Do negative interest rates make banks less safe?*

Federico Nucera[a] Andre Lucas[b]

Julia Schaumburg[b] Bernd Schwaab[c]

[a] LUISS Guido Carli University

[b] VU University Amsterdam and Tinbergen Institute

[c] European Central Bank, Financial Research

Abstract

We study the impact of increasingly negative central bank policy rates on banks' propensity to become undercapitalized in a financial crisis ('SRisk'). We find that the risk impact of negative rates depends on banks' business models: Large banks with diversified income streams are perceived as less risky, while smaller and more traditional banks are perceived as more risky. Policy rate cuts below zero trigger different SRisk responses than an earlier cut to zero.

Keywords: negative interest rates; bank business model; systemic risk; unconventional monetary policy measures

JEL classifications: G20, G21

*Author information: Federico Nucera, LUISS Guido Carli University, Viale Romania, 32, 00197 Rome, Italy, Email: fnucera@luiss.it. André Lucas, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands, Email: a.lucas@vu.nl. Julia Schaumburg, Vrije Universiteit Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands, Email: j.schaumburg@vu.nl. Bernd Schwaab, European Central Bank, Kaiserstrasse 29, 60311 Frankfurt, Germany, Email: bernd.schwaab@ecb.int.Schaumburg thanks the Dutch National Science Foundation (NWO, grant VENI451-15-022) for financial support. The views expressed in this paper are those of the authors and they do not necessarily reflect the views or policies of the European Central Bank.

Non-technical summary

Since the onset of the financial crisis in 2007, many central banks have implemented unprecedented standard and non-standard monetary policy measures, lowering key interest rates to approximately zero. To stimulate post-crisis economies characterized by low growth and low inflation, some central banks, including the European Central Bank (ECB), have even adopted negative policy rates. The rationale for negative rates is that they provide additional monetary stimulus, and in this way support growth and a return to target inflation.

At least two main concerns have been voiced by critics of negative policy rates. First, negative rates put pressure on the profitability of financial institutions. Banks may therefore lend to riskier borrowers ('risk shifting'). Second, a 'search for yield' among institutional investors could lead to a disproportional demand for high-yielding risky assets. If so, the implied asset price inflation could impair financial stability.

Which types of banks become more or less risky at negative rates is as yet unclear. In addition, it is currently unknown whether cuts to negative rates are 'special,' for example because they imply a different financial stability response than comparable cuts to non-negative rates. In this paper we contribute to answering these questions. To do so, we study the risk impact as perceived by financial markets of three successive deposit facility rate (DFR) cuts by the ECB to negative values, each by 10 basis points (bps) on June 5, 2014, September 4, 2014, and December 3, 2015. Furthermore, we examine whether the impact of these cuts is qualitatively different from an earlier cut of the DFR from 25 bps to zero on July 5, 2012.

A bank's risk is measured using 'SRisk'. SRisk is the estimated capital shortfall of a bank, conditional on a 40% drop in a world equity index over a six months-ahead horizon. The measure is modelled as a function of a bank's equity market valuation, leverage ratio, the volatility of its stock price, and the correlation of its stock price with the world index. SRisk estimates are available for 44 listed euro area banks at a monthly frequency. To ensure a representative sample, and to include more banks in our analysis, we apply a matching procedure to infer SRisk for non-listed banks. Specifically, we match 67 non-listed banks to 'nearest neighboring' banks for which market data are available. The matching is based on accounting data, which are available for all 111 banks.

Using panel regressions we find that after a cut to an increasingly negative interest rate, some, but not all, banks are perceived as more risky, i.e., more prone to become undercapitalized in a potential future financial crisis. The risk impact depends on banks' business models. Large banks with sufficiently diversified income streams are perceived to be less (systemically) risky. Such banks appear to benefit in net terms from negative rates. By contrast, smaller banks that follow a more traditional business model and rely predominantly on deposit funding, are perceived as potentially more risky. The documented heterogeneity is in line with other studies that argue that bank characteristics become an important determinant of monetary policy transmission at negative rates.

A 'placebo' DFR cut from +25 bps to zero in July 2012 triggered different SRisk responses than the 2014 and 2015 cuts below zero. This suggests that cuts to negative rates may be 'special' in that they have a different financial stability impact than more conventional cuts to non-negative rates.

