted by assuming full pass-through to deposit rates, $\Omega = 1$. Additionally, rather than assuming $\phi(R^*) = \bar{\phi}$ as above, assume the yield curve flattens (nonlinearly) as the level of the policy rate moves lower and eventually turns negative. To capture this we assume $\phi(R^*)$ is convex, so $\partial\phi(R^*)/\partial R^* \geq 0$ and $\partial^2\phi(R^*)/\partial R^{*2} > 0$. We also allow for an effective lower bound to the (gross) policy rate, $\underline{R}^*$ (which is less than one to accommodate a negative net policy rate) and further assume $\lim_{R^* \to \underline{R}^*} \phi(R^*) = \gamma > 0$ and $\lim_{R^* \to \underline{R}^*} \partial\phi(R^*)/\partial R^* = 0$.

With these assumptions in mind, consider the change in NIMs with respect to the policy rate

$$\frac{\partial NIM}{\partial R^*} = (1-\chi)\mu - (1-\eta)\lambda + (\chi - \lambda\eta)\frac{\partial\phi(R^*)}{\partial R^*}.$$

The first two terms capture the deposit margin and liquidity-management channels discussed above; absent shocks to the economy, these two channels are linear in the policy rate. In contrast, the third term captures a potential nonlinearity that occurs through a flattening of the yield curve that gets more pronounced as the level of the policy rate declines and eventually turns negative. For most banks, the share of long-term assets in total interest interest-earning assets exceeds that of long-term liabilities, so that $\chi > \lambda\eta$, implying that the flattening of the yield curve will increasingly depress NIMs as the level of the policy rate declines.

This leads to the following testable hypothesis:

HYPOTHESIS 3. *As the level of interest rates moves into negative territory, a progressive flattening of the yield curve leads to amplified NIM compression.*

We can proxy for the strength of the yield curve compression channel using balance sheet data that assess the duration sensitivity of the bank, $\chi - \lambda\eta$. Banks that face the greatest exposure to yield curve compression are those that have considerably longer maturities and repricing times on the asset side of their balance sheet relative to the liability side.

5.2 Empirical Model

We test our three hypothesized nonlinearities using the following regression framework:

$$y_i = \alpha + \beta X_i + \lambda D_i + \theta Size_i + \varepsilon_i, \tag{4}$$

where y_i is a measure of bank-specific sensitivity to negative interest rates, which we proxy with the estimated coefficient from equation (3), normalized by its standard error.[21] To explain this bank-specific sensitivity, we include a set of two dummy variables, denoted D_i, to proxy for bank business models. The first dummy takes on the value of one if the BHC is a custodial bank. Custodial banks are unique in that they do not follow a traditional banking business model but instead take on custodial functions in transactions between third parties. These banks tend to hold a larger share of assets in cash and securities than other banks in our sample. We also include a second dummy variable for BHCs that are considered global systemically important banks. The G-SIB dummy captures the systemic nature and complexity of the largest banking organizations. Finally, we also include bank size, $Size_i$, measured as the log of total assets (in billions of dollars). This variable is included because banks' size generates differences in economies of both scale and scope

[21] This approach to testing channels of exposure relies on previous output generated using equation (3). See Pagan (1984) for a discussion of complications that arise for statistical inference with a generated regressand.

that might help a bank deal with the nonlinear effects of negative interest rates. For example, large banks are more likely to have the expertise and personnel to more effectively hedge interest rate risk using derivatives.

The focus of the analysis is to uncover a systematic link between the sensitivity to negative rates and bank balance sheet characteristics, denoted generically as X_i. As touched upon above, the exact measurement of X_i is tailored to each hypothesis.

In order to test the *retail deposit channel,* we measure $1-\eta$ using data on the share of retail deposits in total interest-bearing liabilities. Combining this with data on the share of interest-bearing liabilities in total interest-earning assets, our measure of λ, we construct $X_{L_d} = (1-\eta)\lambda$ and include it in the regression above to proxy for the degree to which the bank is reliant on short-term retail deposit funding. Allowing $\hat{\beta}_{L_d}$ to denote the estimated coefficient on X_{L_d}, the following tests the empirical validity of this channel of exposure:

$$H1_0 : \hat{\beta}_{L_d} = 0.$$

Rejecting the null hypothesis in favor of the one-sided alternative of $H1_1 : \hat{\beta}_{L_d} < 0$ supports exposure through the retail deposit channel.

