SN Bus Econ (2021) 1:49
https://doi.org/10.1007/s43546-020-00038-1

ORIGINAL ARTICLE

Measuring the effect of negative interest rate on New Zealand banks

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Received: 2 October 2020 / Accepted: 30 December 2020 / Published online: 24 February 2021

Abstract
We derive an equilibrium lending and deposit rates from a constrained profit optimization model, and estimated them over the period from 1999 to 2020. Then, dynamic stochastic baseline projections of these equilibrium rates and bank profit, and their projections under a counterfactual scenario of a negative interest rate, were produced for the period 2020–2024. The model predicts that a negative official cash rate (OCR) lowers the lending and deposit rates on average over the period Jun 2020 to Dec 2024; but the lending rate is higher than the deposit rate. It also increases the volatility of these rates relative to baseline projections. Negative OCR increases both incomes and costs; however, bank profit increases on average, by about 19% relative to baseline projections over the period Sep 2020 to Dec 2024. However, that increase of bank profit is associated with more uncertainty.

Keywords Lending rate · Deposit rate · Bank profit · Negative interest rate

JEL Classification C15 · C51 · G21

Introduction

Bernanke and Blinder (1988) derived the lending channel of monetary policy, which essentially predicted that low (policy) interest rate, e.g., the Federal Fund Rate, increases the bank supply of loans (i.e., increases credit). Bernanke and Blinder (1992) and Jimenze et al. (2012) are among others who provided empirical support for this theory. Goodfriend (2000), however, was the first to argue that negative policy interest rate is a possible solution to the zero lower bound (i.e., the nominal interest rate reaches zero and monetary policy becomes ineffective in stimulating the economy).

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Madaschi and Nuevo (2017) is a study of Sweden and Denmark banking systems. Both countries' banks have been operating under a negative interest rate for some time. They estimate the effect of the change in the official interest rates on bank lending and deposit rates using a regression, error-correction specification, and show that bank profit remained stable during the Great Recession period (the period that followed the global financial crisis (GFC) in 2007–2008).[1] Banks in both countries have positive lending rates, but Sweden's banks have paid depositors negative rates while the Danish banks kept it at zero. For Sweden, the average repo rate from January 2018 to-date has been negative − 0.35, the lending rate averaged 0.40, however, the deposit rate average has been − 0.98. The deposit rate has been reduced well below the repo rate while the lending rate was positive. For Denmark, the average end-of-month policy rate since 2018 has been zero, the deposit rate is zero, and the lending rate is 0.05.

Jobst and Lin (2016) use a DSGE model to study the effect of negative interest rate in the EU area on bank profitability. They found that such monetary policy, which lowers bank funding cost and boosts asset prices, increases credit flow, increases lending and bank profit. However, they speculated that although negative effects on bank profitability have not occurred, further significant decline in negative interest rate would "likely entail diminishing returns since the lending channel is crucially influenced by the bank's expected profitability."

Boungou (2019) used a very large dynamic panel model with data for 28 European countries and reported a strong negative impact of negative interest rate on bank net interest margins, which prompted banks to increase the non-interest margins. The effect on bank productivity depended on the bank-specific balance sheet characteristics. He found that banks tend to take less risk under a negative interest rate regime.

Arseneau (2017), analyzed the expected effect of a negative interest rate on U.S. banks. He uses a Fed unique confidential survey data to answer the same question. He argued that heterogeneity affects the results, whereby banks that provide liquidity to borrowers expect lower profitability because of the decline in interest-income. The opposite is true for banks that provide liquidity to depositors because they benefit from short-term funding cost.[2]

[1] The regression is $\Delta br_t = \alpha\left(br_{t-1} - \mu - \beta r_{t-1}\right) + \delta \Delta r_t + \sum_{i=0}^{T} \lambda_i \Delta br_{t-i} + \varepsilon_t$, where the dependent variable is either the bank lending rate or the deposit rate; and r_t is the official policy rate.

[2] He examined bank-level expectations about the impact of negative short-term interest rates on their profitability (net interest margins) using a confidential supervisory data called Comprehensive Capital Analysis and Review (CCAR). This is part of the Fed's stress testing procedure. His method of analysis is based on 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 allowed him to isolate how individual banks view their net interest margins as evolving in a negative rate environment, even after controlling for underlying macroeconomic developments and bank-specific characteristics. He uses three vintages of the CCAR data. Each vintage has five different scenarios including a baseline scenario. A panel regression equation of bank net interest margins is regressed on a constant term, lagged dependent variable, lagged three-month Treasury rate, lags of the spread between the 10-year bond rate and 3-month Treasury rate, real GDP growth, and a number of bank-specific factors. He uses the predicted values from this regression and compares them to the banks projections. These deviations are regressed on an indictor 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.

The RBNZ has already said that it is willing to reduce the OCR to negative if needed. Most observers expected the OCR to be negative early in 2021, March or April. This paper attempts to measure the effect of negative interest rate on lending rates, deposits rate, and bank profit in New Zealand. Banks in New Zealand hold reserves in the Settlement Cash Account at the Reserve Bank (RBNZ). The lending channel hypothesis predicts that a negative interest on this account (i.e., negative OCR) encourages banks not to hold more reserves with the RBNZ, hence increasing lending, and that would stimulate demand. A low and negative interest rate should also increase asset prices (e.g. Razzak and Moosa 2018) and reduce the cost of funds (e.g. reduce the interest rate on deposits). Together, these changes, depending on the relative magnitudes, affect bank income and profit.

We are unaware of any other papers on this subject about New Zealand. Our paper is methodologically different from the studies cited earlier. We accomplish our objective by estimating the equilibrium lending rate and the deposit rate in New Zealand then making projections of the effect of a negative OCR in New Zealand on the future bank lending rate, deposit rate, and profit. We derive an equilibrium lending and deposit rates from a constrained bank-profit maximization problem, i.e., a partial equilibrium rather than the DSGE *panel* model used for the Euro Area. Then, we use an unrestricted VAR to summarize the dynamics of the equilibrium rates instead of single-equation regressions. Then the VAR model is solved using a dynamic and stochastic method, whereby the innovations are produced using bootstraps to produce baseline projections over the period from Sep 2020 to Dec 2024. Thus, we provide genuine out-of-sample baseline projections. We follow the same methodology to make projections under a counterfactual scenario, whereby the OCR is negative. Similarly, we produce baseline projection and out-of-sample projection under counterfactual scenario for the period from Jun 2020 to Dec 2024 under a negative OCR, bank interest income, non-interest income, interest cost, and non-interest cost, which allow us to analyze bank profit under baseline and under a negative OCR scenario.

We found that both the equilibrium lending and deposit rates decline significantly when the OCR turns negative, and they both turn negative as the projection horizon increases. On average—over the projection horizon—however, the lending rate remained higher than the deposit rate. In addition, net interest income increased. We project that a negative OCR increases bank profit relative to baseline by about 19% on average over the period Sep 2020 to Dec 2024, which is consistent with Bernanke and Blinder (1988). However, the trade-off is having more uncertainty. Interest income and costs, and non-interest income, among all the components of profit (i.e., income from derivatives, trade, fees etc.) becomes more volatile when the OCR turns negative.

Next, we derive the equilibrium lending rate and the deposit rate from constrained profit maximization. In Sects. 3 and 4, we estimate the dynamic of the equilibrium lending and deposit rates using a VAR, and provide a dynamic stochastic baseline projection up to Dec 2024. Then we provide projections of the equilibrium lending and the deposit rates under scenarios of negative OCR. Section 5 is a similar analysis of the effect of the OCR on the bank profit. Section 6 is a conclusion.

Deriving the equilibrium lending and deposit rates

These equilibrium rates result from the interaction of supply and demand curves of loans and deposits. Let us assume a representative bank, which takes deposits D_{t} from households, firms, and the government to make loans L_{t} to firms and households. The interest paid on deposits is $r_{\mathrm{t}}^{\mathrm{d}}$ and the lending rate is $r_{\mathrm{t}}^{\mathrm{l}}$. Banks receive interest $r_{\mathrm{t}}^{\mathrm{ocr}}$ on the deposits D_t^s in the Settlement Cash account held at the RBNZ. r_t^{ocr} is the OCR.[3] Banks can invest in bonds B_{t} or other financial products in the money and bond markets and obtain returns. We assume that the money and bond markets are one market for simplicity.

