

MARKET POWER IN BANKING

An investigation into cost and profit efficiency, economies of scale, market concentration, and market power for New Zealand banks.

A STUDY OF
NEW ZEALAND
BANKS

MARKET POWER IN BANKING: A STUDY OF NEW ZEALAND BANKS

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Objectives: The main objective of the study is to construct measures of bank efficiency, market concentration, scale economies and market power for New Zealand banks.

Findings: We obtain consistent findings across different measures of market structure indicating the presence of moderate market power in the industry. We find New Zealand banks achieve overall relatively high levels of cost efficiency while profit efficiency is also high albeit lower than cost efficiency. We also find that most banks operate under increasing returns to scale with cost elasticities of scale (an inverse measure of economies of scale) for loans being less than one. Time-series analysis indicates that banks generally do not pass on the full extent of OCR changes with the short-run response of mortgage rates to OCR changes being larger for OCR increases than decreases, a finding consistent with the proverbial “rockets up, feathers down”.

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1. Introduction

The high concentration of the New Zealand banking industry coupled with sustained high profitability levels for modest risk has renewed interest about the level competition in the industry. Recent increases in interest rates following a tightening of monetary conditions by central banks to combat rising inflationary pressures, has also renewed interest globally about the pass-through of policy rates to retail interest rates. At the centre of the debate is the degree of market power in the market for loans recognising that lending spreads globally and in New Zealand have widened considerably. For example, mortgage spreads are now well above those present during the early stages of the COVID-19 pandemic and are approaching levels last seen during the 2008 financial crisis. Similarly, small business loans have been approaching double digit levels in many OECD countries for the first time in decades raising concerns about the future state of the global economy. Net interest margins in New Zealand are up more than 25% in the last three years to September 2023.

Whereas antitrust authorities generally infer the competitiveness of banking markets from measures of market concentration (e.g., the Herfindahl-Hirschman index - HHI), the empirical banking literature has long recognised that concentration might not accurately reflect the degree of competition in banking markets (e.g., [Berger, Demirgüç-Kunt and Levine, 2004](#); [Koutsomanoli-Philippaki, Margaritis and Staikouras, 2009a,b](#); [Wheelock and Wilson, 2019](#), among many others). Concentration measures focus on how markets are proportioned between firms, which may be related to firms' pricing power, but they do not tell us whether market power is the result of cost efficiencies, economies of scale or uncompetitive behaviour.¹ Firms in concentrated markets might have little pricing power, especially if the barriers to entry are not too tight ([Wheelock and Wilson, 2019](#)). In addition, market concentration measures are not firm-specific which may result in the loss of valuable firm-specific information noting that in modern antitrust considerations the focus is more about the exercise of market power rather than the absolute size of the firm.

¹ In fact, it can be shown that in a Cournot model of competition with linear marginal costs, the HHI is equal to the sum of bank profit margins weighted by the banks output market shares times the price elasticity of demand. In this sense, a high HHI (showing greater market concentration) would be expected to be associated with higher prices recognising that firms that charge relatively high prices in concentrated markets are likely to be able to maintain them or at least more likely to do so than in more competitive markets.

Accordingly, most modern studies use the Lerner index (Lerner, 1934), measured as the difference between a firm's output price and its marginal cost at the profit-maximising rate of output, or the Panzar-Rosse H-statistic (Rosse and Panzar, 1977; Panzar and Rosse, 1982, 1987), measured as the sum of the revenue elasticities with respect to input prices, to estimate the market power of individual banks. By focussing on the social loss from monopoly as the divergence between price and marginal cost, rather than the commonly accepted relationship between price and average cost, Lerner redirected attention from the monopolist's profits to the allocative inefficiency created by the pursuit of those profits (Elzinga and Mills, 2011). While in essence complimentary, the two measures capture different aspects of market power, the Lerner index focusses on the average level of the price cost spread whereas the Panzar-Rosse index looks at the changes in that spread (Bolt and Humphrey, 2015).

Our approach allows us to study the relationship between market structure and firm efficiency by linking the Lerner index to a measure of bank cost efficiency. This is important recognising the potential negative relation between firm efficiency and market power that has received much attention in the literature as well as in policy circles. For example, market structure and efficiency considerations have underpinned regulatory changes to enhance competition in many industries of both industrialised and developing economies. Some important caveats are in place. First, measures of the Lerner index for outputs in banking assume that the market for deposits is competitive so that the cost function can be expressed as a function of bank outputs and cost minimising input prices. Second, risk is an important determinant of performance in banking. We address these caveats by incorporating measures of bank risk in our model specifications as well as by controlling for bank-specific characteristics.

We also provide measures of bank efficiency by estimating a profitability function. Profit functions are assumed to be functions of input and output prices, but these theoretical specifications are correct for prices prevailing in competitive markets. Instead, we estimate an alternative profit function in which profit is a function of output levels and input prices which in turn provides a means for controlling for the presence of imperfect competition and hence pricing power in bank output markets (see Berger and Mester, 1997). The standard practice in the literature is to estimate a translog profit function but as Kumbhakar (2006) has noted using (log) profits as a dependent variable is not consistent with the standard translog specifications of cost and (alternative) revenue functions. Instead, we use (log) revenue over cost (profit margin) as the dependent variable.

Market power may result in higher costs (rather than higher profits) due to inefficiencies arising from the reduction of competitive pressures, as the management is under less pressure to minimise costs - the so-called “quiet life effect” (Hicks, 1935; Berger and Hannan, 1998). In contrast, higher bank competition can erode market power, decrease profit margins, and result in reduced franchise value, encouraging banks to take on more risk to increase returns (Keeley, 1990; Berger et al., 2009).

Researchers have found evidence of considerable inefficiency in banking, in relation to measures of cost, profit, and revenue inefficiency (e.g., Berger and Humphrey, 1991; Wilson, 2021), and in terms of scale (e.g., Wheelock and Wilson, 2012, 2018; Hughes and Mester, 2013). Any inefficiency in the use of inputs or failure to maximise profits will bias estimates of market power derived from the Lerner index. Koetter, Kolari and Spierdijk (2012), for example, find that adjusting for cost and profit inefficiencies increases Lerner index estimates for U.S. banks by approximately 30 percent. Similarly, Spierdijk and Zaourasa (2018) note that in the presence of economies of scale, Lerner index values greater than zero can reflect the infeasibility of marginal-cost pricing rather than market power. Their estimates of a “scale-corrected” Lerner index for U.S. banks are significantly higher than uncorrected estimates over a majority of their sample period (2000–2014).

By encompassing a complete characterisation of technology in the form of a distance function in the quantity space and its value dual, the cost function, our framework readily models heterogeneous bank behaviour with respect to forgoing possible rents in exchange for inefficiencies as required by the quiet life hypothesis (see also Koetter, Kolari and Spierdijk, 2012). We test the quiet life hypothesis by empirically analysing the relationship between bank efficiency and market power controlling for bank-specific characteristics and macroeconomic variables. In doing so, we also provide further insights at the relationships between efficiency, market power and several indicators of bank performance.

The report is organised as follows. We present the main findings and discussion in the main part of the report with more technical material deferred to appendices. By way of motivating a study on market power, we first present aggregate time-series results on the pass-through from policy interest rates to retail rates under asymmetry. We then present results for bank cost and profit efficiency, cost elasticity of scale, measures of market power, followed by an empirical

analysis of the relationship between bank efficiency and market power controlling for bank-specific and macro variables.

2. The Pass-Through of the OCR

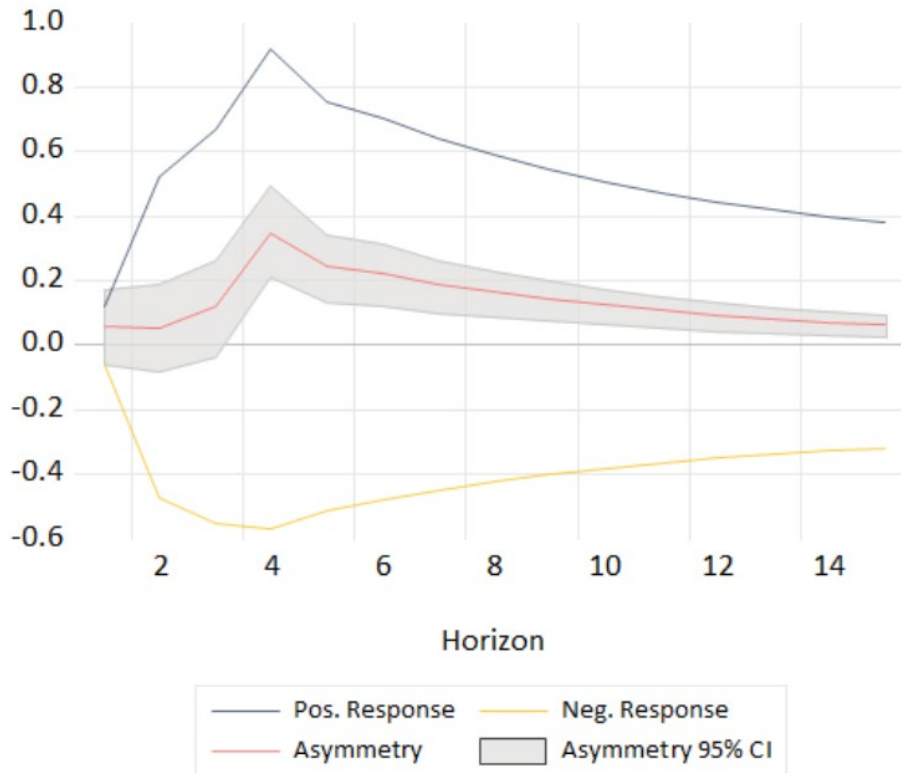
March 1999 marked a major shift in the monetary control mechanism in New Zealand, a change from quantity targets (settlement cash balances) towards price based monetary policy settings. At the time it was envisaged that under a price regime the role of interest rates in the transmission mechanism will become much more transparent, hence we would expect that there will be a closer relationship between the OCR and short-term interest rates (see [Liu, Margaritis and Tourani-Rad, 2008](#)). By way of motivating a study into market power and firm efficiency, we start with a time series analysis at the industry level asking the basic question of whether there is an asymmetry in the way mortgage interest rates (R_{HH}) change in response to changes in the official cash rate (OCR). The findings have implications for both the level of competition in the market for loans and the transmission mechanism of monetary policy.