SRisk in the euro area falls markedly between mid-2012 and mid-2014, possibly initially sparked by the ECB's announcement of Outright Monetary Transactions in August 2012 and subsequently driven by the gradual recovery in economic growth and improving bank capital buffers. Given pronounced variation in the level of SRisk for all banks, the impact of the three DFR cuts to negative rates is of a relatively small(er) magnitude.

Our regression results remain qualitatively similar if only listed banks are included in the sample. The differential effects, however, become statistically insignificant in this case. The results for non-listed banks should therefore be taken as tentative.

1 Introduction

Exceptional times can require exceptional policy measures. Since the onset of the financial crisis in 2007, many central banks have implemented unprecedented standard and non-standard monetary policy measures, lowering key interest rates to approximately zero. To stimulate post-crisis economies characterized by low growth and low inflation, some central banks, including the European Central Bank (ECB) and the central banks of Denmark, Switzerland, Sweden, and Japan, have even adopted negative policy rates. The rationale for negative rates is that they provide additional monetary stimulus, giving banks an incentive to lend to the real sector, and in this way support growth and a return to target inflation; see e.g. Coeuré (2014).

At least two main concerns have been voiced by critics of negative policy rates; see e.g. Hannoun (2015) and Dombret (2017). First, negative rates put pressure on the profitability of financial institutions (Brunnermeier and Koby, 2016). As a result, banks might lend to riskier borrowers without being fully compensated for it ('risk shifting'). Indeed, Heider et al. (2017) find evidence for such effects in the euro area. Second, a 'search for yield' among institutional investors can lead to a disproportional demand for high-yielding risky assets; see Rajan (2013). The implied asset price inflation can undermine financial stability (Reinhart and Rogoff, 2009), and crowd out private investment (Acharya and Plantin, 2017).

On the one hand, banks might benefit from the additional monetary stimulus implied by negative policy rates, e.g., via fewer non-performing loans, or via increases in asset prices. On the other hand, banks can also suffer from negative rates via squeezed interest rate margins for new business. Which types of banks benefit and which suffer is as yet unclear. In addition, it is currently unknown whether cuts to negative rates are 'special,' for example because they imply a different financial stability response than comparable cuts to non-negative rates. In this paper we contribute to answering these questions. To do so, we study the risk impact of three successive deposit facility rate (DFR) cuts by the ECB to negative values, each by 10 basis points (bps). Specifically, we study the rate cuts on June 5, 2014, September 4, 2014, and December 3, 2015. Furthermore, we examine whether the impact of these cuts is qualitatively different from an earlier cut of the DFR by 25 bps to zero on July 5, 2012.

We measure a bank's risk using 'SRisk'. SRisk is a measure for a bank's propensity to become undercapitalized in a crisis; see Brownlees and Engle (2017). We interpret SRisk as a bank-specific risk measure that captures forward-looking market perceptions.[1] Using panel regressions we find that after a cut to an increasingly negative interest rate, some, but not all, banks are perceived as more risky, i.e., more prone to become undercapitalized in a crisis. The risk impact depends on banks' business models. Large banks with sufficiently diversified income streams are perceived to be less (systemically) risky. Such banks appear to benefit in net terms from negative rates. By contrast, smaller banks that follow a more traditional business model and rely predominantly on deposit funding, are perceived as more risky. The documented heterogeneity supports the key result of Heider et al. (2017) that bank characteristics become an important determinant of bank behavior and monetary policy transmission at negative rates. Finally, we find that the July 2012 a 'placebo' DFR cut from +25 bps to zero in July 2012 triggered different SRisk responses than the three later cuts below zero. This suggests that cuts to negative rates have a different financial stability impact than more conventional cuts to non-negative rates.

We proceed as follows. Section 2 presents our empirical methodology, including the data. Section 3 summarizes the empirical findings.