The representative one-period bank maximizes profit, which is, total revenues less total cost. The profit function is:

$$\Pi_{\mathrm{t}} = \left\{ r_{\mathrm{t}}^{l} L_{\mathrm{t}} + r_{\mathrm{t}}^{\mathrm{ocr}} D_{\mathrm{t},}^{\mathrm{s}} + r_{\mathrm{t}}^{\mathrm{b}} B_{\mathrm{t}} + r_{\mathrm{t}}^{\mathrm{n}} NP_{\mathrm{t}} - r_{\mathrm{t}}^{\mathrm{d}} D_{\mathrm{t}} - c(.) \right\}, \tag{1}$$

[4]Π_{t} is bank profit. $r_{\mathrm{t}}^{\mathrm{l}}$ is the lending rate. L_{t} is the quantity of loans of the bank. $D_{\mathrm{t}}^{\mathrm{s}}$ is the settlement cash balance at the RB, which is paid $r_{\mathrm{t}}^{\mathrm{ocr}}$, $r_{\mathrm{t}}^{\mathrm{b}}$ is the interest rate on bonds. B_{t} the RB bonds held by the bank and $r_{\mathrm{t}}^{\mathrm{d}}$ is the deposit rate paid by the bank and D_{t} is bank deposit. NP_t is the bank net position of the bank in the money and bond market, whereby banks invest in these markets, and $r_{\mathrm{t}}^{\mathrm{n}}$ is the market interest rate. $c(.)$ is the bank managing cost; it is strictly convex and twice continuously differentiable.

Assume that the net position of the bank is given by:

$$NP_{\mathrm{t}} = D_{\mathrm{t}} - L_{\mathrm{t}} - D_{\mathrm{t}}^{\mathrm{s}} - B_{\mathrm{t}}. \tag{2}$$

We specify a simple quadratic cost function.

$$c_{\mathrm{t}} = \frac{1}{2}\left(\alpha_1 D_{\mathrm{t}}^2 + \alpha_2 L_{\mathrm{t}}^2\right). \tag{3}$$

The parameters α_1 and α_2 are positive marginal costs of deposits and loans. Substitute both (2) and (3) in (1).

The bank maximizes Π_{t}

$$\Pi_{\mathrm{t}} = \underbrace{max}_{L_{\mathrm{t}}, D_{\mathrm{t}}^{\mathrm{s}}, D_{\mathrm{t}}, B_{\mathrm{t}}} \left\{ r_{\mathrm{t}}^{\mathrm{l}} L_{\mathrm{t}} + r_{\mathrm{t}}^{\mathrm{ocr}} D_{\mathrm{t},}^{\mathrm{s}} + r_{\mathrm{t}}^{\mathrm{b}} B_{\mathrm{t}} + r_{\mathrm{t}}^{\mathrm{n}}\left(D_{\mathrm{t}} - L_{\mathrm{t}} - D_{\mathrm{t}}^{\mathrm{s}} - B_{\mathrm{t}}\right) - r_{\mathrm{t}}^{\mathrm{d}} D_{\mathrm{t}} - \frac{1}{2}\left(\alpha_1 D_{\mathrm{t}}^2 + \alpha_2 L_{\mathrm{t}}^2\right) \right\}, \tag{4}$$

subject to a constraint. The constraint is on the capital/asset ratio. We write this constraint as $\frac{K_t}{A_t} = \theta$. The assets, $A_t = L_t + x_t$, where L_t is loans and x_t is all the rest of the

[3] In order to discourage banks from accumulating balances, the bank pays OCR less 100 bps on the settlement cash above a certain limit. This limit is reviewed monthly based on the bank's size and payment's business.

[4] Gerali et al. (2010) have banks maximizing a multi period equation of the discounted sum of cash flow instead, which is reduced to a one period profit equation whose arguments are not very different from this equation.

bank assets. For convenience, we rewrite the constraint $\lambda(L_t - \frac{K_t-\theta x_t}{\theta})$, where λ is the one-period Lagrange multiplier.

Solve for the first order conditions (FOC).

$$\text{FOC for } L_\text{t} \rightarrow, r_\text{t}^\text{l} - r_\text{t}^\text{n} - \alpha_2 L_\text{t} + \lambda = 0, \tag{5}$$

$$\text{FOC for } D_\text{t}^\text{s} \rightarrow r_\text{t}^\text{ocr} - r_\text{t}^\text{n} = 0, \tag{6}$$

$$\text{FOC for } D_\text{t} \rightarrow -r_\text{t}^\text{d} - \alpha_1 D_\text{t} + r_\text{t}^\text{n} = 0, \tag{7}$$

$$\text{FOC for } B_\text{t} \rightarrow r_\text{t}^\text{b} - r_\text{t}^\text{n} = 0, \tag{8}$$

So from (6), the OCR, r_t^ocr is equal to the risk-free money market rate r_t^n.

From (5),

$$r_\text{t}^\text{l} = r_\text{t}^\text{n} + \alpha_2 L_\text{t} - \lambda. \tag{9}$$

We replace the risk-free market interest rate r_t^n with the OCR r_t^ocr and rewrite Eq. (9):

$$r_\text{t}^\text{l} = r_\text{t}^\text{ocr} + \alpha_2 L_\text{t} - \lambda. \tag{10}$$

Therefore, the optimal supply of loans is:

$$L_\text{t}^\text{s} = \frac{r_\text{t}^\text{l} - r_\text{t}^\text{ocr} + \lambda}{\alpha_2}. \tag{11}$$

We postulate the demand for loans to be negatively related to the lending rate and positively to demand.

$$L_\text{t}^\text{d} = \beta \tilde{y}_\text{t} - \gamma r_\text{t}^\text{l}, \tag{12}$$

Equate the supply and the demand and solve for the lending rate.

$$\frac{r_\text{t}^\text{l} - r_\text{t}^\text{ocr} + \lambda}{\alpha_2} = \beta \tilde{y}_\text{t} - \gamma r_\text{t}^\text{l}; \tag{13}$$

$$r_\text{t}^\text{l} - r_\text{t}^\text{ocr} + \lambda = \alpha_2 \beta \tilde{y}_\text{t} - \alpha_2 \gamma r_\text{t}^\text{l}. \tag{14}$$

The optimal (equilibrium) lending rate is:

$$r_\text{t}^\text{l} = \frac{r_\text{t}^\text{ocr} + \alpha_2 \beta \tilde{y}_\text{t} - \lambda}{1 + \alpha_2 \gamma}. \tag{15}$$

Thus, $\frac{\partial r_\text{t}^\text{l}}{\partial r_\text{t}^\text{ocr}} > 0$, and $\frac{\partial r_\text{t}^\text{l}}{\partial \tilde{y}_\text{t}} > 0$. Figures 1 and 2 are scatter plots of the actual data. The high positive correlations are tested using $\chi^2_{(0.95,2)}$ Confidence Ellipse. The $\text{cov}\left(r_\text{t}^\text{l}, r_\text{t}^\text{ocr}\right) > 0$ and $\text{cov}\left(r_\text{t}^\text{l}, \tilde{y}_\text{t}\right) > 0$, i.e., the lending rate is positively correlated

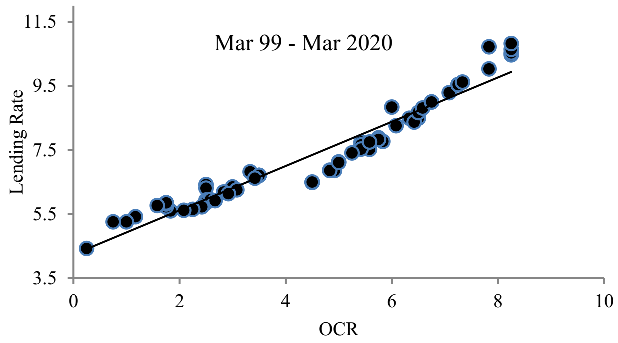

Fig. 1 Mar 99–Mar 2020

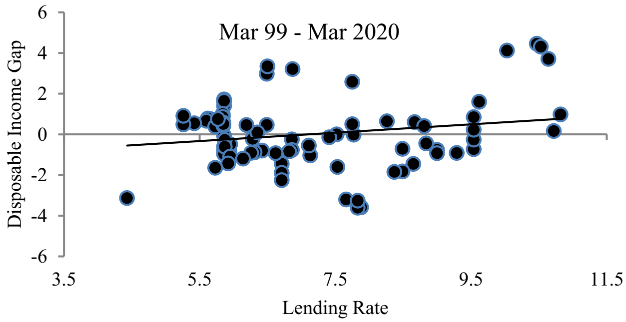

Fig. 2 Mar 99–Mar 2020

with the OCR, and with income. Similarly, we could derive the equilibrium deposit rate as a positive function of $r_{\mathrm{t}}^{\mathrm{ocr}}$ and a negative function of aggregate saving.