We estimate a nonlinear dynamic autoregressive distributed lag (NARDL) model of retail (floating mortgage) interest rates in which short-run and long-run nonlinearities are modeled as positive and negative partial sum decompositions of the explanatory variables representing measures of the cost of funds, namely the OCR and the 6-m deposit rate controlling for the spread between the 10y bond rate and 90d bill rate. The model is estimated during the OCR regime period starting in April 1999. The estimation window is 1999M04-2024M11. The main finding is that banks tend to respond faster to increases in the OCR and that this asymmetry holds for both the short- and the long-run albeit as to be expected the long-run effect fades after a few months. **Figure 1** shows the banks' floating mortgage rate cumulative response to one-time change in the OCR.

Since we assume the effect of the OCR is asymmetric in both the long-run and short-run, we expect the dynamic multiplier curves to differ in both the long-run and short-run. Our empirical analysis indicates an asymmetry in the short-run but not the long-run. This relationship is seen in the fact that the absolute difference between these paths (the dotted line within the shaded Confidence Interval - CI) gradually approaches zero indicating that the asymmetry is statistically significant in the short-run. The remaining lines display the cumulative dynamic multipliers (CDMs) for the positive and negative changes starting off at different values

indicative of the contemporaneous asymmetry in response (stronger for increases than decreases in the OCR). **Figure 1** shows that a 1 percentage point increase in the OCR produces a 0.9 percentage point increase in the mortgage rate after four months, whereas a 1 percentage point decrease in the OCR yields a 0.57 percentage point decrease in the mortgage rate after four months. See **Appendix 3** for more details.

Figure 1: Cumulative Dynamic multiplier: OCR on R_HH

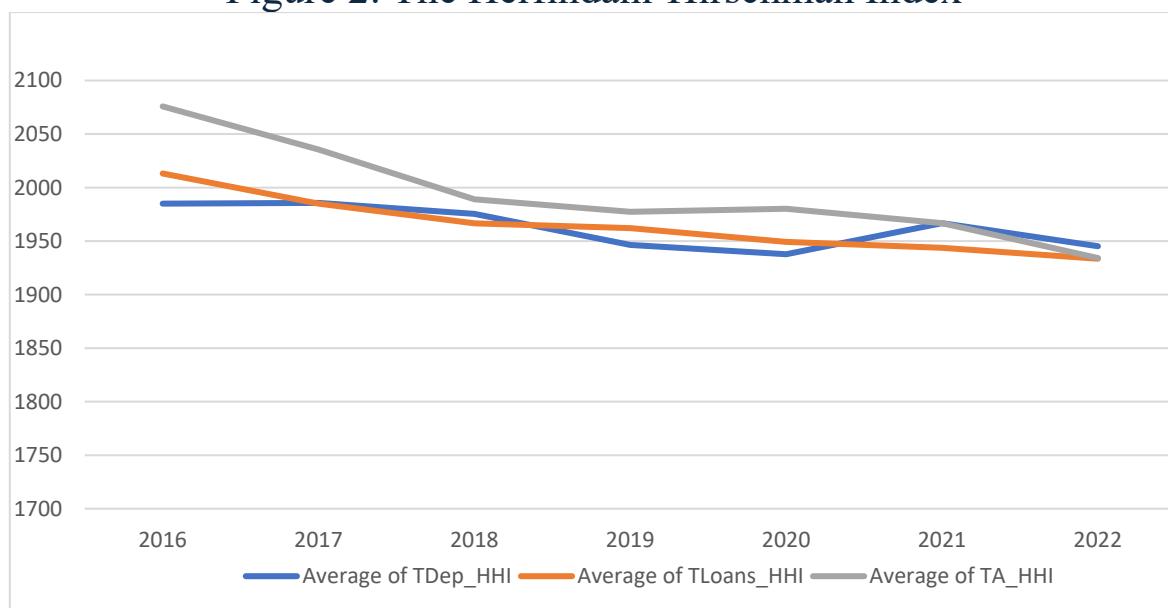


3. The Herfindahl-Hirschman Index

The Herfindahl-Hirschman Index (HHI) is generally a preferred measure of industry concentration by regulators than the more readily interpretable C4 or C5 concentration indices showing the percentage of market share held by the top four or five firms, respectively, in an industry. The HHI is calculated by taking the square of the share of each firm in the market and summing all squares not just the first four or five shares. In this sense, HHI provides a more comprehensive measure of industry concentration, especially in situations where there will be more significant competition beyond the first few firms. The higher the index the higher the level of concentration and potentially the level of market power. An index value of 1,500 to 2,500 indicates modest concentration with values of more than 2,500 reflecting high market

concentration. For example, for a single monopoly firm in the market with a 100% share the index value will be 10,000 whereas in a perfectly competitive market with thousands of small firms with market shares close to zero the index value will be close to zero. Clearly, the C4 and C5 indices will demonstrate very high concentration in our banking industry, in contrast to the moderate level indicated by HHI.² Since our interest is in market structure, the HHI, which accounts for the distribution of market shares across all banks, is our preferred measure. **Figure 2** displays the index for total deposits, total loans, and total assets indicating in all cases moderate concentration in the New Zealand banking industry.

Figure 2: The Herfindahl-Hirschman Index



4. Cost Efficiency

Conventional accounting cost efficiency measures typically compare actual costs incurred by banks to some benchmark or standard, such as industry averages or historical performance. Common metrics include cost-to-income ratio or operating expenses as a percentage of total assets. While these measures are straightforward and easy to compute, they offer a simple albeit partial way to assess cost efficiency and may not fully capture the underlying cost efficiency of banks, as they do not account for differences in bank size, market conditions, or technology. Frontier estimation methods, such as Stochastic Frontier Analysis (SFA), are generally used in

² For example, as reported by the RBNZ, the four large Australian-owned banks (ANZ, ASB, BNZ, Westpac) are responsible for about 85% of bank lending.

literature to estimate production functions in the quantity space or their dual value functions, such as the cost, revenue, and profit functions. As such they provide more comprehensive measures of bank performance, with the extra advantage that the underlying model specifications are rooted in economic theory.

We specify a standard stochastic cost function model in which total cost is a function of bank outputs and input prices. More specifically, we adopt a flexible functional form, namely the translog to model empirically the cost function. We measure cost efficiency as the distance between the bank's actual cost and the cost frontier representing optimal cost. Hence, cost efficiency measures how effectively banks minimise costs given their level of outputs and input prices. SFA is then used to decompose observed costs into two components: the optimal level of cost efficiency shown by a point on the cost frontier and a composite error representing deviations from the frontier due to inefficiency and measurement errors.