2 Data and empirical methodology

2.1 Business model classification

Based on balance sheet variables from SNL Financial, $N = 111$ banks located in the euro area are allocated to six business model groups. The balance sheet variables as well as business model groups coincide with the ones identified and described in detail in Lucas et al. (2016). Our classification sample ranges from 2012Q2 to 2014Q2. As a result, the business model classification is less influenced by the severe euro area sovereign debt crisis between 2010 and 2011, and predetermined with respect to the DFR cuts in 2014 and 2015. Banks that

[1] SRisk is often interpreted as a 'systemic' risk measure. In the conditioning event of a financial crisis, many banks will be undercapitalized simultaneously. This situation would make it very costly for undercapitalized banks to raise equity from the private sector, giving them a strong incentive to turn to the government (the taxpayer) and demand a bailout. The 'systemic' interpretation of SRisk is optional for the purposes of this paper, but lends additional urgency to our questions.

underwent distressed mergers, were acquired, or ceased to operate for other reasons between 2012 and 2014, are excluded from the analysis.

We proceed in two steps. First, we allocate 'clear-cut' cases based on threshold rules. These rules are described below. 'Clear-cut' cases identify the cluster labels. Second, we use the finite mixture model introduced in Lucas et al. (2016) to allocate the remaining banks. Allocating clear-cut cases in a first step helps us to interpret the clustering outcomes.

We distinguish six business model groups:

(A) **Large universal banks, including G-SIBs** (15.3% of banks). Banks with total assets of more than €800 bn [large], and a share of net interest income of less than 70% of operating revenue [universal], are allocated to this group with probability one.

(B) **Corporate/wholesale-focused banks** (19.8%). Banks with total assets of at least €50 bn, and a share of retail loans to total loans of less than 20% [corporate-focused], are in this group with probability one.

(C) **Fee-focused banks/asset managers** (16.2%). Banks with a share of net fee & commission income to operating revenue of at least 50% [fee-focused] are in this group with probability one.

(D) **Small diversified lenders** (28.8%). Banks with total assets of less than €50 bn [small], a share or retail loans to total loans between 40–60% [diversified across borrowers], and a loan to assets ratio of at least 60% [predominantly a lender] are in this group with probability one.

(E) **Domestic retail lenders** (11.7%). Banks with a share of domestic loans to total loans of at least 90% [domestic] and a share of retail loans to total loans of at least 70% [retail] are in this group with probability one.

(F) **Mutual/co-operative-type banks** (8.1%). Banks with total assets of less than €100 bn, a loans to assets ratio of at least 70%, and a deposits to total assets ratio of at least 50% are in this group with probability one. Banks in this cluster turn out to often be organized as a local savings bank or co-operative bank; thus the label.

2.2 SRisk for listed and non-listed banks

SRisk is the estimated capital shortfall of a bank, conditional on a 40% drop in a world equity index over a six months-ahead horizon; see Brownlees and Engle (2017). The measure is modelled as a function of a bank's equity market valuation, leverage ratio, the volatility of its stock price, and the correlation of its stock price with the world index. Estimates are publicly available for euro area financial firms at a monthly frequency on https://vlab.stern.nyu.edu.

We observe SRisk for 44 listed euro area banks, together with quarterly balance sheet data from the SNL Financial database. For 67 non-listed euro area banks, however, we observe only the accounting data. To ensure a representative sample, and thus to include all banks in our analysis, we apply a matching procedure to infer SRisk for non-listed banks. Specifically, we match non-listed banks to the 'nearest neighboring' banks for which market data are available.

The details of the matching procedure are as follows. For any unlisted bank i with average accounting data $\bar{y}_{i\cdot}$, we compute the J_i nearest listed neighbors based on the Mahalanobis distance, $\hat{\mathrm{D}}(\bar{y}_{i\cdot}, \bar{y}_{j\cdot})^2 = (\bar{y}_{i\cdot} - \bar{y}_{j\cdot})'\hat{\Omega}^{-1}(\bar{y}_{i\cdot} - \bar{y}_{j\cdot})$ for $i \neq j = 1, \ldots, J_i$. Banks are matched on 12 indicators in five categories: banks' total assets [size], leverage with respect to CET1 capital, net loans to assets ratio, credit risk to total risk ratio, assets held for trading, derivatives held for trading [complexity], share of net interest income, share of net fees & commissions income, share of trading income, ratio of retail loans to total loans [activities], ratio of domestic loans to total loans [geography], and loans to deposits ratio [funding]; see Lucas et al. (2016) for details.