From (7),

$$D_{\mathrm{t}}^{\mathrm{d}} = \frac{r_{\mathrm{t}}^{\mathrm{ocr}} - r_{\mathrm{t}}^{\mathrm{d}}}{\alpha_1}. \tag{16}$$

And we postulate that the supply of deposits is a positive function of aggregate savings S_t and the deposits rate $r_{\mathrm{t}}^{\mathrm{d}}$.

$$D_{\mathrm{t}}^{\mathrm{s}} = \phi S_{\mathrm{t}} + \varphi r_{\mathrm{t}}^{\mathrm{d}}. \tag{17}$$

The equilibrium deposit rate is:

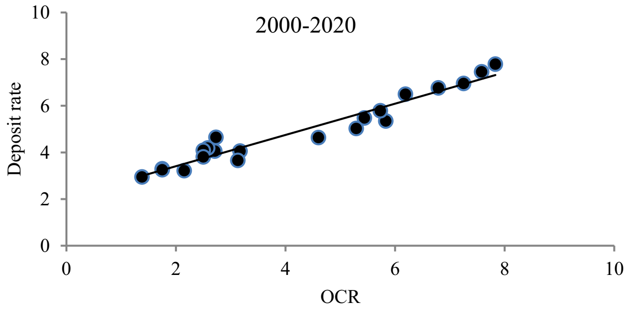

Fig. 3 2000–2020

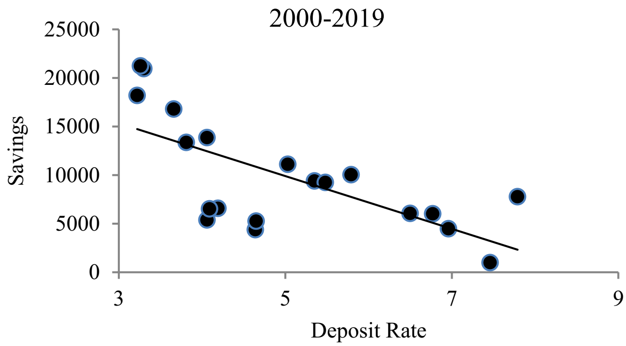

Fig. 4 2000–2019

$$r_{\mathrm{t}}^{\mathrm{d}} = \frac{\left(r_{\mathrm{t}}^{\mathrm{ocr}} - \alpha_1 \phi S_{\mathrm{t}}\right)}{1 + \alpha_1 \varphi}. \tag{18}$$

Thus, $\frac{\partial r_{\mathrm{t}}^{\mathrm{d}}}{\partial r_{\mathrm{t}}^{\mathrm{ocr}}} > 0$ and $\frac{\partial r_{\mathrm{t}}^{\mathrm{d}}}{\partial S_{\mathrm{t}}} < 0$ and $\mathrm{cov}\left(r_{\mathrm{t}}^{\mathrm{d}}, r_{\mathrm{t}}^{\mathrm{ocr}}\right) > 0$, and $\mathrm{cov}\left(r_{\mathrm{t}}^{\mathrm{d}}, S_{\mathrm{t}}\right) < 0$, The increase in savings is associated with a lower deposit rate. Figures 3 and 4 are scatter plots of the actual deposit rate and the OCR, and the deposit rate and savings, which we them tested using a $\chi^2_{095,2}$ Confidence Ellipse.

Next, we estimate the dynamics of the lending and deposit rates.

Estimating the dynamic of the equilibrium lending rate

We analyze the equilibrium lending rate over the sample from Mar 1999 to Jun 2020.[5] We summarize the dynamics of OCR, lending rate, and a measure of household demand in order to make baseline dynamic stochastic projections and projections of a counterfactual scenario of a negative OCR out-of-sample covering the

[5] The data sources are in the data appendix Table 7.

period up to 2024, which we chose arbitrarily. Therefore, we use a standard unrestricted VAR.[6] The VAR is given by the standard form

$$y_{\mathrm{t}} = A_1 y_{t-1} \cdots A_p y_{t-p} + \varepsilon_t, \tag{19}$$

where $y_t = \left(y_1, y_{2t}, \cdots y_{kt}\right)'$ is a $k \times 1$ vector of endogenous variables.

There is also an exogenous constant term, $\varepsilon_t = \left(\varepsilon_{1t}, \varepsilon_{2t}, \cdots \varepsilon_{kt}\right)'$ is a $k \times 1$ vector of white-noise innovations with $\left(\varepsilon_t\right) = 0$; $E\left(\varepsilon_t \varepsilon_t'\right) = \sum \varepsilon$, and $E\left(\varepsilon_t \varepsilon_s'\right) = 0$ for $t \neq s$.

Let $(pk + d) \times 1$ vector:

$$Z_t = \left(y_{t-1}' \cdots y_{t-p}'\right)',$$

And write the VAR is a compact form:

$$Y_t = BZ_t + \epsilon_t \tag{20}$$

Y is $\left(r_{\mathrm{t}}^{\mathrm{ocr}}, \tilde{y}_{\mathrm{t}}, r_{\mathrm{t}}^{\mathrm{l}} \right)$; ϵ is $\left(\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t} \right)$ both are matrices of the endogenous variables are the innovations. The matrices $B = \left(A_1, A_{2,} A_{3,} \text{constant}\right)$ and $Z = \left(Z_{1t}, Z_{2t}, Z_{3t} \right)$ are the matrix of coefficients and matrix of regressors, respectively.[7]

The RBNZ reports two lending rates; a business lending rate and a housing lending rate. Here we report our analysis of the housing lending rate r_t^l as a measure of the lending rate. Because we use the house lending rate instead of the business lending rate, it seems more appropriate to use household disposable income gap than the output gap to measure demand, $\tilde{y}_t$.[8]

Figure 5 plots the three variables of the VAR, the OCR, the disposable income gap, and the housing lending rate (we also plot the business lending rate to show how closely correlated it is to the housing lending rate). The VAR is estimated for

[6] Estimating an SVAR does not alter the results, therefore, we do not report the result. The results are available on request. The observed residuals e_t have a covariance matrix $\sum\left(ee'\right)$. The structural VAR model is $Ae_t = Bu_t$, where u_t is a matrix of unobserved shocks, which we want to identify. This matrix has an identity covariance matrix $\sum\left(uu'\right) = I$. Different methods can be used to identify shocks, but the orthogonality of the shocks implies that the identifying restrictions on A and B are of the form $A \sum A' = BB'$. Since the matrices on both sides of the equality sign are symmetrical, we have $k(k+1)/2$ restrictions on the $2k^2$ unknown elements in A and B. To identify A and B, additional $2k^2 - (k+1)/2$ identifying restrictions are needed. We use short-run restrictions on B. These restrictions imply that the OCR is unaffected by the lending rate and disposable income and it is a function of its own past, disposable income is a function of its own past values and the OCR past values, and the lending rate depends on its own lags, disposable income lags, and OCR lags.

[7] We tested a dummy variable that takes a value of 1 during the period Mar 2009 to Dec 2009 to account for the significant drop in interest rate. We found it to be statistically insignificant and only marginally significant in the income equation.