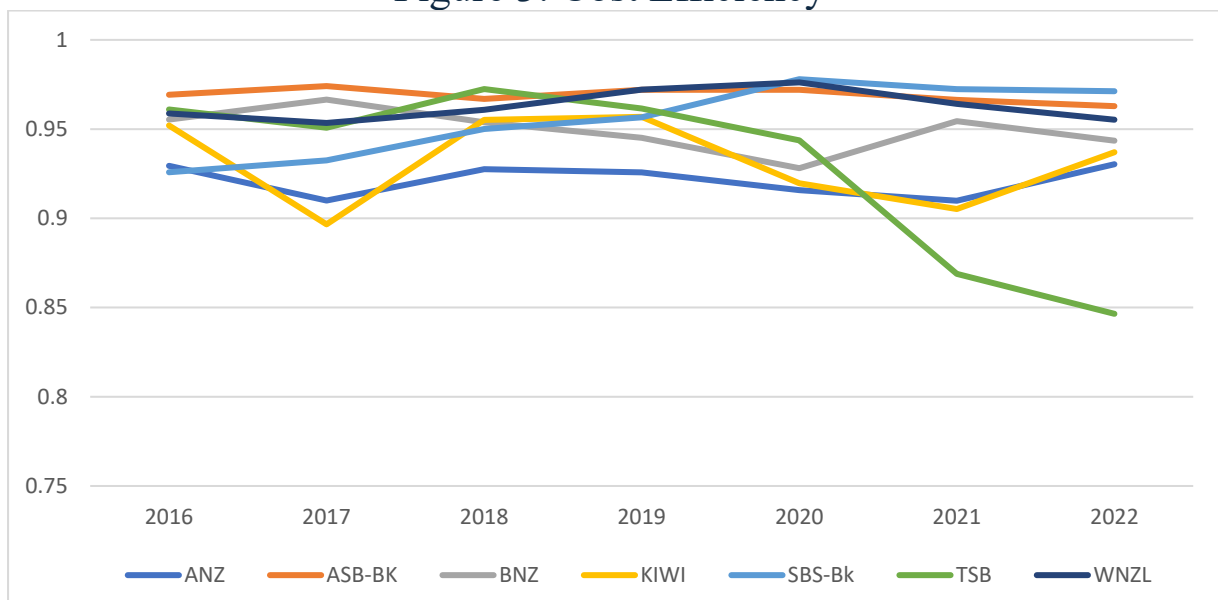
We use the standard intermediation approach to model the bank's cost function, with total loans, total debt securities, and non-interest income as bank outputs, and three input prices, namely the prices for labour, premises and fixed assets, customer deposits and other borrowed funds. We include (log) total equity as a quasi-fixed input to control in part for differences in risk across banks (Berger and Mester, 2003) and a time variable to control for changes in regulation, technology, and the pandemic crisis. We also include bank size measured as (log) total assets, the equity to assets ratio, and ratio of interest income to total income as control variables in the specification of the one-sided error term capturing cost inefficiency (see Appendix 4A for more details). Cost efficiency is calculated using the Jondrow, Lovell, Materov and Schmidt (1982) estimator to separate empirically the composite error term into the one-sided error term measuring inefficiency and the two-sided error term representing the usual statistical noise assumed in regression analysis.

Overall, we find New Zealand banks operate with relatively high-cost efficiency, generally in the 80-90% mark. Figure 3 presents the cost efficiency results for the four Australian-owned banks (ANZ, ASB, BNZ, Westpac – WNZL), Kiwibank, SBS, and TSB. Perhaps the most notable finding is that ANZ's cost efficiency tracks below its main rivals. Also noteworthy are the cost efficiencies of Kiwibank and TSB which drop off after 2019. To take a closer look at their underlying performance, we present in Figures 4a and 4b efficiency ratios calculated as total operating expenses over total income for select groups of banks. A lower efficiency ratio indicates that a bank is operating more efficiently because it is using a smaller portion of its

revenue to cover its operating expenses. While such metrics are extensively used by practitioners, they should be interpreted with caution as they depend on various underlying factors. For example, factors such as bank size or the bank’s business model are captured by our cost efficiency measure but not by the efficiency ratio. **Figure 4a** shows that TSB’s efficiency ratio increases after 2019 indicating the bank is using a larger proportion of its revenue on operating expenses. While Kiwibank’s efficiency ratio remains relatively stable, it is significantly above the efficiency ratios of its main competitors as shown more clearly in **Figure 4b**.

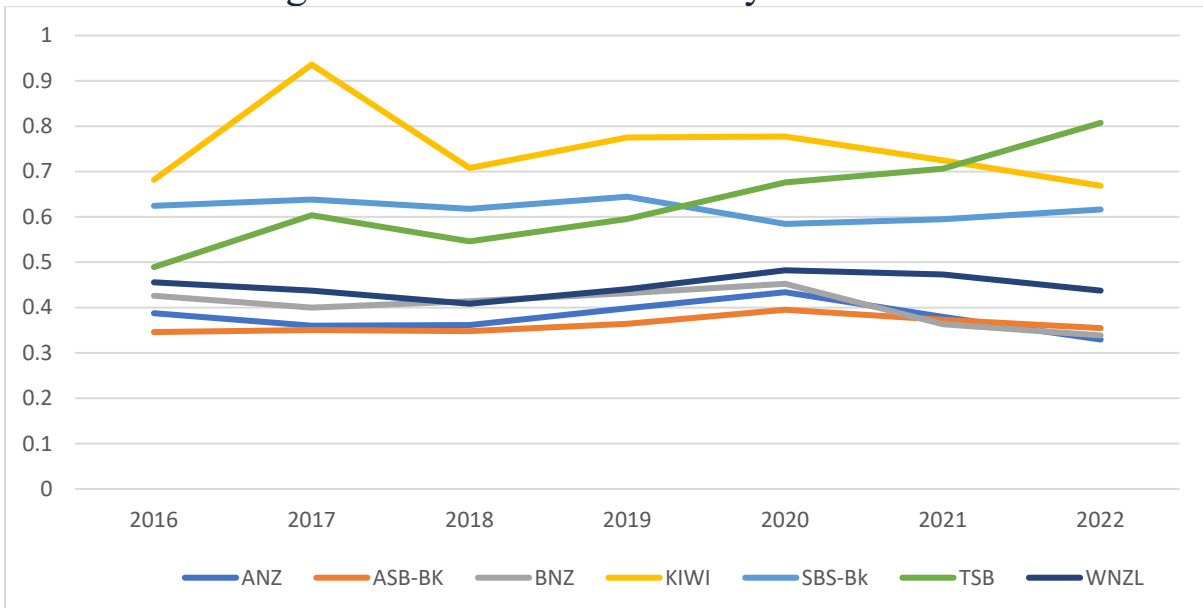
Since cost efficiency captures both (1) technical efficiency, namely the bank’s ability to produce more output given inputs or to produce a given output with minimum resource use; and (2) allocative efficiency, namely using an optimal input mix for given input prices to produce a given level of output, further analysis may provide more insights about the sources of underlying inefficiencies. We address this question further in Sections 5 and 9 below. Two further remarks are in order. First, the cost efficiency findings remain robust when we exclude from our sample banks with mainly a wholesale focus in the market. Second, our findings are consistent with much evidence in the empirical literature reporting mixed results about the relationship between cost efficiency and bank size.

Figure 3: Cost Efficiency



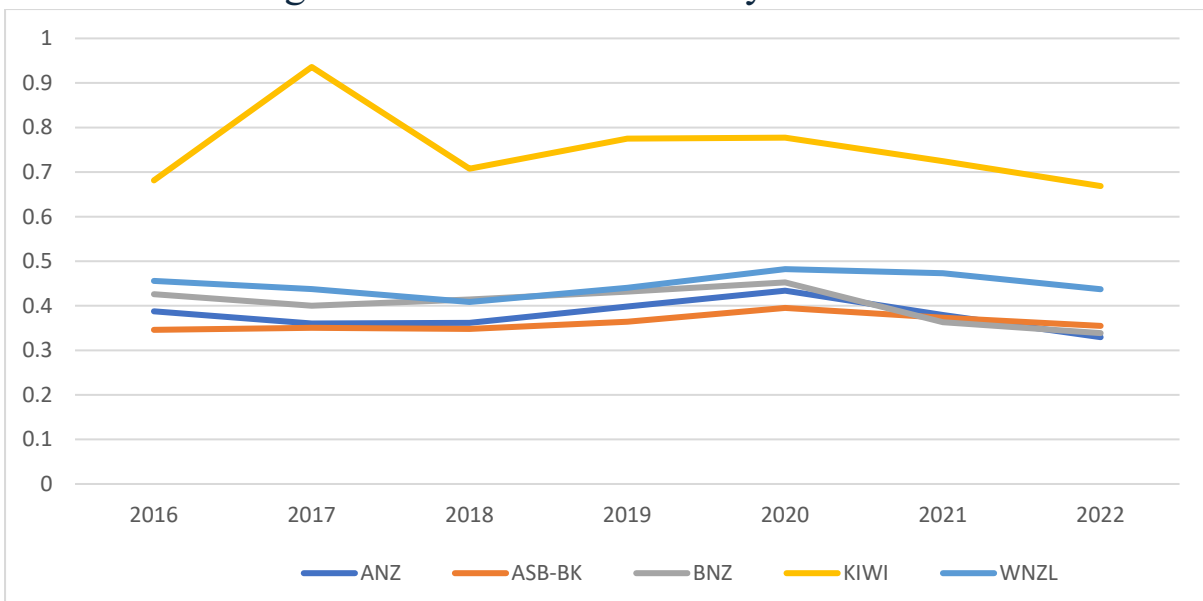
Note: Cost efficiency is estimated using the translog functional form (see **Appendix 4A**) in which (log) cost is a function of (log) output quantities and input prices and their squares and cross products.

Figure 4a: 7-Banks Efficiency Ratio



Note: The efficiency ratio is calculated as total operating expenses over total income. Higher values of the ratio indicate lower efficiency.

Figure 4b: 5-Banks Efficiency Ratio



Note: The efficiency ratio is calculated as total operating expenses over total income. Higher values of the ratio indicate lower efficiency.

5. Profit Efficiency

Standard profit measures typically focus on assessing the profitability of banks using traditional accounting-based metrics, such as return on assets (ROA), return on equity (ROE), and net interest margin (NIM). While these measures are widely used and easy to compute, they may

not fully capture the underlying profit efficiency of banks, as they do not account for differences in bank size, risk, business model or operational efficiency. Frontier estimation methods provide a more comprehensive way to assess how well banks utilise their inputs and outputs to generate profits, relative to best practice in the industry, given input and output prices.

