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Do negative interest rates make banks less safe?☆

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HIGHLIGHTS

- Banks' systemic risk reactions to rate cuts into negative territory differ across bank business models.
- Large universal banks and fee-focused banks appear to have benefited from rate cuts into negative territory.
- Rate cuts in positive territory appear to have a different impact.

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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.

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

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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 data 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 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 modeled 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, $\hat{D}(\bar{y}_{i\cdot}, \bar{y}_{j\cdot})^2 = (\bar{y}_{i\cdot} - \bar{y}_{j\cdot})'\hat{\Omega}^{-1}(\bar{y}_{i\cdot} - \bar{y}_{j\cdot})$ 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., $\hat{D}(\bar{y}_{i\cdot}, \bar{y}_{j\cdot}) \leq \hat{D}(\bar{y}_{i\cdot}, \bar{y}_{j+1,\cdot})$. Using the J_i nearest listed neighbors

[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.