[8] We also used the business lending rate and then the average of the business and the housing lending rates, and the real GDP output gap instead of disposable income gap. The results are qualitatively similar, but the statistics differ slightly. We do not report these results but they are available on request. The HP filter is used to de-trend the real disposable income.

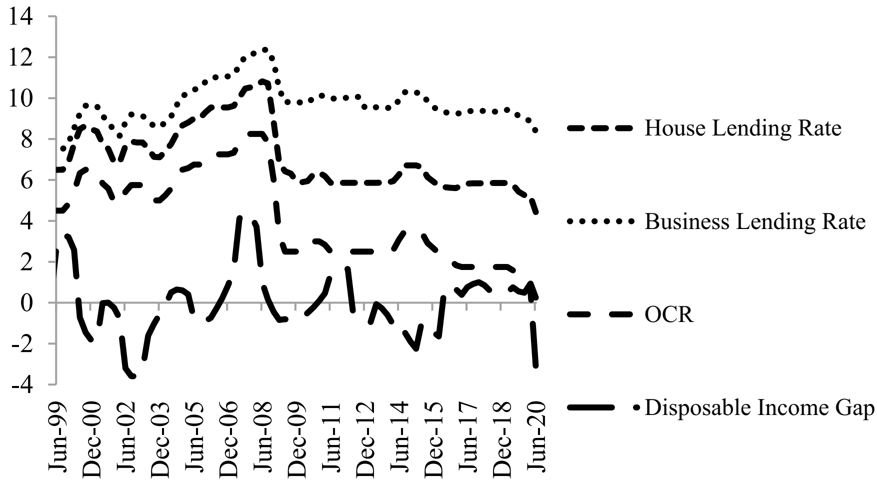

Fig. 5 The quarterly time series data

New Zealand using quarterly data from March 1999 to Jun 2020.[9] The VAR includes a constant term. We fit three lags.[10] Figure 6 plots the generalized impulse response functions, Pesaran and Yongcheol (1998).[11] The standard errors of these impulse response functions are computed using a Monte Carlo with 1000 repetitions. The responses are consistent with the theory and Eq. (15).[12] The middle plot in the first

[9] The standard Dickey-Fuller test for unit root is a weak test against stationary alternative, however, we adjust the test for a break in the data, especially during the Global Financial Crisis, and we could easily reject the null hypothesis of a unit root in interest rates. For the disposable income gap is stationary by design.

[10] The VAR satisfies the stability conditions with all roots are inside the unit circle. The joint Wald statistic for lag-exclusion test has *p*-values of 0.0000, 0.0001, and 0.0211 for lags 1–3. The AIC, SC, and HQ Information Criteria to determine the lag structure suggested three lags. The residuals are tested for serial correlation using the LM test. The null hypothesis that the residuals are serially uncorrelated at lag 1, 2, and 3 cannot be rejected. The *P* values are 0.0771, 0.0611, and 0.2939, respectively. When testing the null hypothesis of no serial correlation at lag 1–3, the *P* values of the Edgeworth expansion corrected likelihood ratio statistic are 0.0771, 0.2162, and 0.0501, respectively. The *F* statistics in Eqs. (1–3) are highly statistically significant.

[11] The order of the variables does not seem to matter. We tested that and found that the standard Choleski impulse response functions to be the same. Further, Koop, Pesaran and Potter (1996) and Isakin and Ngo (2020) show that when models are linear, traditional IRFs and variance decomposition.

[12] First, the actual data of the output gap, and the disposable income gap and the OCR are positively correlated over the sample from Mar 1999 to Mar 2020. There is no correlation if June 2020 data are included because output and income fell significantly after COVID-19. These positive correlations between the short-term nominal OCR and real output suggest that aggregate demand shocks dominate. Theoretically, take for example, a simple IS-LM, AD-AS model. If shocks were dominantly positive (negative) shocks in the goods market, the IS curve shifts up (down), and both the OCR (on the vertical axis) and output (on the horizontal axis) decline (i.e., move in the same direction). The AD would also shift in the same way. Second, since the RBNZ reacts to aggregate demand shocks, it responds by increasing the OCR when the output gap opens up. Thus, the OCR response to the output gap is positive as shown by the IRF (Fig. 6, row 1, middle plot).

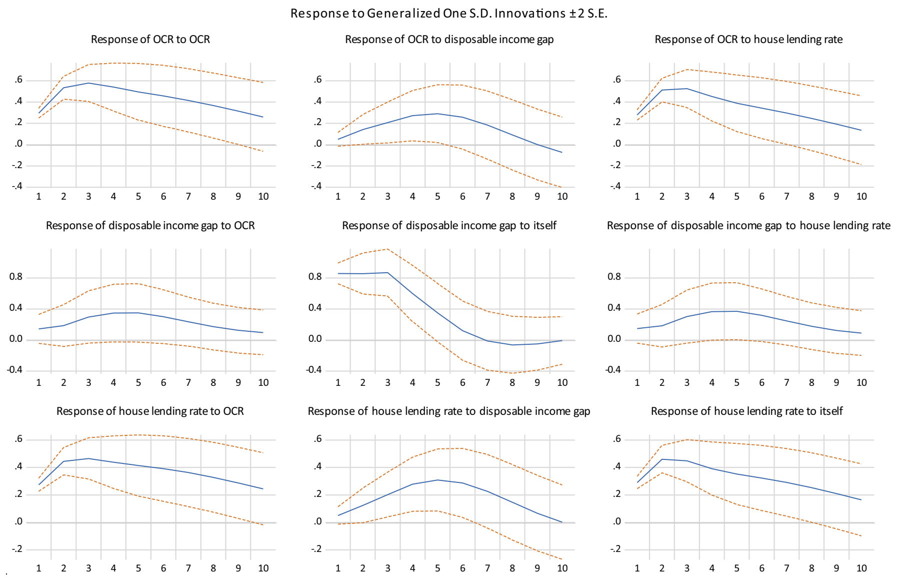

Fig. 6 Response to generalized one S.D. innovations ± 2 S.E

row of Fig. 6 shows that the OCR responds positively to the disposable income gap. The first plot in the second row shows that the disposable income gap responds positively to the OCR. The third row shows that the lending rate is highly positively responsive to the OCR and income. These responses are reasonable.

Baseline projections of the lending rate

The next step is to produce a baseline dynamic stochastic projection of the lending rate for the period from Sep 2020 to Dec 2024. This end date is arbitrary. The model is solved and dynamic and stochastic projections are produced, whereby the innovations are generated using bootstrapping with 1000 iterations over the period Mar 1999 to June 2020.[13] Figure 7 plots the dynamics of the baseline projections. The projections show periods of slow decline until Mar 2023 followed by periods of increasing rates. It steadily and slowly increases until it reaches 5.1% in Dec 2024.[14]

[13] Dynamic Stochastic solution of the model has been used before in the literature to deal with the Lucas critique. When solving, we use an approximated Jacobian to linearize the model. Then the approximation is updated each iteration by comparing the residuals, which result from the new trial value of the endogenous variables with the residuals of the linear equation. The method is not significantly different from Newton, but it runs faster. We generate the innovations to the stochastic equations by drawing a set of random shocks from a standard normal distribution each period. To match the variance–covariance system, we scale these draws by multiplying the vector by its standard deviation because the covariance matrix is diagonal.