SFA separates observed profits into two components: the stochastic profit frontier representing the optimal level of profit efficiency, and a composite error term representing deviations from the frontier and measurement errors, respectively. By accounting for differences in bank characteristics, risk, and market conditions, SFA provides a more robust assessment of profit efficiency compared to traditional profit measures. SFA can identify inefficiencies in banks' profit generation processes, allowing for targeted improvements in resource allocation, risk management, and operational effectiveness, making it a valuable tool for evaluating profit efficiency in banking.

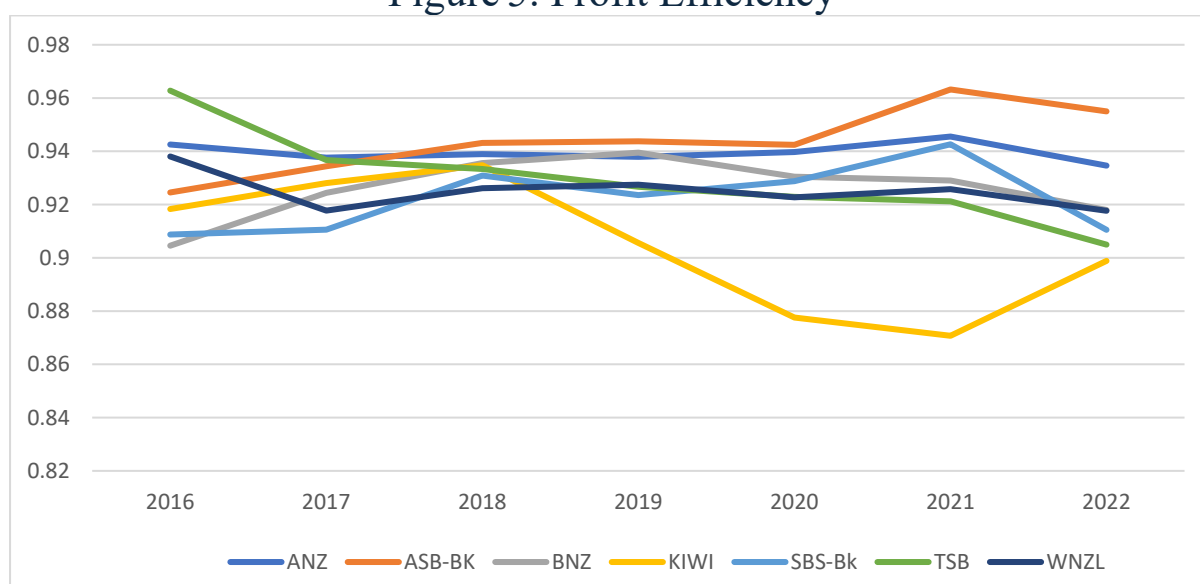
We provide measures of profit efficiency by estimating an alternative profit function. Profit functions are generally assumed to be functions of input and output prices, but these theoretical specifications are correct for prices prevailing in competitive markets, in which firms are price-takers. Instead, we estimate an alternative profit function in which the profit markup, measured as (log) revenue over cost, is a function of output quantities and input prices. This alternative specification provides a means of controlling for the presence of imperfect competition and hence pricing power in output markets (see [Berger and Mester, 1997](#)). The standard practice in the literature is to estimate a translog profit function but as [Kumbhakar \(2006\)](#) has noted using (log) profits as a dependent variable rather than the markup of (log) revenue over cost is not consistent with the standard translog specifications of cost and (alternative) revenue functions. See **Appendix 4B** for more details on the specification and estimation of the profitability function.

Figure 5 provides further evidence of high efficiency levels for New Zealand banks. While slightly below cost efficiency, profit efficiency ranges in the 75-90% mark for most banks, which is on the high side relative to empirical evidence reported for banks in overseas studies. Overall, the evidence from **Figure 3** (cost efficiency) and **Figure 5** (profit efficiency) indicates that ASB is consistently tracking at the top of the cost and profit efficiency metrics during the assessment period. In contrast, the profit efficiency of Kiwibank appears to track lower in

comparison to the profit efficiency of its main rivals. We take a further look at underlying drivers of profit performance in **Figures 6-9**. **Figure 6** clearly shows that Kiwibank (and the smaller TSB) track well below their peers on the ROE metric. We obtain similar evidence from **Figure 7** indicating that ROA is more likely driving the ROE gap of Kiwibank rather than risk, noting that $ROE = ROA \times EM$ where EM is the equity multiplier defined as the ratio of total assets over total equity.

A further breakdown of bank's profitability is illustrated in **Figures 8 and 9** which factor ROA as the product of the profit margin (PM) ratio (net income over total operating income) times the asset utilisation (AU) ratio (total operating income over total assets) or $ROA = PM \times AU$. High PM values reflect the bank's ability to control expenses -- the better the expense control, the more profitable the bank is -- whereas AU measures the ability of the bank to generate income from its assets. The evidence from these figures indicates that Kiwibank's profit margin tracks below the PM ratios of its rivals, however its drop of profit efficiency after 2018 shown in **Figure 5** appears to be more closely related to the AU ratio shown in **Figure 9**. Hence, the less income generated per dollar of assets, the less profitable the bank. In contrast, the profitability metrics shown in **Figures 6-8** corroborate ASB's strong cost and profit efficiency performance shown in **Figures 3 and 5** above.

Figure 5: Profit Efficiency



Note: Profit efficiency is estimated applying SFA in which the “mark-up” ratio of operating revenue over operating cost is a function of output quantities and input prices.

Figure 6: Return on Equity (ROE)

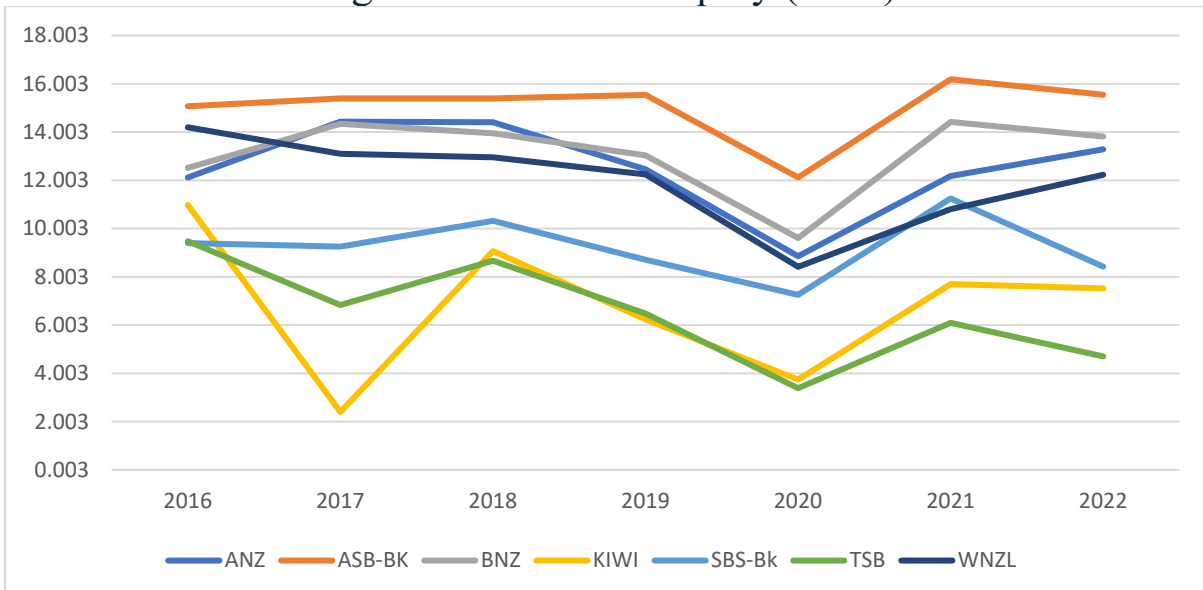


Figure 7: Return on Assets (ROA)