To safeguard interpretability, we require that all listed nearest neighbors come from the same business model group as bank i. The Mahalanobis distance scales the data by their unconditional covariance matrix $\hat{\Omega} = N^{-1}\sum_{i=1}^{N}(\bar{y}_{i\cdot} - \bar{y}_{\cdot\cdot})(\bar{y}_{i\cdot} - \bar{y}_{\cdot\cdot})'$ with $\bar{y}_{\cdot\cdot} = N^{-1}\sum_{i=1}^{N}\bar{y}_{i\cdot}$. The nearest neighbors are ordered from close to far, i.e., $\hat{\mathrm{D}}(\bar{y}_{i\cdot}, \bar{y}_{j\cdot}) \leq \hat{\mathrm{D}}(\bar{y}_{i\cdot}, \bar{y}_{j+1,\cdot})$. Using the J_i nearest listed neighbors for an unlisted bank i, we impute bank i's SRisk by $\mathrm{SRisk}_{it} = \sum_{j=1}^{J_i}\mathrm{SRisk}_{jt} \cdot w_j$, where the kernel weights are given by $w_j = j^{-1}/\sum_{j=1}^{J_i} j^{-1}$. Note that banks that are closer in term of Mahalanobis distance receive a larger weight. Matching to multiple neighbors with declining weights increases the robustness of the matching procedure compared to only using a single closest match.

2.3 Regression setup

We examine changes in SRisk around three DFR cuts by the ECB to negative values: from zero to -10 basis points (bps) on June 5, 2014, from -10 to -20 bps on September 4, 2014, and from -20 bps to -30 bps on December 3, 2015. Euro area money market rates, such as the euro overnight index average (EONIA), track the ECB's DFR closely and turned increasingly negative at these times as well.[2]

We study group means based on the panel regression

$$\mathrm{SRisk}_{it} = \alpha + \beta \mathrm{P}_t + \sum_{k=1}^{K-1} \gamma_k \mathrm{BM}_{ik} + \sum_{k=1}^{K-1} \delta_k \mathrm{P}_t \cdot \mathrm{BM}_{ik} + \epsilon_{it}, \tag{1}$$

where P_t is a dummy variable equal to zero before an ECB DFR cut and equal to one thereafter, BM_{ik} is a dummy variable equal to one if bank i belongs to business model group k and zero otherwise, α, β, γ_k, and δ_k, $k = 1, \ldots, K-1$ are unknown coefficients, and ϵ_{it} is a zero mean error term that is uncorrelated with the regressors. For inference, we cluster error terms at the bank level.

The regression equation (1) allows us to benchmark the time differences to a reference group reference group via the coefficients δ_k. We select the fee-focused banks (C) as our reference group. A high share of net fees & commissions income implies that these banks should be less affected by squeezed net interest margins for new business. Instead, fee-focused banks could be exposed to the beneficial aspects of negative rates.