To test the *liquidity-management channel,* we begin by examining the short-term asset and liability side of the balance sheet separately. First, we use data on the share of reserves in total interest-earning assets to measure $1-\xi$. Letting $X_{A_s} = 1-\xi$, this enters into the regression framework above to proxy for the exposure of NIMs to short-term interest rates through the asset side of the balance sheet. On the liability side, we use data on the share of short-term wholesale funding in total interest-bearing liabilities to measure $1-\eta$. Combining this with the measure of λ described above, we let $X_{L_s} = (1-\eta)\lambda$ proxy for the exposure of NIMs to interest rates through short-term liabilities.

Allowing $\hat{\beta}_{A_s}$ and $\hat{\beta}_{L_s}$ to denote the estimated coefficients on X_{A_s} and X_{L_s}, respectively, we can test the following null hypotheses to assess the empirical validity of this transmission channel:

$$H2_0 : \hat{\beta}_{A_s} = 0; \hat{\beta}_{L_s} = 0.$$

Rejecting the null hypothesis in favor of the one-sided alternative of $H2_1 : \hat{\beta}_{A_s} < 0; \hat{\beta}_{L_s} > 0$ is evidence of exposure through liquidity management.

In addition, we also examine separately exposure through the net repo position—that is, securities purchased under agreement to resell (on the asset side of the balance sheet) net of securities sold under agreement to repurchase (on the liability side). A larger net repo position implies that a bank is more actively engaged in liquidity provision through the repo market relative to its reliance on the repo market for short-term funding. The coefficient on the net position is expected to be negative in sign so that liquidity provision (for example, through the interbank market) exposes the bank to greater losses in a negative interest rate environment. One complicating factor owes to the fact that G-SIBs tend to be much more active in the repo market relative to other banks in the sample. The reason is that G-SIBs have large broker-dealer subsidiaries which rely heavily on short-term funding obtained through the repo market.[22] In light of this, we treat the G-SIBs differently by interacting the G-SIB dummy with the net repo position.

Finally, to test the *yield curve compression channel*, we measure $\chi - \lambda\eta$ using the maturity gap measure developed in English, van den Huevel, and Zakrajsek (2018). While we leave the details regarding the construction of this metric to that paper, the authors use granular balance sheet data on U.S. banks to construct a metric that captures the degree of mismatch between the maturity and repricing time of a bank's assets relative to those of its liabilities. If the yield curve flattens disproportionately as the level of interest rates declines below zero, we would expect banks with a larger maturity gap—that is, banks that have a higher proportion of assets with longer maturities and repricing times relative to liabilities—to be most exposed to a decline in its NIM as the yield curve progressively flattens.

Letting $X_{MGAP} = \chi - \lambda\eta$, this enters into the regression framework above to proxy for the exposure of NIMs to the progressive flattening of the yield curve in a negative interest rate environment. Allowing $\hat{\beta}_{MGAP}$ to denote the estimated coefficient on X_{MGAP},

[22]See, for example, Kirk et al. (2014).

the following tests the empirical validity of this transmission channel:

$$H3_0 : \hat{\beta}_{MGAP} = 0.$$

Rejecting the null hypothesis in favor of the one-sided alternative of $H3_1 : \hat{\beta}_{MGAP} < 0$ is evidence in favor of the yield curve compression channel.

Summary statistics for all the variables used in this part of the analysis are shown in table A.2 in the online appendix.

5.3 Results

Results are presented in table 2, with robust standard errors reported in parentheses below each coefficient estimate.[23]

Column 1 examines exposure through the retail deposit channel. If banks were hesitant to pass negative rates through to their depositor base, we would expect those with the highest share of retail deposits to be the most exposed to the adverse effects of negative interest rates. The estimated coefficient is negative in sign, so the results are broadly consistent with this view. However, it is not statistically significant and the effect is small in economic magnitude, especially when compared with the other channels of exposure shown elsewhere in the table (see columns 2 through 4). A 1 percent increase in the share of retail deposits increases exposure, leading to a roughly 10 basis point reduction in NIMs as a result of negative interest rates.[24] The size of this effect is only about one-fifth of the historical standard deviation of NIMs averaged across all the banks in the sample (0.62). All told, these results suggest that large U.S. banks do not face significant exposure through the retail deposit channel.