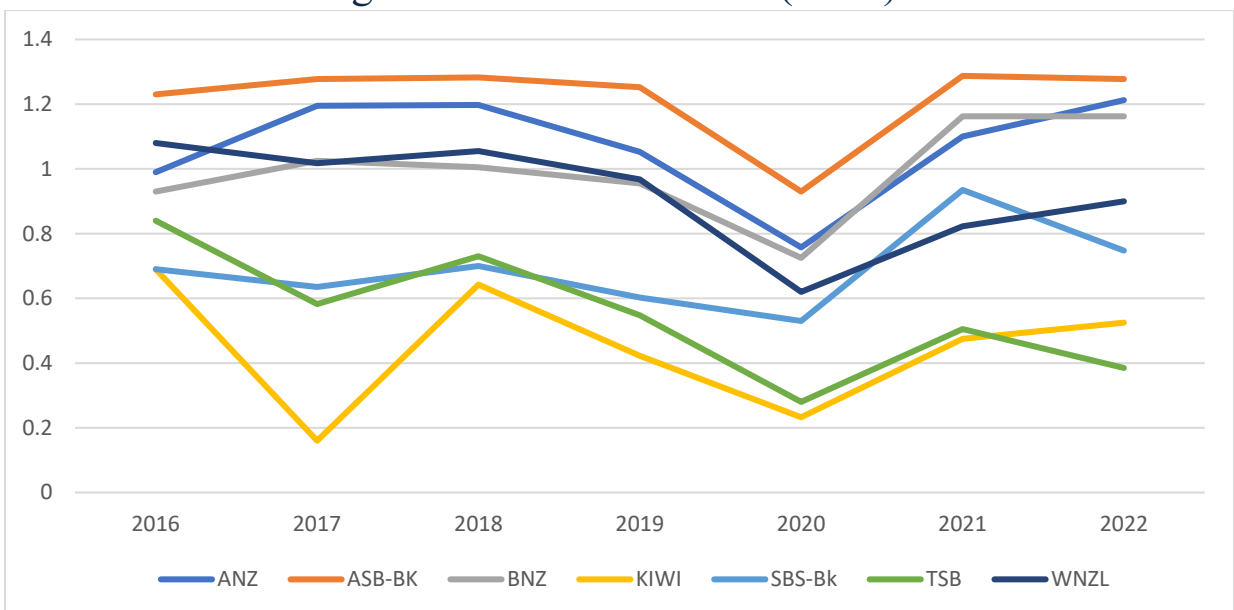
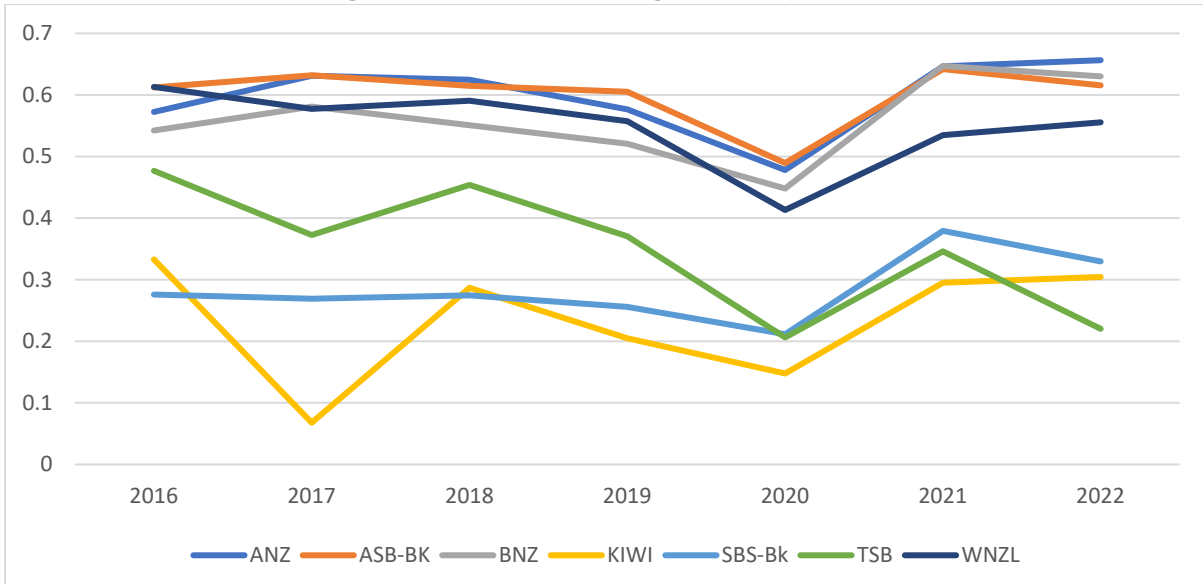
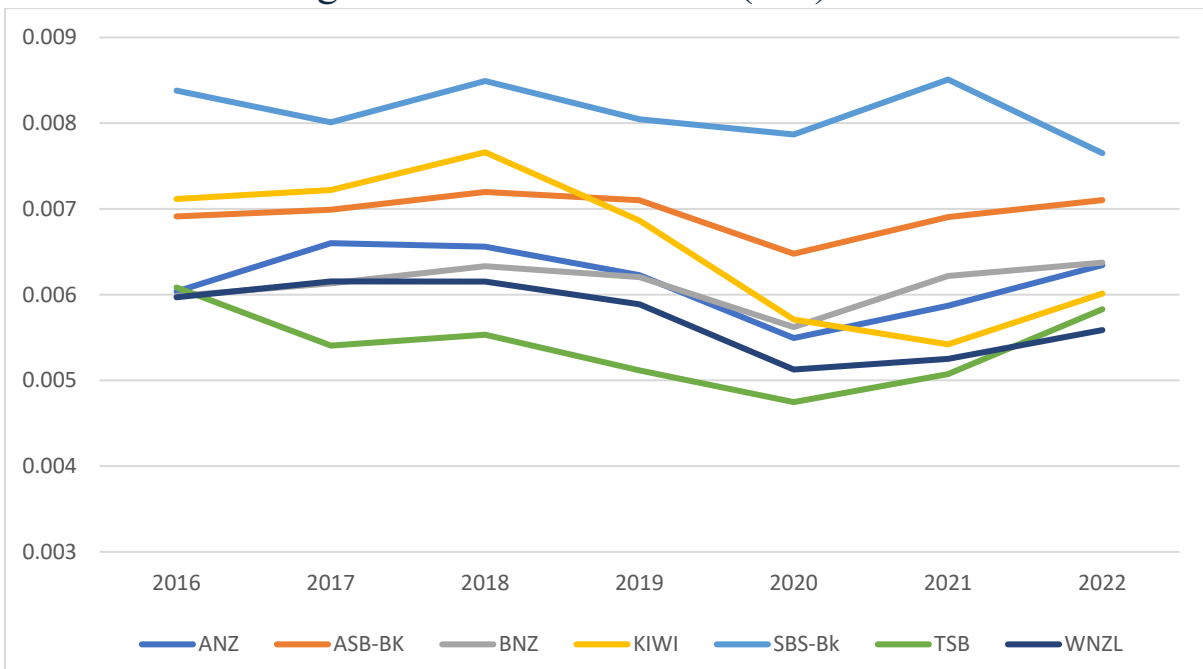


Figure 8: Profit Margin (PM) Ratio



Note: Profit margin is calculated as a ratio of net profit before tax over total operating income.

Figure 9: Asset Utilisation (AU) Ratio



Note: Asset utilisation is calculated as the ratio of total operating income over total assets.

6. Cost Elasticity

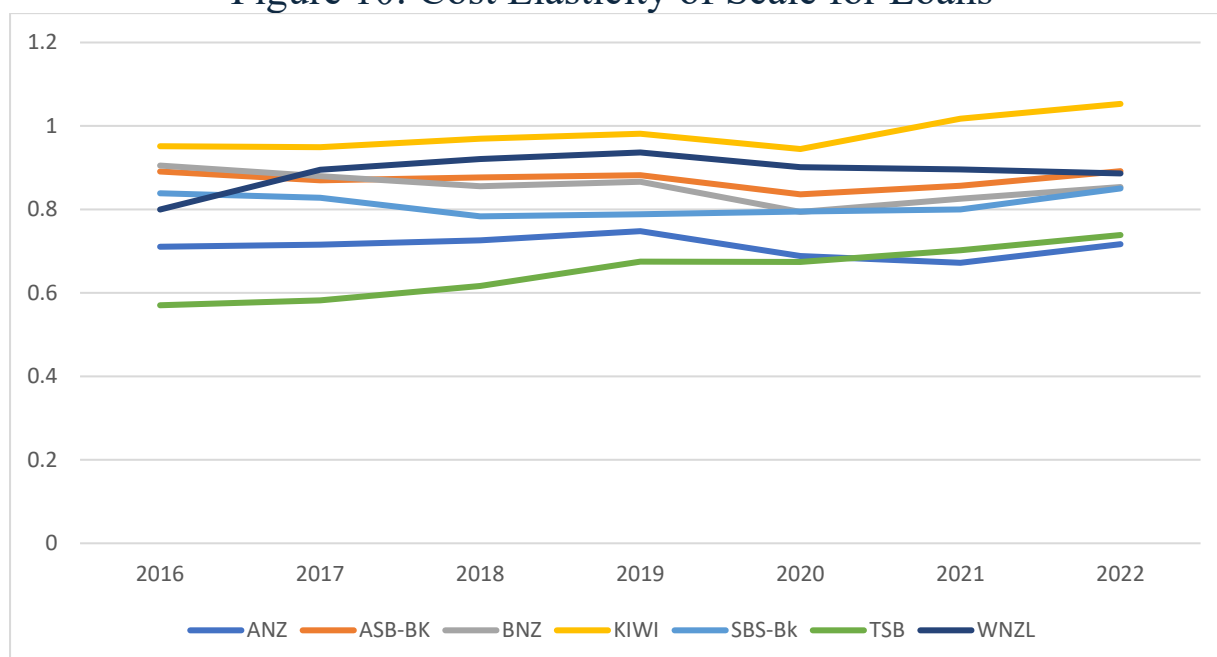
The cost elasticity of scale is a measure of the responsiveness of costs to changes in the size of the bank's operations. Cost elasticity is the inverse of the scale elasticity, an empirical measure of economies of scale. In simple terms, cost elasticity measures how much costs change when

the scale of production changes. It is computed as the percentage change in costs divided by the percentage change in scale. Values of the scale elasticity greater than one indicate that costs increase proportionally more than the increase in bank outputs. This suggests that the bank operates under diseconomies of scale, which may be indicative of inefficiencies in production or other factors including management and governance quality. The cost elasticity of scale is an important measure of bank performance as it helps banks make decisions about optimal production levels and resource allocation. The cost elasticity of scale is also important for regulators making decisions about optimal scale such as decisions on mergers and acquisitions. See **Appendix 5** for more details on cost elasticity measurement.