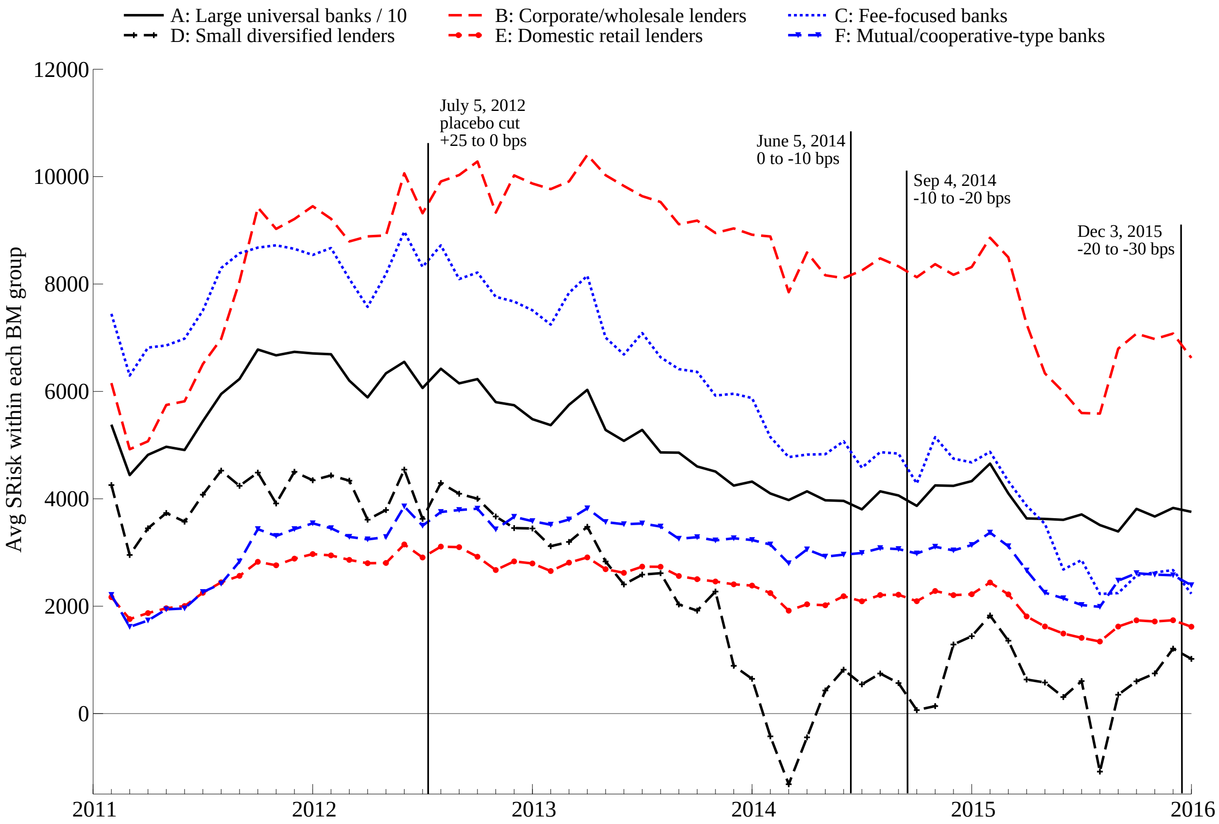
Our SRisk measures are influenced to some extent by changes in common factors, such as common regulation and monetary policy, and they depend positively on the economic outlook. SRisk may increase or decrease on a month-to-month basis for this reason. Benchmarking SRisk to a reference group (C) robustifies our analysis against such common factors.

We identify the impact of the rate cuts based on a narrow window. For example, for the cut on June 05, 2014, regression (1) implicitly compares the end-of-May 2014 with the end-of-June 2014 (T=2) cross-sections of SRisk.

[2] The tight link between EONIA and the ECB's DFR is due to a fixed-rate full allotment procedure that is used to allocate central bank money.

Figure 1: Average SRisk per firm across six business model groups

Average SRisk in US$ million at the group level. The SRisk of group A is scaled down by a factor of 1/10 to allow a visual comparison. The sample ranges from 31 January 2011 until 31 December 2015. The bank business model groups A–F are constructed in Section 2.1.



3 Main findings

Figure 1 plots the average $SRisk_{it}$ within each business model group over time. Vertical lines indicate the ECB's DFR cuts into negative territory in 2014 and 2015, and the 'placebo cut' from 25 bps to zero in July 2012.

Overall, SRisk within each group increases during the euro area sovereign debt crisis between 2011 and early 2012, before reaching a peak around mid-2012. SRisk falls between mid-2012 and mid-2014, possibly initially sparked by the ECB's announcement of Outright Monetary Transactions (OMT) in August 2012 and subsequently driven by the gradual recovery in economic growth and improving bank capital buffers. Given the pronounced variation in the level of SRisk for all banks, Figure 1 also illustrates that the impact of the various DFR cuts on SRisk has a relatively smaller magnitude.

Large universal banks (group A) exhibit by far the highest SRisk levels. Figure 1 scales this group's average by a factor of 1/10 to allow for a better visual comparison. Groups B and C are third and second in terms of average SRisk in 2011, and switch positions thereafter. Again, banks in group C rely on net fees and commissions as the dominant income source. By contrast, banks in group B rely more heavily on net interest income. Cuts to negative rates have been criticized for squeezing net interest income.

Differences across business models are also apparent for the smaller banks in D to F. The evolution of SRisk is quite similar for these banks until mid-2012. Post-2012, banks in D are perceived as less prone to being undercapitalized in a crisis compared to banks in groups E and F. In 2014 and 2015, average SRisk in group D is occasionally negative, suggesting that these banks would be able to withstand a future financial crisis with positive leftover capital. Banks in group D ('small diversified lenders') tend to be diversified across both retail and corporate borrowers as well as across borders. This flexibility may make them more able to cope with a low or negative interest rate environment.