This finding contrasts sharply with Heider, Saidi, and Schepens (2019), which finds strong evidence of the exposure of European

[23]We reiterate the caveat of footnote 21 regarding statistical inference on a generated regressand.

[24]The proxy for the sensitivity to negative rates is the estimated coefficient on the indicator variable for negative rates in equation (3) normalized by its standard error. Hence, to arrive at a 10 basis point reduction in NIMs, we multiply the coefficient reported in column 1 of table 2 (-0.87) by the average standard deviation (0.11) obtained from the estimated coefficients across all banks in equation (3).

Table 2. Tests of Hypothesized Channels of Exposure of U.S. Banks to Negative Interest Rates

	$H1_0$: $\hat{\beta}_{L_d} = 0$ Imperfect Pass-Through to Deposit Rates	$H2_0$: $\hat{\beta}_{A_s} = 0$; $\hat{\beta}_{L_s} = 0$ Direct Exposure via Short-Term Assets and Liabilities			$H3_0$: $\hat{\beta}_{MGAP} = 0$ Yield Curve Compression
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Constant	0.36	7.76	0.25	12.28	10.59
	(20.14)	(18.54)	(20.51)	(20.10)	(19.74)
Retail Deposits	−0.87				
	(3.16)				
Reserves		-14.74^{*}			
		(6.28)			
Short-Term Wholesale Funding			10.19^{***}		
			(3.13)		
Net Repo Position				-25.43^{***}	
				(7.39)	
Net Repo Position × G-SIB				20.60^{**}	
				(7.45)	
Duration Gap					−6.52
					(7.89)
Ln (Size)	0.10	−0.29	0.06	−0.56	−0.35
	(1.09)	(0.96)	(1.07)	(1.05)	(1.05)
Processing Bank Dummy	−2.27	−1.61	−2.01	−2.85	−3.51
	(1.79)	(1.26)	(1.64)	(1.56)	(1.86)
G-SIB Dummy	−2.81	−1.61	−2.41	−1.00	−1.25
	(2.68)	(2.23)	(2.40)	(2.50)	(2.39)
Adj. R^2	0.15	0.22	0.17	0.23	0.21
Obs.	30	30	30	30	29

Source: Author's calculations.
Notes: Robust standard errors are reported in parentheses below each coefficient estimate. *** denotes significance at the 0.01 level; ** denotes significance at the 0.025 level; and * is significance at the 0.05 level.

banks to negative rates through retail deposits. One interpretation is that the results presented here highlight that the U.S. banking system may face very different exposures to the effects of negative interest rates relative to European banks.

The next three columns present results for exposure through the liquidity-management channel. If the negative policy rate is passed through to interest rates on short-duration assets and liabilities (beyond retail deposits), we would expect this to affect profitability through reduced interest income (expenses) on these short-term assets (liabilities). Asset- and liability-side exposure are tested separately, followed by a test of exposure through net activity in the repo market.

Column 2 shows that banks with a higher share of reserves are heavily exposed to amplified losses in a negative interest rate environment. The estimated coefficient is negative in sign, statistically significant at the 5 percent level, and quantitatively large. For every additional percentage point increase in exposure through reserves, NIMs decline by roughly 160 basis points. Based on the average historical volatility of NIMs for all the banks in the sample, this is roughly a 2.5-standard-deviation shock that persists over a nine-quarter horizon. Turning to column 3, banks that rely more heavily on short-term wholesale funding anticipate a boost to their NIMs through a reduction in funding costs. The estimated coefficient is positive, statistically significant at the 1 percent level, and quantitatively about as large (in absolute value) as exposure through reserves. Increasing reliance on short-term wholesale funding boosts NIMs by about 110 basis points, a nearly two-standard-deviation shock that persists over nine quarters.

Results on exposure through the net repo position are presented in column 4. For the average CCAR bank, an increase in the net repo position lowers NIMs in a negative rate environment by about 275 basis points, a shock that is four-and-a-half times the average historical standard deviation for the banks in the sample. Economically, this is a very large shock and the coefficient is statistically significant at the 1 percent level. It is worth keeping in mind, however, that non–G-SIB banks tend to have relatively small net exposure to the repo market. The average net position for these banks is only about 2.5 percent of total assets. Nevertheless, these results suggest that U.S. banks face significant exposure via pass-through of the negative policy rate into the repo market. The more active a bank is in providing liquidity to borrowers via repo, the larger the expected NIM compression in a negative rate environment.