Figure 10 shows that most banks operate under cost economies of scale in the market for loans with the exception of Kiwibank after 2020. This finding corroborates our findings on cost efficiency shown in **Figure 3** suggesting that banks actual costs, given the scale of their operations, are near minimum achievable cost defined in relation to industry benchmarks, namely the cost efficiency of the best performing peers. An interesting question, and one that has come up in recent media reports, is whether a recapitalisation of Kiwibank by Government to increase its market share is desirable.

While more research is needed to address this question, the evidence shown in **Figure 10** in conjunction with the information drawn from **Figures 3-9** may not be encouraging, at least to the extent the strategic objective of a larger Kiwibank is to become a dominant competitive player in the lending segment of the market. Certain qualifications are important, notably (1) a bigger Kiwibank may be a different bank, perhaps one with a different mandate than the one envisaged at the time of its founding; (2) the cost elasticity shown in **Figure 10** is only marginally above one yet not significantly below one to strengthen a case for expansion; (3) most of Kiwibank's performance metrics show an improvement after 2020/2021 albeit the main challenge for the bank stands, namely to present robust evidence about its ability to control costs. In contrast, **Figure 10** shows that smaller banks like SBS and TSB have the potential to benefit from a larger size.

Figure 10: Cost Elasticity of Scale for Loans

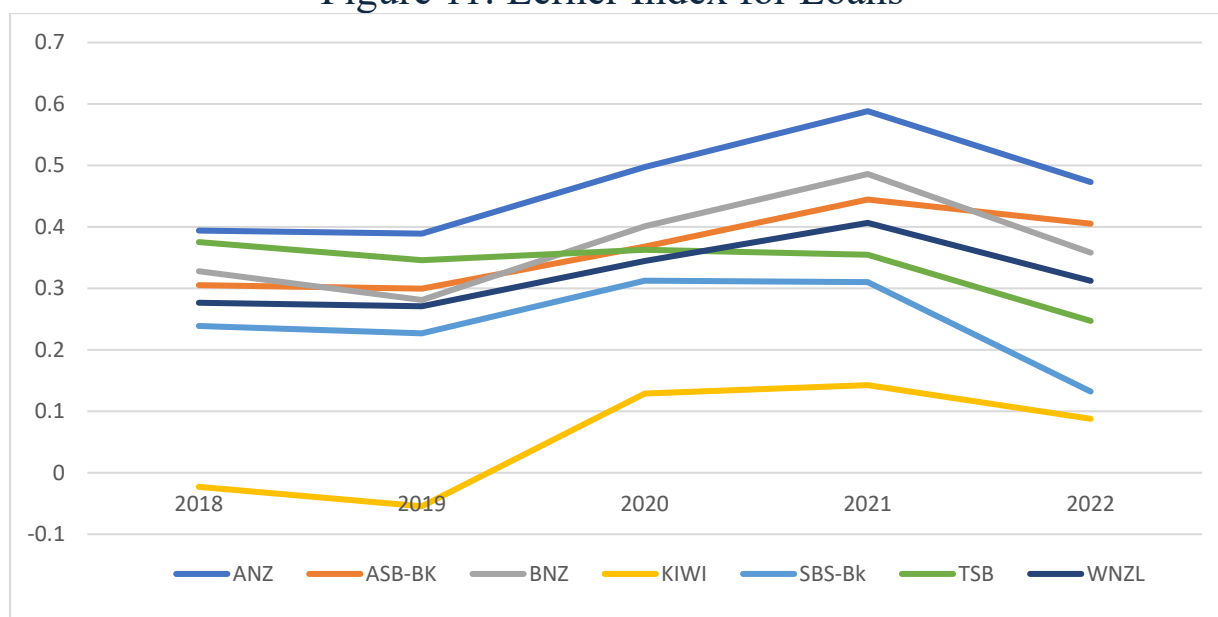


Note: Loan Cost Elasticity of Scale is computed by taking the derivative of the cost function obtained from SFA with respect to loans.

7. Market Power: The Lerner Index

The Lerner Index provides an assessment of the degree of market power exercised by firms -- see [Färe, Margaritis and Grosskopf \(2024\)](#) for more details on the Lerner Index and its applications. A higher Lerner Index indicates greater market power and the potential for firms to extract consumer rents. The index is measured by the spread between price and marginal cost divided by price. Values of the index around zero indicate a competitive market whereas a value around one indicates the presence of monopoly power, with values between zero and one being indicative of imperfectly competitive markets. At the competitive equilibrium, price is equal to marginal cost for the price-taking firm with no market power, hence a value of the index equal to zero is consistent with the competitive equilibrium zero profit level. Here we need to distinguish between the broad economic measure of profit that includes both explicit and implicit costs such as opportunity costs or best alternative use costs, and the more conventional accounting definition of profit which is the difference between revenue and cost. Note that it is possible for the index to take on values below zero as prices at times may fall below marginal cost. **Figure 11** provides evidence of moderate market power in the market for loans, with Kiwibank exhibiting more competitive pricing behaviour whereas ANZ tracks on top of its rivals, exhibiting the closest to monopoly like pricing behaviour.

Figure 11: Lerner Index for Loans



Note: The Lerner Index for loans is calculated as the difference between price and marginal cost, divided by price. Marginal costs are derived using SFA. Price data was only available after 2018.

8. Market Power: The Panzar-Rosse H-Statistic

The Panzar-Rosse H-statistic is another measure of the degree of competition in the banking market. It is obtained from a standard reduced-form revenue model as the sum of elasticities of total revenue with respect to input prices. Under perfect competition, an increase in input prices raises both marginal cost and total revenue by the same amount, and hence the H-statistic equals 1. Under a profit-maximising monopoly, an increase in input prices results in a rise in marginal cost, a fall in output, and a decline in revenue, leading to an H-statistic of less than zero. The reason for the H-statistic taking on negative values is that the monopolist generally operates in the elastic (price elasticity > 1) part of the market demand curve since the marginal cost (MC) curve intersects the marginal revenue (MR) curve from below.

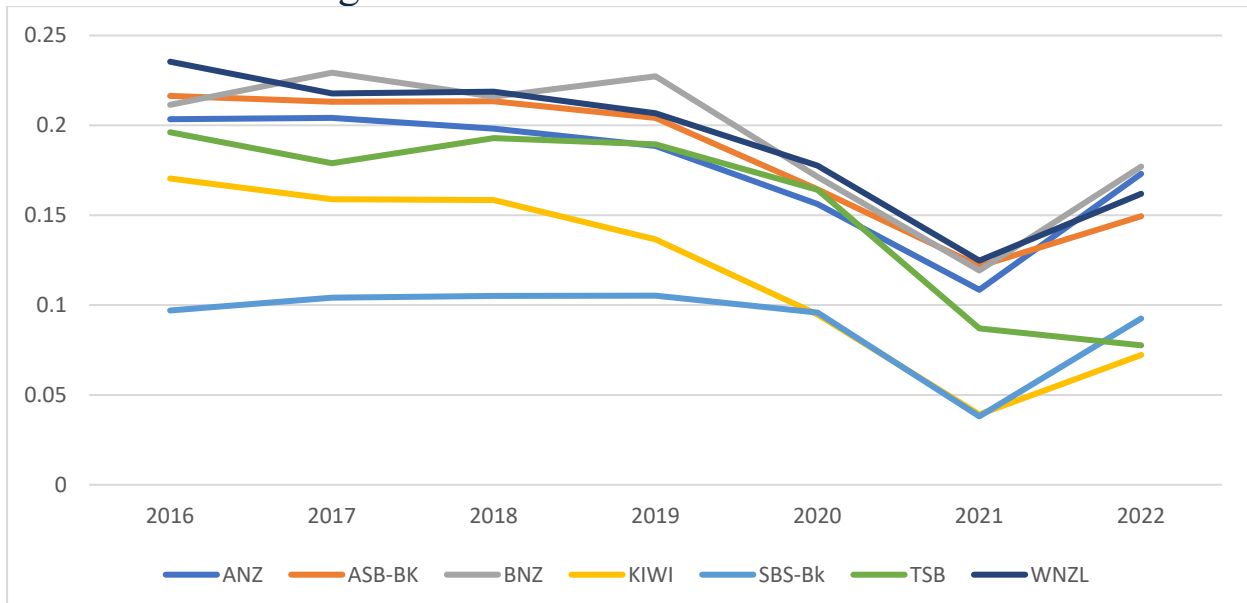
Monopoly equilibrium is at the point where $MR = MC$ but the equilibrium price is higher since the MR curve lies below the demand curve. Hence, an increase in price lowers the quantity demanded in the market by proportionally more, thereby leading to a decrease in the monopolist's revenue. Values of the H-statistic between 0 and 1 are generally interpreted as indicative of imperfect competition (Panzar and Rosse, 1987) albeit other possibilities exist (see Bikker, Shaffer and Spierdijk, 2012). In a more recent study, Shaffer and Spierdijk (2015) identify situations under economically plausible parameter values where a positive H-Statistic

cannot rule out a high degree of market power, contrary for example to the claim by [Bikker, Shaffer and Spierdijk \(2012\)](#) that positive H-statistic values are inconsistent with imperfect competition.