[14] The solution is described in the technical appendix Table 8

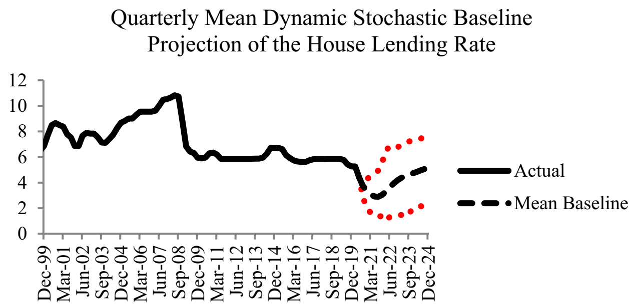

Fig. 7 Quarterly mean dynamic stochastic baseline projection of the house lending rate

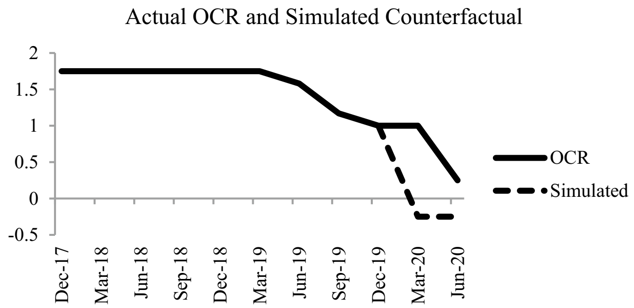

Fig. 8 Actual OCR and simulated counterfactual

Counterfactual projections of the lending rate under a negative OCR

The final step is to produce projections of the lending rate under a counterfactual scenario. We assume that the OCR was reduced in Mar 2020 to a negative 0.25 and it remained − 0.25 in Jun 2020.[15] We make no assumptions about the OCR after June 2020. Figure 8 displays the actual OCR and the negative OCR that we assumed for the counterfactual scenario. We re-estimate the VAR over the same sample from Mar 1999 to Jun 2020. The optimal number of lags is three. The residuals are serially uncorrelated.[16] Then the model is solved, and dynamic and stochastic projections for the period Sep 2020 to Dec 2024 are produced; the innovations were generated using 1000 Bootstraps.

Figure 9 plots the projections under this counterfactual negative OCR scenario and the standard error bands. The housing lending rate declines more under a negative OCR scenario relative to the baseline projections. Figure 10 plots the actual rate, the baseline projections, the projections under the counterfactual scenario and the deviations of the counterfactual projections from the baseline, which clearly

[15] The RBNZ announced that it could reduce the OCR to a negative rate in 2021 if more stimuli needed to deal with the downturn caused by COVID19.

[16] We do not report the statistics to save space, but they are available on request.

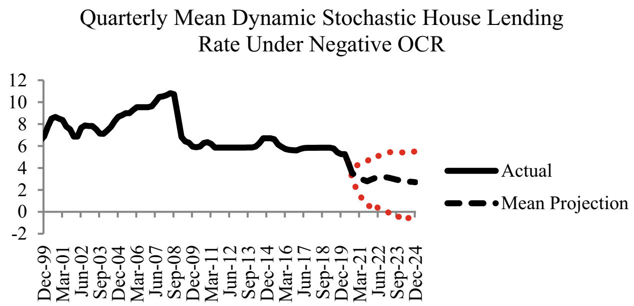

Fig. 9 Quarterly mean dynamic stochastic house lending rate under negative OCR

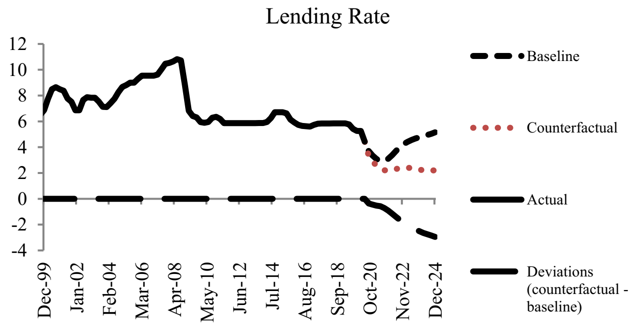

Fig. 10 Lending rate

shows that the lending rate falls significantly under the counterfactual scenario of a negative OCR.

Table 1 reports data of the actual housing lending rate, the baseline projections, the projections under the counterfactual scenario, and the deviations from the baseline. Under the counterfactual scenario of a negative OCR, the lending rate declines steadily from 3.35%, in Sep 2020, to 2.20%, in Dec 2024. On average over the projection horizon, the average of the house lending rate under the counterfactual scenario of a negative OCR is 2.39%. The average baseline projection of the lending rate is 4.15%. In addition, note that the projections of the lending rate under the counterfactual scenario of a negative OCR are significantly less volatile than the baseline projection. The standard deviations are 0.30 and 0.69 for counterfactual projections and the baseline projections, respectively. We examined the business lending rate and the average of the business lending rate and the housing lending rate with the real GDP output gap. The results are qualitatively similar.[17]

[17] We do not report the results to save space, but they are available on request.

Table 1 Housing lending rate projections

	Actual	Baseline	Counterfactual	Deviations
Jun-20	4.43			
Sep-20		3.71	3.35	− 0.36
Dec-20		3.47	2.91	− 0.56
Mar-21		3.31	2.56	− 0.75
Jun-21		3.20	2.35	− 0.85
Sep-21		3.22	2.21	− 1.00
Dec-21		3.36	2.19	− 1.17
Mar-22		3.61	2.23	− 1.37
Jun-22		3.89	2.31	− 1.58
Sep-22		4.14	2.38	− 1.77
Dec-22		4.34	2.40	− 1.93
Mar-23		4.48	2.41	− 2.07
Jun-23		4.58	2.37	− 2.21
Sep-23		4.67	2.30	− 2.37
Dec-23		4.75	2.26	− 2.49
Mar-24		4.84	2.21	− 2.63
Jun-24		4.95	2.20	− 2.75
Sep-24		5.05	2.19	− 2.86
Dec-24		5.16	2.20	− 2.96
Average		4.15	2.39	
STD		0.69	0.30	

The counterfactual is the projections under the assumption that the OCR was negative − 0.25 in Mar and June 2020

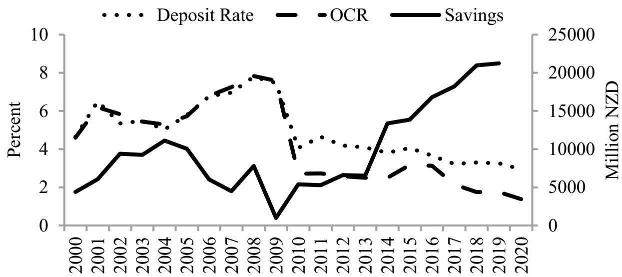

Fig. 11 The annual time series data

Estimating the dynamic of the deposit rate

Equation (18) and scatter plots (3) and (4) show that $\mathrm{cov}\left(r_{\mathrm{t}}^{\mathrm{d}}, r_{\mathrm{t}}^{\mathrm{ocr}}\right) > 0$, and $\mathrm{cov}\left(r_{\mathrm{t}}^{\mathrm{d}}, S_{\mathrm{t}}\right) < 0$. Figure 11 plots the annual time series of the deposit rate, aggregate national savings, and the OCR. We use annual data from 2000 to 2019 because the RBNZ reports annual savings only and the data are available to 2019. We use national savings because the savers include not only households, but also businesses,

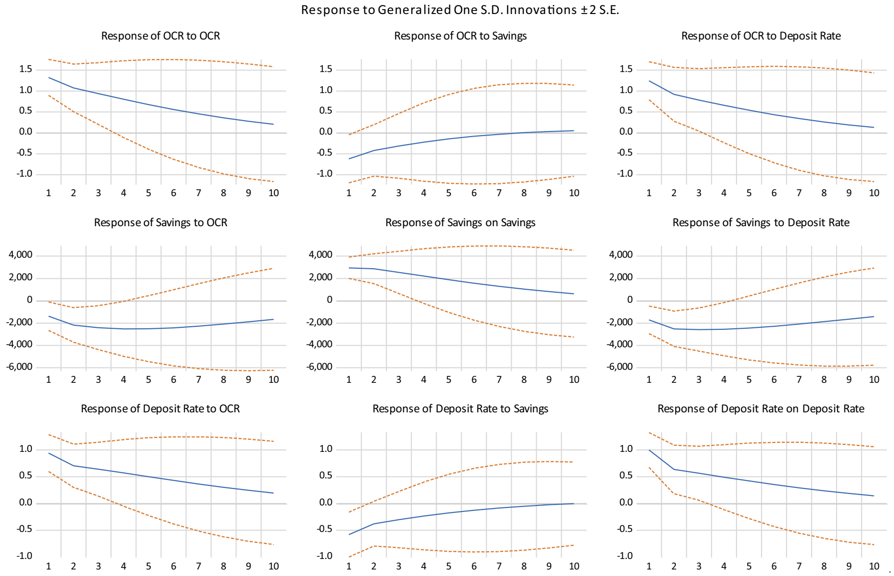

Fig. 12 Response to generalized one S.D. innovations ± 2 S.E

and the government; all have savings. Figure 11 shows that the correlations are consistent with the model.