Table 1 presents the parameter estimates for a pooled regression (top panel) and the results with respect to reference group C, i.e., regression specification (1) (bottom panel). Table 1 remains qualitatively similar if only listed banks are included in the panel regressions. The columns correspond to the four policy rate cuts indicated in Figure 1.

We draw two main conclusions from Table 1. First, business models play an important role in capturing the cross-sectional variation in SRisk measures around rate cuts. The three cuts to negative values lead, overall, to a lower level of SRisk; see the top panel of Table 1. This total effect, however, averages over substantially heterogeneous group-specific effects, see the bottom panel of Table 1. In addition, it mainly reflects the impact on the largest banks with the highest SRisk measures.

Large universal banks (A) and fee-focused banks (C, the reference group) appear to have benefited rather than suffered from the cuts to negative values in terms of reductions in SRisk. By contrast, relatively smaller banks that follow more traditional business models do not decrease their SRisk around the rate cuts, i.e., increase their SRisk relative to the decreasing level of the reference group (C). The interaction terms are significant on the first two cut dates for group F, and on the second cut date for group E. Domestic retail lenders and mutual/co-operative-type banks do not appear to benefit in net terms from negative

Table 1: Estimation results

The top panel presents parameter estimates for the pooled regression $\text{SRisk}_{it} = \alpha + \beta \text{P}_t + \epsilon_{it}$. The bottom panel presents parameter estimates for the panel regression specification (1). The regressions are centered around three cuts of the ECB DFR into negative territory, and one 'placebo' cut to zero on July 5, 2012. The dependent variable *SRisk* measures the US$ amount a bank would be undercapitalized in a financial crisis. P_t is a dummy variable which is equal to one in the month following a DFR cut, $t = 1, 2$. A, B, C, D, E, F indicate business model groups: A: large universal banks, B: corporate/wholesale-focused lenders, C: fee-focused banks/asset managers, D: small diversified lenders, E: domestic retail lenders, F: mutual/co-operative-type banks. Group C is the reference group. Standard errors are clustered at the bank-level; t-statistics are in parentheses.

	cut 1	cut 2	cut 3	'placebo'
Date	Jun 5, 2014	Sep 4, 2014	Dec 3, 2015	Jul 5, 2012
Cut in bps	0 → -10	-10 → -20	-20 → -30	+25 → 0
P_t	**-378.93**	**-592.41**	**-353.53**	**968.05**
	(-4.19)	(-6.50)	(-2.76)	(5.81)
const.	**9226.90**	**9328.24**	**8447.32**	**14152.36**
	(5.19)	(5.21)	(5.09)	(5.91)
R-squared	<0.01	<0.01	<0.01	<0.01
Obs	222	222	222	222
$\text{P}_t \cdot$ A	**-1078.08**	**-1375.45**	-280.34	**3179.24**
	(-2.34)	(-4.44)	(-0.53)	(5.90)
$\text{P}_t \cdot$ B	**636.53**	353.48	-13.09	191.91
	(2.91)	(1.41)	(-0.05)	(0.81)
$\text{P}_t \cdot$ D	220.52	52.84	255.50	267.03
	(1.00)	(0.21)	(0.61)	(0.65)
$\text{P}_t \cdot$ E	399.25	**434.24**	319.55	-197.15
	(1.72)	(2.02)	(1.31)	(-0.88)
$\text{P}_t \cdot$ F	**523.87**	**474.53**	255.22	-145.33
	(2.48)	(2.33)	(1.06)	(-0.65)
P_t	**-492.79**	**-556.38**	-439.78	401.00
	(-2.34)	(-2.73)	(-1.82)	(1.81)
A	**34535.02**	**35776.39**	**35618.44**	**52320.52**
	(5.74)	(5.86)	(6.68)	(7.61)
B	3038.13	3488.95	4405.35	998.66
	(0.67)	(0.82)	(1.11)	(0.18)
D	**-4254.36**	**-4273.91**	-1509.68	**-4692.20**
	(-2.66)	(-2.72)	(-1.62)	(-2.09)
E	**-2886.48**	**-2627.60**	-933.94	**-5412.66**
	(-2.09)	(-1.97)	(-1.24)	(-2.61)
F	-2111.61	-1778.59	-96.67	**-4821.00**
	(-1.57)	(-1.38)	(-0.14)	(-2.35)
const.	**5071.36**	**4841.54**	**2671.56**	**8318.89**
	(3.79)	(3.77)	(3.85)	(4.06)
R-squared	0.50	0.52	0.56	0.64
Obs	222	222	222	222

central bank deposit rates.