We obtained the Panzar-Rosse measure of market power by running panel regressions of (log) total revenue on (log) input prices and bank specific control variables using two specifications of the (log) revenue function (1) a simple log-log (Cobb-Douglas) constant elasticity of input price specification; and (2) a more general translog specification that includes the squares and cross-products of (log) input prices, and hence allows for non-constant input price elasticities. We have also included fixed-effects and time effects in both specifications. The constant elasticity (log-log) model produced a sum of elasticities of less than zero. However, the H-Statistic, namely the t-test of the sum of the input price coefficients (input elasticities) estimated with robust standard errors, could not reject the null hypothesis that the sum of these elasticities was equal to zero. We obtained a similar finding after we included control variables.

Figure 12 reports the H-Statistic values obtained using the translog model with fixed-effects, time-effects, and bank-specific control variables (loans to total assets ratio, loans to deposits ratio, and equity to total assets ratio). Since we use a translog functional form the elasticities are no longer constant, and they vary across banks and across time. **Figure 12** shows the H-Statistic consistently takes on values greater than zero, which similar to the findings obtained using the Lerner Index are indicative of moderate market power. Note that the H-Statistic reported here is an overall measure of market power, in contrast to the Lerner Index reported earlier which was specifically a measure of market power for loans. Note an overall measure of market power can also be obtained using the Lerner index by applying the denominator rule for share-weighting aggregation (see [Färe and Karagiannis, 2017](#); [Färe, Grosskopf and Margaritis, 2024](#)).

Figure 12: Panzar-Rosse H-Statistic



Note: The H-Statistic values estimated using the translog model with fixed-effects, time-effects, and bank-specific control variables.

9. Market Power, Cost and Profit Efficiency Panel Regressions

We turn next to analyse the determinants of market power using panel regressions. Estimates should be interpreted with caution as we do not claim causal relationships, hence the results are only indicative of the association between variables. We have not addressed endogeneity issues other than using fixed effects regressions to control for endogeneity at least the part associated with omitted time-invariant covariates.

Table 1 reports the results of the Lerner Index of market power. The coefficient estimates of both cost and profit efficiency are positive and significant supporting the efficiency structure hypothesis that argues that competitive pressures lead firms to operate at their most efficient levels, as they seek to gain market share and maximise profits. In competitive markets, inefficient firms are typically driven out, leading to a concentration of resources in the hands of more efficient firms. Arguably this finding strengthens our choice for using market power as the dependent variables. To put differently, support for the efficiency hypothesis over the Hicksian quiet life hypothesis, suggests that causality is more likely to run from efficiency to market power than the other way around. Similarly, we find a positive relationship between

economies and scale and the Lerner Index noting that our measure of cost elasticity of scale is the inverse of economies of scale.

We also find a positive and significant association between measures of bank profitability such as NIM, ROA and ROE and market power. Size measured by (log) total assets has a positive and significant association with market power. The efficiency ratio also has a positive association with market power noting that it is measured by the ratio of operating expenses to operating income, hence lower values of the ratio indicate greater efficiency.

We obtain mixed results for the loans to total assets ratio, often use as a risk measure, noting the sign of the association with the Lerner depends on whether securities income to total interest income and derivatives income to total interest income are included in the regression. The overnight interbank cash rate has a negative association with the Lerner index.

Table 1: Fixed Effects Panel Regressions - Lerner Index 2018:Q3-2023:Q3

	LLI	LLI	LLI	LLI	LLI	LLI	LLI
Cost_eff	0.583***	0.586***	0.717***	0.354**			
Profit_eff					1.437***	1.347***	0.922***
CEL				-0.999***			-0.873***
ROE	0.014***				0.013***		
ROA		0.141***				0.123***	
NIM			0.118**	0.137***			
Eff_Ratio				-0.359***			-0.431***
LnTA	0.320***	0.330***	0.343***	0.518***	0.388***	0.389***	0.513***
Loan/TA	-1.014***	-1.030***	-1.133***	0.477	-0.883***	-0.863***	0.680**
Deriv/IntInc				-1.066***			-1.024***
SecInc/IntInc				-1.663***			-1.569
OICR	-0.044***	-0.045***	-0.048***	-0.038***	-0.051***	-0.052***	-0.036***
Const.	-2.632***	-2.709***	-3.009***	-4.619***	-4.165***	-4.097***	-5.038***
R_Sq	0.2416	0.2568	0.257	0.2614	0.2447	0.2541	0.2423

Notes 1: LLI is the Lerner Index for loans; Cost_Eff and Profit_eff represent our measures of cost efficiency and profit efficiency, respectively; CEL denotes cost elasticity of loans; LnTA is the natural logarithm of total assets; Eff_Ratio denotes the ratio of total operating expenses to total operating income; Loan/TA and Deriv/IntInc are the ratios of total loans to total assets and derivatives income to total interest income, respectively; SecInc/IntInc measures the ratio of securities income to total interest income; OICR stands for Over Night Interbank Cash Ratio; Symbols *, **, *** indicate statistical significance at the 10%, 5%, 1% levels, respectively.

10. Performance Metrics: Bank Groups

This section is self-explanatory and is presented for information only without any further discussion.

A. A Three Distinct Categories of New Zealand Banks

Banks are grouped into three distinct categories in this section. The first group comprises Australian-owned banks that conduct their operations in New Zealand, the “big four”. The second group includes New Zealand based banks. The third group consists of branches or subsidiaries of global banks.