We estimate a VAR for the OCR, aggregate savings, and the deposit rate using annual data from 2000 to 2019. The Information Criteria identifies three lags.[18] Figure 12 displays the generalized impulse response functions. The deposit rate responds positively to the OCR and negatively to aggregate savings as predicted by Eq. (18). Then, we solve the model and produce a dynamic stochastic baseline projection, where the innovations were generated using 1000 bootstraps exactly like what we did for the lending rate.

Counterfactual projections of the deposit rate under a negative OCR

We estimate the VAR under the counterfactual scenario using the same methods as before. The OCR is − 0.25 in 2019 and remained negative in 2020. The model is solved from 2021 to 2024 and the innovations were generated by 1000 bootstrapping. Table 2 reports the actual deposit rate, the mean dynamic stochastic baseline projection, and then the mean dynamic stochastic projections under the counterfactual scenario, followed by the deviations from the baseline. The projections of the

[18] The VAR satisfies the stability condition. The F statistics for Eqs. (1), (2) and (3) are 10.72619, 18.08870, and 8.171596. The LM test of the residuals has a P value of 0.5231. The null hypothesis of no serial correlation cannot be rejected. The residuals are multivariate normal in Eqs. (2) and (3), but not in Eq. (1) of the OCR.

Table 2 Deposit rate projections

	Actual	Baseline	Counterfactual	Deviations from baseline
2020	2.95	3.01	2.37	− 0.64
2021		3.19	2.11	− 1.09
2022		3.41	1.99	− 1.42
2023		3.58	1.86	− 1.72
2024		3.72	1.75	− 1.97
Average		3.38	2.02	
STD		0.29	0.24	

The counterfactual assumes the OCR to be − 0.25 in 2020

Table 3 The average lending and deposit projections over the period 2020–2024

Baseline projection		Counterfactual under negative OCR	
Lending rate	Deposit rate	Lending rate	Deposit rate
4.05	3.4	2.39	2.02

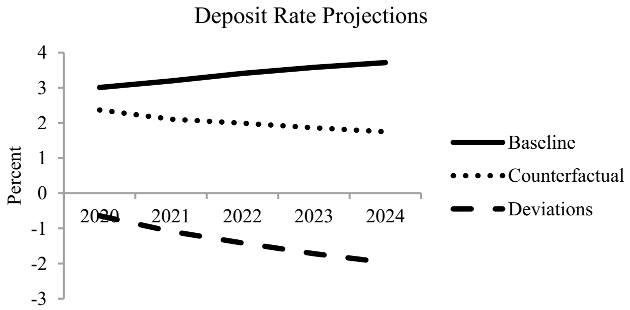

Fig. 13 Deposit rate projections

deposit rate under the counterfactual scenario declined significantly, and turned negative in 2023 and 2024.

Table 3 compares the average baseline projections of the lending and deposit rates, and the mean of the projection scenarios. Under the baseline projection, the lending rate (4.05%) is above the deposit rate (3.4%). Under the counterfactual scenario that the OCR is − 0.25, the averages of both the lending rate and the deposit rate over the projection's horizon fall to 2.39 and 2.02%, respectively. Figure 13 plots the deviations of the deposit rate projection under the counterfactual scenario from the baseline projection, which is a negative steady decline over time.

The results of the above analysis of the housing lending rate and the deposit rate under a negative OCR indicate that both rates would fall. Over the projection horizon from 2020 to 2024, the lending rate falls by about 1.65% and the deposit rate by about 1.38%. On average and over the period 2020 to 2024, the deposit rate is projected to

Table 4 Bank Profit.

Bank profit $(A - B + C) - D$[a]			
Total income $A - B + C$			Non-interest cost
Net interest income $A - B$			
A	*B*	*C*	*D*
Interest income	Interest cost	Non-interest income	Operating cost
Cash and deposits	Deposits	Derivatives	Fees and commissions
Debt securities	Debt securities	Trading	Impairment
Loans Floating mortgages Fixed mortgages Business loans Other loans Derivative interest	Borrowing Derivative interest	Fees and commissions Share of profit/loss of associates and joint ventures	Individual provisions for losses on loans Collective loan loss provisions Debt right offs Recoveries Other

[a]The cost also includes "impairment"

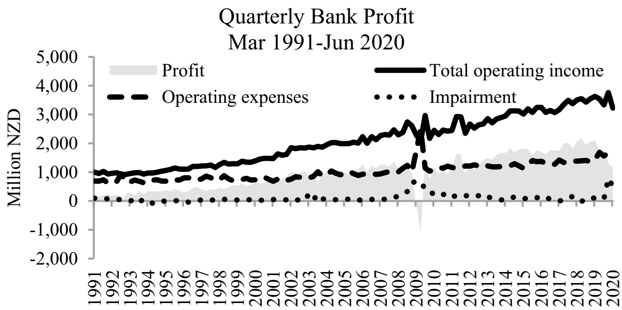

Fig. 14 Quarterly bank profit Mar 1991–Jun 2020

be lower than the lending rate by about 0.25%. However, it is unclear what would be the effect on bank profit because profit depends on interest and non-interest incomes and costs such as derivatives, trade, fees and commissions among more. Negative OCR is a monetary policy response to anticipated economic slowdown, which has adverse effects on equities, assets, derivatives, fees and commissions, etc. Next, we examine the bank profit data.

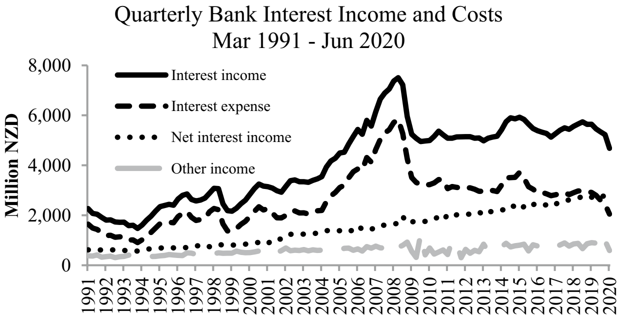

Fig. 15 Quarterly bank interest income and costs Mar 1991–Jun 2020

Profit, the global financial crisis and the following recession

The RBNZ reports quarterly time series data on bank income, expenses, and profit from June 1991. Table 4 describes the data. The OCR affects interest and non-interest incomes and costs differently. Figure 14 plots bank profit (before tax); it had a negative spike during the Great Recession that followed the Global Financial Crisis (GFC) in June–September 2009. Bank profit declined sharply even though bank income was positive in these two quarters; it was most clearly related to a significant spike in the operating cost, which increased significantly by 54% and 37% in June and in Sep quarters, respectively. During that recession, the output gap fell significantly, − 2% and − 1.7%. The RBNZ slashed the OCR. It remained, relatively, low until 2020. The OCR dropped from an average of 6.25% to 2.35% over the subsamples from 1999 to 2008, and 2009 to 2020 respectively, as shown in Fig. 5. The lending rate kept falling for more than two quarters before and after the recession; it fell by 1.8% and 0.37% in these two quarters. The deposit rate, however, fell significantly by 0.30% in 2009 and by 3.2% in 2010.

Bank profit is the sum of interest and non-interest incomes less interest and non-interest costs. The final effect of negative OCR on bank profit depends on the magnitudes of the various costs and incomes. During the 2009 recession, bank total cost increased (interest and non-interest costs) substantially while income (interest and non-interest income) remained unchanged, which resulted in a sharp decline in bank profit in those two quarters. However, despite this downward spike, the overall trend of bank profit from 1999 to 2020 has been positive. The RBNZ reduced the OCR from 1% to 0.25% in Mar 2020 in response to COVID-19; and expected to make the OCR negative in Mar 2021.