However, the effect for G-SIBs is much smaller, likely due to the importance of their broker-dealer subsidiaries. In a negative interest rate environment, G-SIBs anticipate benefiting from lower funding costs through these subsidiaries as the negative policy rate passes through to repo rates. The difference in exposure of G-SIBs versus non–G-SIBs through the net repo position is further evidence of the heterogeneous nature of bank exposure to negative rates.

Finally, the last column presents results for exposure through the yield curve compression channel. If the primary transmission comes through a progressive flattening of the yield curve as the policy rate turns negative, we would expect banks to suffer compressed NIMs as the policy rate turns negative. In this case, we would expect the estimated coefficient on the measure of the duration gap to be negative and statistically significant. As can be seen from the table, it is negative in sign, but the estimate is insignificant and economically small. Claessens, Coleman, and Donnelly (2018) showed that the sensitivity of net interest margins tends to increase as the level of interest rates declines. The results here suggest this sensitivity is not further amplified when rates turn negative.

5.4 Robustness

The baseline results presented in table 2 control for size and bank business model through the inclusion of two dummy variables indicating if the bank is either a processing bank or a G-SIB. Hence, our results are not driven simply by size, a basic indicator for bank business model, or by the systemic importance of the bank.

Additionally, we did a wider set of robustness tests for each hypothesized transmission channel. The results can instead be found in the online appendix in tables C.2–C.6. In short, the baseline results are robust to controlling for the intensity of trading activity (measured as the share of held-for-sale plus held-to-maturity assets over total assets) as well as two different measures of foreign exposure (foreign deposits over total liabilities and C&I (commercial and industrial) loans to borrowers with foreign addresses over total assets). They are also robust to controlling for regulatory capital holdings, including both the CET1 capital ratio (a risk-weighted measure) and the tier 1 leverage ratio (which is not risk weighted) for each bank. The results are largely robust to liquidity regulation with the exception of the statistical significance of exposure through reserves. This can be explained by the fact that reserves make up a large fraction of HQLA, so the two are highly correlated.

A final robustness check extends the analysis in section 4.1. Specifically, we replaced our baseline estimates used to measure bank-specific exposure to negative rates (the dependent variable in equation (4) and that which is being explained in table 2) with the alternative estimates detailed in section 4.1 (that is, the robustness estimates obtained from the alternative NIM models, as well as those obtained from the alternative specifications for equation (3)). Using these alternative estimates, we reestimated equation (4) to see whether there is any impact on the statistical or economic relevance of each hypothesized transmission channel. The results can be found in the online appendix in table C.7. In short, the main qualitative results of the paper are largely robust to these many alternative specifications of the models in each step of the analysis.

6. Conclusion

There is no historical experience from which to draw upon to understand how U.S. banks would fare in a negative interest rate environment. In light of this, the contribution of this paper is to exploit a unique new data source to empirically examine expectations of the banks themselves regarding how they believe they would fare in a negative rate environment.

The results reveal a significant degree of heterogeneity in bank exposure through the lens of net interest margins. The most significant channel of adverse exposure comes from the pass-through of negative rates to short-term liquid assets held on the balance sheet. At the same time, on the liability side, banks that rely more heavily on short-term wholesale funding, including financing through the repo market, may benefit from negative rates through a reduction in funding costs. This is especially relevant for G-SIBs, which have large broker-dealer subsidiaries that rely heavily on repo financing. While the results point to a variety of idiosyncratic exposures for individual U.S. banks, these effects likely wash out at the aggregate level as liquidity provision is sufficiently well diversified across the banking sector.

There are some important policy implications. First, absent any available historical experience upon which to draw, this paper offers the only empirical evidence that can inform the policy debate on the potential effects of a negative rate policy on the U.S. banking sector. Additionally, the finding that negative interests have largely distributional effects suggests that policymakers should focus their attention on the safety and soundness of those specific institutions which are most exposed to elevated losses in a negative interest rate environment. Finally, these results also potentially suggest that liquidity regulation could interact with a negative interest rate policy in an important way. By forcing banks to hold more liquid assets on their balance sheet, compliance with the liquidity coverage ratio may amplify losses in a negative interest rate environment.

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