Second, rate cuts to negative values lead to different SRisk responses than the July 2012 cut; see the right column in Table 1. For example, SRisk for smaller deposit-taking banks in groups E and F decreases in 2012 relative to reference group C, and in absolute terms shows an (insignificant) increase, contrary to what is observed for most later cuts. Large universal banks (A) are perceived as more risky around the July 2012 cut, possibly reflecting less dramatic valuation gains from increasing asset prices. Again, the 2012 impact is different from what is observed for the later cuts. We conclude that cuts to negative rates appear to be different ('special') in terms of their financial stability impact.

References

Acharya, V. and G. Plantin (2017). Monetary easing and financial instability. *NYU working paper*.

Brownlees, C. T. and R. Engle (2017). SRISK: A conditional capital shortfall measure of systemic risk. *The Review of Financial Studies 30(1)*, 48–79.

Brunnermeier, M. and Y. Koby (2016). The "reversal interest rate": An effective lower bound on monetary policy. *Working Paper*.

Coeuré, B. (2014). Life below zero: Learning about negative policy rates. *Speech at the annual dinner of the ECB's market contact group, on 09 September 2014, available at http://www.ecb.int*.

Dombret, A. (2017). The ECB's low-interest-rate policy - a blessing or a curse for the economy, consumers and banks? *Speech delivered at the Sparkassen-Gesprchsforum, Witten, 1 February, 2017*.

Hannoun, H. (2015). Ultra-low or negative interest rates: what they mean for financial stability and growth. *Speech given at the BIS Eurofi High-Level Seminar in Riga, 22 April 2015*.

Heider, F., F. Saidi, and G. Schepens (2017). Life below zero: Bank lending under negative policy rates. *Working paper, available at SSRN: https://ssrn.com/abstract=2788204*.

Lucas, A., J. Schaumburg, and B. Schwaab (2016). Bank business models at zero interest rates. *Tinbergen Institute Discussion Paper 066/IV*, 1–56.

Rajan, R. (2013). A step in the dark: unconventional monetary policy after the crisis. *BIS Andrew Crockett Memorial Lecture, 23 June 2013*.

Reinhart, C. M. and K. S. Rogoff (2009). The aftermath of financial crises. *American Economic Review 99*(2), 466–472.

Appendix

The appendix provides two robustness checks. First, we check whether our main empirical results reported in Table 1 remain qualitatively similar if only the 44 listed banks are used in the analysis. This is the case. Table A.1 presents the respective testing outcomes. We needed to pool over banks in groups E and F for data sparsity reasons. Statistical significance is lost in some cases due to fewer observations in each regression. Table 1, however, remains qualitatively similar.

Second, we implement a formal test (a "placebo test") of parallel trends. Table A.2 is obtained by counter-factually assuming that the three DFR cuts occurred one month earlier than they actually did. With one exception, no interaction effect is significant for the three DFR cuts below zero. In the one exception, the coefficient is of the opposite sign. Our differential estimates therefore appear to be associated with the actual DFR cuts.

Table A.1: Estimation results: SRisk subsample of listed banks

The top panel presents parameter estimates for the pooled regression $\text{SRisk}_{it} = \alpha + \beta \text{P}_t + \epsilon_{it}$. The bottom panel presents the parameter estimates for the panel regression specification (1). The regressions are centered around three cuts of the ECB deposit facility rate into negative territory, and one cut to zero in July 2012. The dependent variable *SRisk* measures the US$ amount a bank would be undercapitalized in a financial crisis. P_t is a dummy variable which is equal to one following a deposit rate cut. A, B, C, D, E indicate business model groups: A: large universal banks, B: corporate/wholesale-focused lenders, C: fee-focused banks/asset managers, D: small diversified lenders, E: domestic retail lenders. Group C is the reference group. T-statistics are in parentheses.