Figure 15 plots the total interest income, total interest cost (or expense), and the net interest income. Note that interest income and expenses grew significantly over time and peaked in Dec 2008, during the GFC, then fell sharply in March 2009. They are also highly correlated. After Dec 2008, interest income fluctuated slightly, but remained almost unchanged while interest expense declined a little and the difference between interest income and expense (the net interest income) increased over time.

Table 5 Average growth rates

	Interest income	Interest cost	Net interest income	Non interest income	Total operating income	Operating cost	Profit
2009	– 6.16	– 9.38	0.82	9.59	12.64	12.92	37.16
2020	– 11.07	– 17.77	– 5.50	– 50.57	– 15.42	– 5.60	– 13.72

The average growth rate from Mar 2009 to Dec 20,029 and the average growth rate of Mar and Jun 2020

Table 5 compares the banking system outcomes for the period Mar 2009–Dec 2009, i.e., the recession that followed the GFC with Mar 2020–June 2020, i.e., the lockdown response to COVID-19. We show that the negative impact of the lockdown on bank profit has been very substantial compared with the effects of the recession in 2009. We report the average growth rates over the period Mar 2009 to Dec 2009 and over the first two quarters in 2020, March and June. The average growth rate of interest income fell sharply in the past two quarters compared to 2009, – 11% compared with -6%. The interest cost average growth rate fell more during the pandemic compared with 2009; – 17.7% compared with – 9.4%. Net interest-income growth rate declined significantly. The average growth rate of non-interest income is – 50.6% in 2020; it was + 9.6% in 2009. These are clearly significant differences and the decline in the growth rate reflects the lockdown of the economy. Essentially, total operating bank income growth rate is – 15.4% in 2020 compared with + 12.6% in 2009. Bank profit before tax growth rate in 2020 is – 13.7%; it was + 37% in 2009. Bank profit went down significantly. Would bank profit recover if the OCR were negative?

Table 6 reports descriptive statistics of bank profit components, in-sample, and the out-of-sample projections. In sample, we report statistics over 2 sub-samples, 1999–2008 and 2009–2020. The components of bank profit are (1) interest cost, (2) non-interest cost, (3) interest income, (4) non-interest income, (5) net interest income (income less cost), (6) net non-interest income (non-interest income less non-interest cost), impairment, and (7) profit (income less cost less impairment). Each column has two statistics, the average over the sample and the correlation of each of the profit components with the OCR. Note that banks were more profitable during the period from 2009 to 2020, when the OCR was relatively lower than the period from 1999 to 2008 when the OCR was high.

As the OCR declined significantly over time, bank profit increased. Lower OCR implied lower interest cost, and more lending (volume)—credit expansion as in Bernanke-Blinder (1988). More lending generated more income to banks; net interest income increased as a result. At the same time, lower OCR also led to higher asset prices. Non-interest income increased too but so did non-interest cost; however, the increase was not sufficient to offset the rise in income. Eventually profit increased from $920 million over the period 1999–2008 to 1463 million over the period 2009 to 2020. The correlation coefficient of each of the profit components and OCR also changed over the two sub-samples; they become smaller. Four of these profit components' correlations with OCR changed signs over the two sub-samples.

The last three columns of Table 6 report the descriptive statistics of the baseline projections and those of the projections under a counterfactual scenario of a negative

Table 6 Descriptive statistics of bank profit components in three different periods

	Average 99–08	Correlation with OCR	Average 09–20	Correlation with OCR	Average baseline 20–24	Average counterfactual 20–24	Deviations from baseline
1. Interest Income	4220	0.87	5341	0.16	4533	5317	784
2. Non-interest income	619	0.63	715	− 0.18	839	857	18
3. Interest Cost	2964	0.88	3087	0.75	2144	2589	445
4. Non-interest cost	880	0.60	1320	− 0.45	1513	1586	73
5. Impairment	74	0.11	185	− 0.16	184	182	− 2
6. Profit	920	0.73	1463	− 0.19	1530	1816	286

1. Profit is 4 + 5 – 2 – 3 – 8; net interest income is 4–2; net non-interest income is 5–3

2. The data are quarterly. The samples correspond to Mar 1999 to Dec 2008; Mar 2009 to Jun 2020; and Sep 2020 to Dec 2024

3. Averages are in millions of NZ dollars

4. Counterfactual is a scenario, whereby the OCR is − 0.25 in Dec 2019 and Jun 2020

0.25 OCR. We produce the projections using these same methodology used earlier by fitting a VAR with six variables, OCR, and the components of profit, which are the interest income, non-interest income, interest cost, non-interest cost, and impairment. The sample is Mar 1999 to Jun 2020. We do not report the details but they are available on request.[19] The baseline projections are from Sep 2020 to Dec 2024. Then we re-estimate the VAR under a counterfactual scenario, whereby the OCR was negative 0.25 in Mar 2020 and June 2020. Then we made dynamic stochastic projections from Sep 2020 to Dec 2024 under this counterfactual scenario.

The baseline projection of bank profit shows declines then increases, but on average over the projection horizon, profit increases by 4.6% relative to actual profit (Mar 2009 to Jun 2020), from $1,463 million to $1,530. The projection under the counterfactual scenario of a negative 0.25 OCR increases to $1,816 million, which is 24% higher than actual on average. However, on average over the projection horizon from Sep 2020 to Dec 2024, the deviations of bank profit projections under the counterfactual scenario of a negative OCR of 0.25 from the baseline are + $286 million, a 19% increase. Most of the projected increase in bank profit under the counterfactual scenario of negative OCR comes from the projected increase in bank interest income; it increases by $784 million. Non-interest income projections also increase by $18 million. Costs also increase under the counterfactual scenario, but by less than the incomes. The interest cost increases by $445 million and the non-interest cost increases by $73 million. Impairments decline by $2 million. Therefore, total income projected to be $802 million and total costs $516 million. Figure 16 plots the

[19] The VAR has two lags according to the same information criteria we used earlier. The residuals are white noise and serially uncorrelated as indicated by the LM test. The *P*-values for lags 1, 2, and 3 were 0.1146, 0.4724, and 0.8103, respectively. The *F* tests for all equations were significantly different from zero.

actual profit, the baseline profit projections, and the projections under the negative OCR scenario.

Bank profit is projected to increase under a negative OCR. However, there is a trade- off for this increase in bank profit. The increase in profit is associated with more uncertainty. For the period from 2009 to 2020, where the average OCR was relatively low, Bank profit, non-interest income, non-interest income, and impairment became more uncertain.[20] For the projection period 2020 to 2024, interest income, non-interest income, and interest costs projections under the counterfactual scenario of a negative OCR are more volatile compared with the baseline projections.[21] So, while banks may benefit from higher income from interest and non-interest operations their incomes become more uncertain under a negative OCR.

Conclusions

We analyzed the lending and deposit rates and bank profit in New Zealand for the period from Mar 1999 to Jun 2020. An equilibrium lending and deposit rate was derived from a constrained profit maximization problem. The actual data show and the model predicts that the official Reserve Bank interest rate, the OCR, which is the rate paid nightly to the Settlement Cash Accounts at the Reserve Bank, is correlated positively with the lending, and deposit rates. We estimated an unrestricted VAR, produced baseline projections, and projections under a counterfactual scenario whereby the OCR is reduced to a negative 0.25 for two periods. The projections under the counterfactual scenario of both, the lending rate, and the deposit rate, over the period Sep 2020 to Dec 2024, declined on average. However, on average, the projected lending rate remained higher than the deposit rate.

Bank profit has five components; the interest and non-interest incomes, the interest and non-interest costs, and impairment residuals. There is a break in the OCR data. The average OCR from Mar 1999 to Dec 2008 was 6.25%. The OCR was reduced during the recession in June and September 2009 that followed the Global Financial Crisis. The average OCR for the period Mar 2009 to June 2020 is 2.24%.

[20] We test the hypothesis that variance for the sub-sample 2009–2020 is equal to the variance for the sub-sample 1999–2008 using the statistic $F_{40,45} = S_1^2 / S_2^2$, where S_1^2 is the sample variance over the period 2009–2020, where the OCR was declining, and S_2^2 is the sample variance over the period 1999–2008 where the OCR was relatively higher. These ratios (P-value) are interest income 0.03615 (1), non-interest income 5.07 (0.0000), interest cost 0.07 (1), non-interest cost 3.6 (0.0000), impairment 6.8 (0.0000), and profit 6.0 (0.0000). The hypothesis that the variances are equal across the two samples is rejected except in the cases of interest income and interest cost.