	cut 1	cut 2	cut 3	cut +
Date	Jun 2014	Sep 2014	Dec 2015	Jul 2012
Cut in bps	0 → -10	-10 → -20	-20 → -30	+25 → 0
P_t	**-726.18**	**-861.79**	-406.79	**1236.86**
	(-3.71)	(-4.40)	(-1.26)	(3.34)
const.	**13394.86**	**13347.77**	**11921.34**	**20196.89**
	(3.29)	(3.25)	(3.18)	(3.92)
R-squared	<0.01	<0.01	<0.01	<0.01
Obs	88	88	88	88
$\text{P}_t \cdot$ A	-1424.90	**-1508.04**	-98.37	**3272.15**
	(-1.65)	(-2.52)	(-0.09)	(2.95)
$\text{P}_t \cdot$ B	283.59	-1150.04	-948.5	338.40
	(0.55)	(-0.97)	(-0.83)	(0.50)
$\text{P}_t \cdot$ D	325.42	-76.04	462.44	242.96
	(0.90)	(-0.17)	(0.62)	(0.34)
$\text{P}_t \cdot$ E	422.09	389.25	545.80	-448.29
	(1.00)	(1.01)	(1.34)	(-1.19)
P_t	-661.09	-548.45	-597.00	578.09
	(-1.91)	(-1.61)	(-1.49)	(1.59)
A	**44055.57**	**45916.72**	**44081.26**	**62788.08**
	(3.72)	(3.84)	(4.12)	(4.73)
B	43840.82	41759.09	42220.14	49076.95
	(1.22)	(1.22)	(1.30)	(1.16)
D	-5091.40	-5027.79	-1757.41	-5336.93
	(-1.87)	(-1.87)	(-1.08)	(-1.42)
E	**-5027.78**	**-4769.10**	**-2525.16**	**-7551.74**
	(-2.21)	(-2.18)	(-2.17)	(-2.17)
const.	**6046.18**	**5699.90**	**2993.36**	**9591.54**
	(2.74)	(2.68)	(2.58)	(2.83)
R-squared	0.56	0.57	0.60	0.65
Obs	88	88	88	88

Table A.2: Estimation results: "Placebo" tests at DFR $t-1$

Parameter estimates for the panel regression specification (1). The regressions are centered **one month before** the three ECB DFR cuts into negative territory. The dependent variable *SRisk* measures the US$ amount a bank would be undercapitalized in a financial crisis. P_t is a dummy variable which is equal to one in the second period. A, B, C, D, E, F indicate business model groups: A: large universal banks, B: corporate/wholesale-focused lenders, C: fee-focused banks/asset managers, D: small diversified lenders, E: domestic retail lenders, F: mutual/co-operative-type banks. Group C is the reference group; t-statistics are in parentheses.

Window	April/May 2014	July/Aug 2014	Oct/Nov 2015
$P_t \cdot$ A	-356.35	-742.22	**1545.63**
	(-0.46)	(-1.91)	(4.02)
$P_t \cdot$ B	-293.44	-121.37	58.72
	(-1.37)	(-0.43)	(0.35)
$P_t \cdot$ D	146.63	-150.44	404.47
	(0.62)	(-1.19)	(1.90)
$P_t \cdot$ E	-72.58	33.72	-19.62
	(-0.45)	(0.40)	(-0.30)
$P_t \cdot$ F	-203.08	10.11	-55.77
	(-1.42)	(0.14)	(-0.83)
P_t	240.72	-27.54	42.77
	(1.74)	(-0.41)	(0.66)
A	**34891.37**	**36518.61**	**34072.81**
	(5.94)	(6.00)	(6.49)
B	3331.57	3610.33	4346.63
	(0.77)	(0.80)	(1.14)
D	**-4400.99**	**-4123.46**	-1914.15
	(-2.76)	(-2.55)	(-1.84)
E	**-2813.89**	**-2661.32**	-914.31
	(-2.19)	(-1.95)	(-1.26)
F	-1908.52	-1788.70	-40.88
	(-1.54)	(-1.35)	(-0.06)
const.	**4830.63**	**4869.08**	**2628.77**
	(3.92)	(3.68)	(3.96)
R-squared	0.51	0.52	0.54
Obs	222	222	222