[21] We test the hypothesis that variance under the counterfactual scenario is equal to the variance under the baseline, against the alternative that it is larger by computing the statistic $F = S_1^2 / S_2^2$, where S_1^2 is the sample variance of each component under the counterfactual scenario of negative OCR, and S_2^2 is the sample variance under baseline. The F stats (P values) are 3.0 (0.01118), 2.8 (0.0174), 2.2 (0.0523), 0.65 (0.8101), 0.50 (0.9193), and 1.13 (0.3946) for interest income, non-interest income, interest cost, non-interest cost, impairment, and profit, respectively. There is evidence of increased volatility under the counterfactual scenario of negative OCR, especially in interest income, non-interest income, and interest cost.

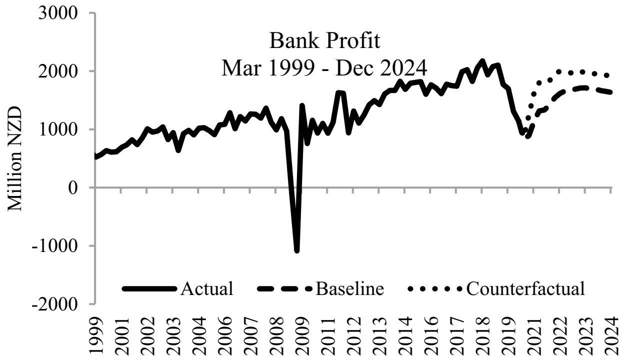

Fig. 16 Bank profit Mar 1999–Dec 2024

The components of bank profit also changed significantly after 2008, and the correlation with the OCR became relatively lower and changed signs. Bank profit increased steadily over the period of low OCR from 2009 to 2020. We also found that the OCR over the period from 2009 to 2020 to be less volatile than the period of high interest rate from 1999 to 2008, however, non-interest income, impairment, and bank profit were more volatile.

On average, a counterfactual scenario of negative 0.25 OCR predicts an increase in bank profit by \$286 million, about 19% relative to baseline projections, because interest and non-interest incomes increase by \$802 million and interest and non-interest costs and impairment increase by \$516 million.

The growth rates of bank interest and non-interest incomes, costs, and profit during the period Mar to Jun 2020 are in a stark contrast to the growth rates during the period Mar to Dec 2009 after the GFC. Actual bank profit's growth rate was about 37.2% in 2009; so far in 2020, bank profit's growth rate is − 13.7%. Most of the decline in bank profit is due to − 50.6% growth rate of non-interest income. Non-interest income is investments, derivatives, trading, fees, and commissions, which have declined significantly due to the shutdown of the economy.

New Zealand Banks benefit from looser monetary policy and benefit more from negative OCR because lending activity increases significantly with the lending rate higher than deposit rate, and net interest income increases. Non-interest income component of bank profit, which is the income from derivatives, trading, fees, commissions etc. also predicted to increase under negative OCR scenario, however, becomes more uncertain compared with the baseline projection. Therefore, there is a trade-off. Instability of bank income increases in the long run as OCR becomes more negative.

Appendix

See Tables 7, 8.

Table 7 Data appendix

Variables	Definition	Source	Table	Frequency	
Housing lending rate	Floating first mortgage new customer housing rate	RBNZ	hb3	Quarterly	Average of monthly data
Business lending rate	SME new overdraft rate	RBNZ	hb3		
Average lending rate	Average of the above two rates				
OCR		RBNZ	hb2	Quarterly	Average of monthly data
Deposit rate	The 6-month term deposit	RBNZ	hb3	Quarterly	
Real disposable income	Seasonally adjusted	Stats NZ		Quarterly	
Bank profit data https://www.rbnz.govt.nz/		RBNZ	hs21	Quarterly	

Table 8 Technical appendix

We solve the VAR using Broyden's method, which is a modified Newton's method. It involves the use of an approximation, rather than the true Jacobian when linearizing the model. We update the approximation at every iteration of the 5000 iterations we used by comparing the residuals from the new trial values of the endogenous variables with the residuals predicted by the linear model based on the current Jacobian approximation. This method is faster than Newton. See, Dennis and Schnabel (1983). We use analytic derivatives. The starting values are actual values. The model is solved both directions. We stop solving when we hit a missing value

In a stochastic simulation, we solve the equations of the model such that the residuals match to randomly drawn errors, and the coefficients and exogenous variables of the model change randomly. The solution generates a distribution of outcomes for the endogenous variables in every period. We approximate the distribution by solving the model many times using different draws (1000) or the random components in the model then calculating statistics over all the different outcomes

Only values of the endogenous variables from before the solution sample are used in the dynamic solution of the projections. Lagged endogenous variables are calculated using the solutions calculated in previous periods, i.e., not from actual historical values. A series for the mean is calculated. We consider one thousand repetitions reasonable to capture the true values; however, some random variation may be present between adjacent observations

The 95% confidence intervals are computed using Jain and Chlamtac (1985) updating algorithm. This updating algorithm provides a reasonable estimate of the tails of the underlying distribution as long as the number of repetitions is not too small

We use bootstrapped innovations; however, bootstrapped innovations drawn from a small sample provides a rough approximation to the true underlying distribution of the innovations. For the diagonal covariance matrix, the diagonal elements are set to zero. We do not scale the variances

Acknowledgements I benefited from discussions with David Triple, and I thank Francisco Nadal De Simone, Michael Reddell, Safaa Haddad, and Dimitris Margaritis for valuable comments. I also thank anonymous referees for their detailed comments and suggestions.

References

Arseneau D (2017) How would US Banks fare in a negative interest rate environment? Federal Reserve Board, Paper No. 30

Bernanke B, Blinder A (1988) Credit, money, and aggregate demand. Am Econ Rev Papers Proc 78(2):435–439

Bernanke B, Blinder A (1992) The federal fund rate and the and the channels of monetary transmission. Am Econ Rev 82(4):901–921

Bernanke BS, Mihov I (1998) Measuring monetary policy. Quart J Econ 113(3):869–902

Boungou W (2019) Negative interest rate, bank profitability, and risk taking. Sciences Po OFCE Working Paper No. 10

Dennis JE, Robert B, Schnabel (1983) Numerical methods for unconstrained optimization and nonlinear equations, society for industrial and applied mathematics

Gerali A, Neri S, Sessa L, Signoretti FM (2010) Credit and banking in a DSGE model of the euro Area. J Money Credit Banking 42(1):107–141

Goodfriend C (2000) Overcoming the zero bound on interest rate policy. J Money Credit Banking 1007–1035

Isakin M, PV Ngo (2020) Variance decomposition analysis for nonlinear economic models. Oxford Bull Econ Statist (forthcoming)

Jain R, Chlamtac I (1985) The P2 algorithm for dynamic calculation of quantiles and histograms without storing observations. Commun ACM 28(10):1076–1085

Jimenez G, Ongena S, Peydro J-L, Saurina J (2012) Credit supply and monetary policy: identifying the bank balance sheet channel with loan applications. Am Econ Rev 102(5):2301–2326

Jobst A, H Lin (2016) Negative interest rate policy (NIRP): implications for monetary transmission and bank profitability in the euro area, IMF Working Paper No. WP/16/172

Koop G, Pesaran MH, Potter SM (1996) Impulse response analysis in nonlinear multivariate models. J Econometr 74(119):147

Madaschi and Nuevo (2017) The profitability of banks in the context of negative monetary policy rates: the cases of Sweden and Denmark. European Central Bank Occasional Paper Series No. 195

Pesaran MH, Yongcheol S (1998) Impulse response analysis in linear multivariate models. Econ Lett 58:17–29

Razzak WA, Moosa IA (2018) Monetary policy, corporate profit and house prices. Appl Econ 50(28):3106–3114. https://doi.org/10.1080/00036846.2017.1418073