Table 2: Groups of New Zealand banks

Group	Banks
1	ANZ, ASB-BK, BNZ, WNZL
2	Kiwibank, TSB, SBS, HEART, CO-OP;
3	BOC, CCB, CITI-BK, HSBC, ICBC, MUFG, RABO-NZ

Figure 13: Net Interest Margin

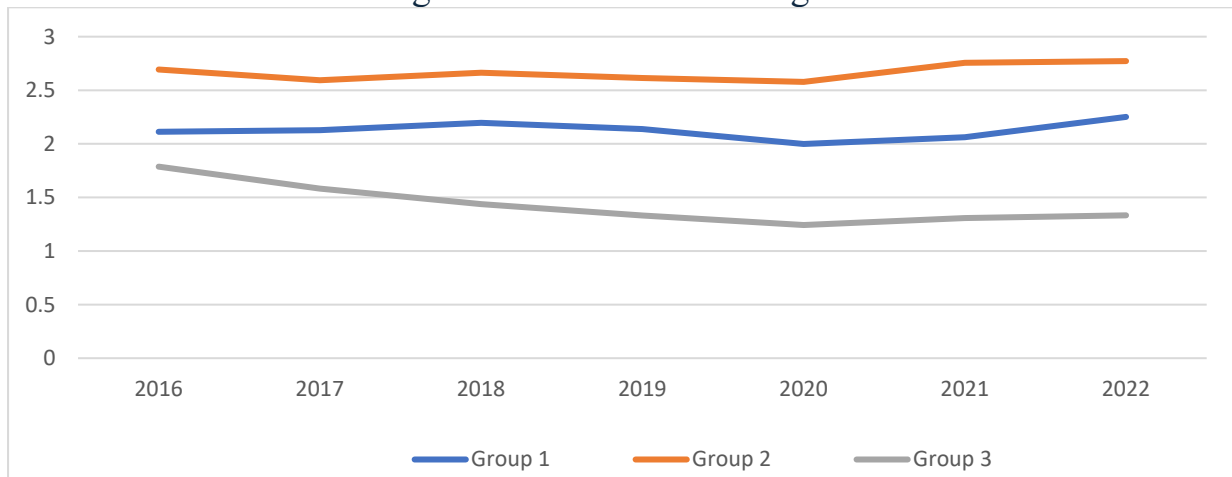


Figure 14: Return on Assets

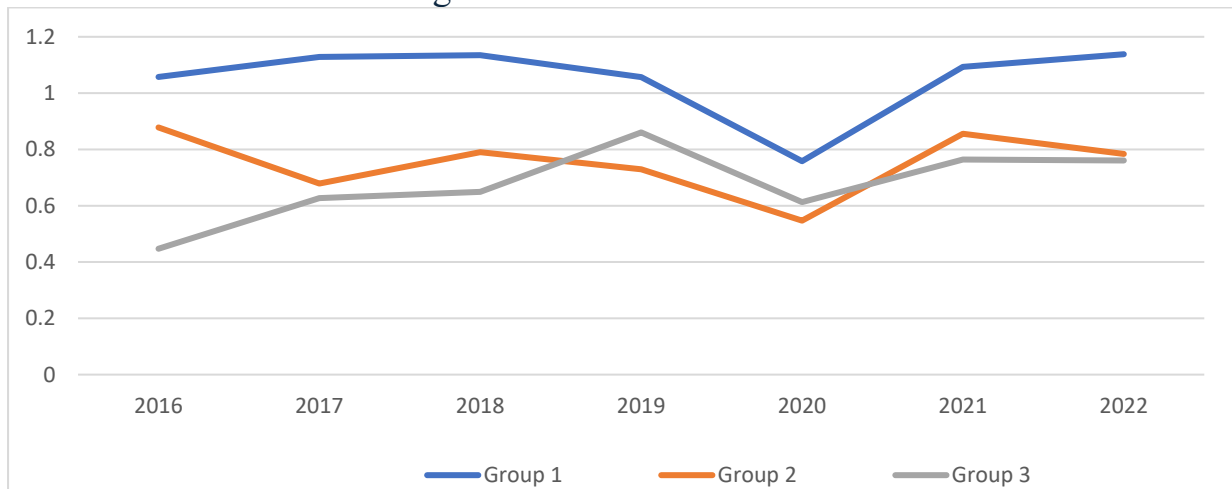


Figure 15: Return on Equity

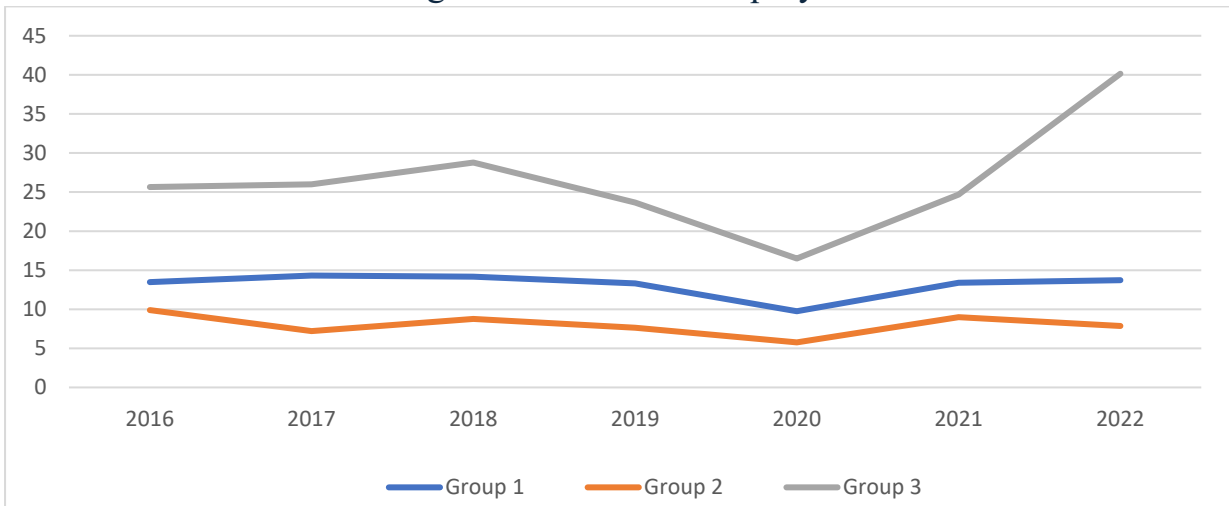


Figure 16: Profit Efficiency

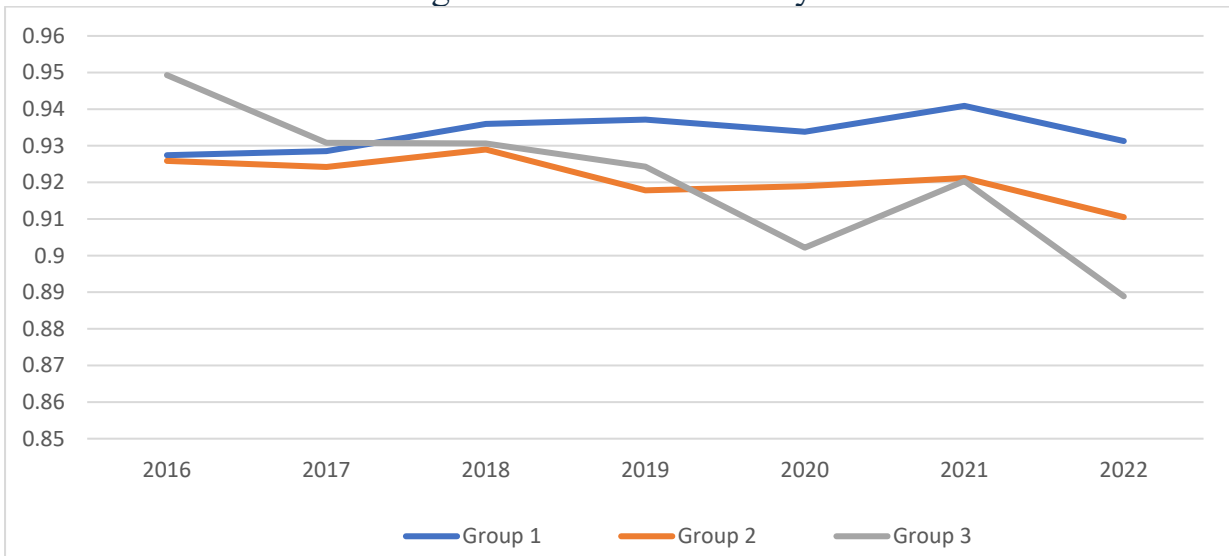


Figure 17: Cost Efficiency

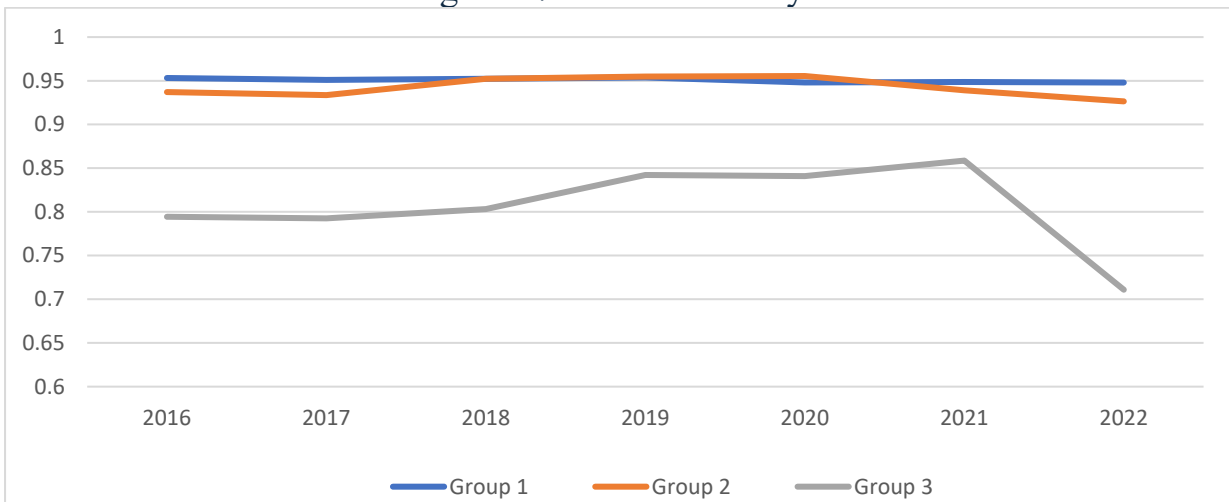


Figure 18: Loans Lerner Index

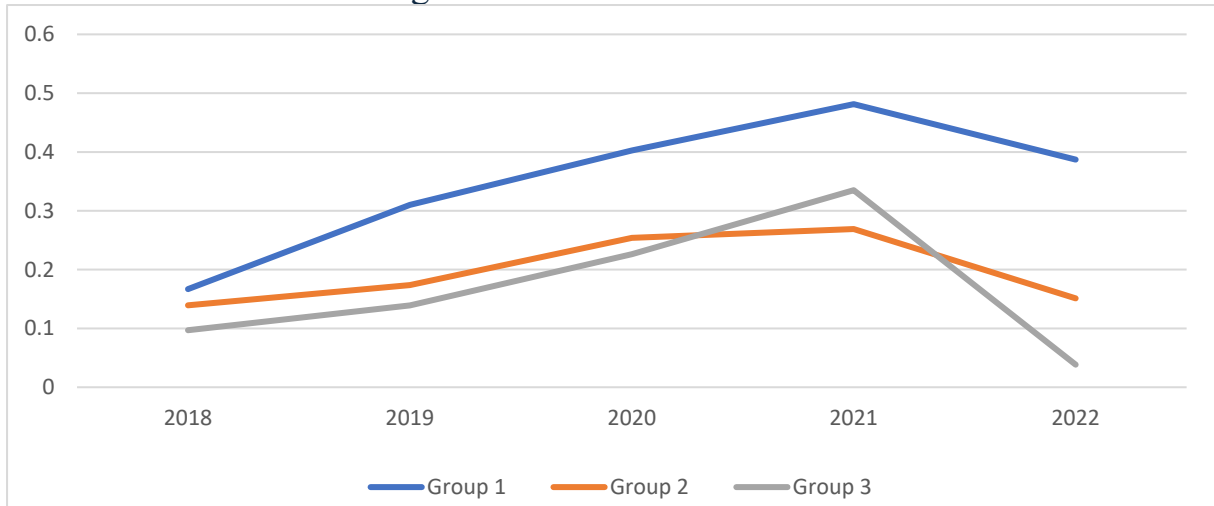


Figure 19: Loans Cost Elasticity of Scale

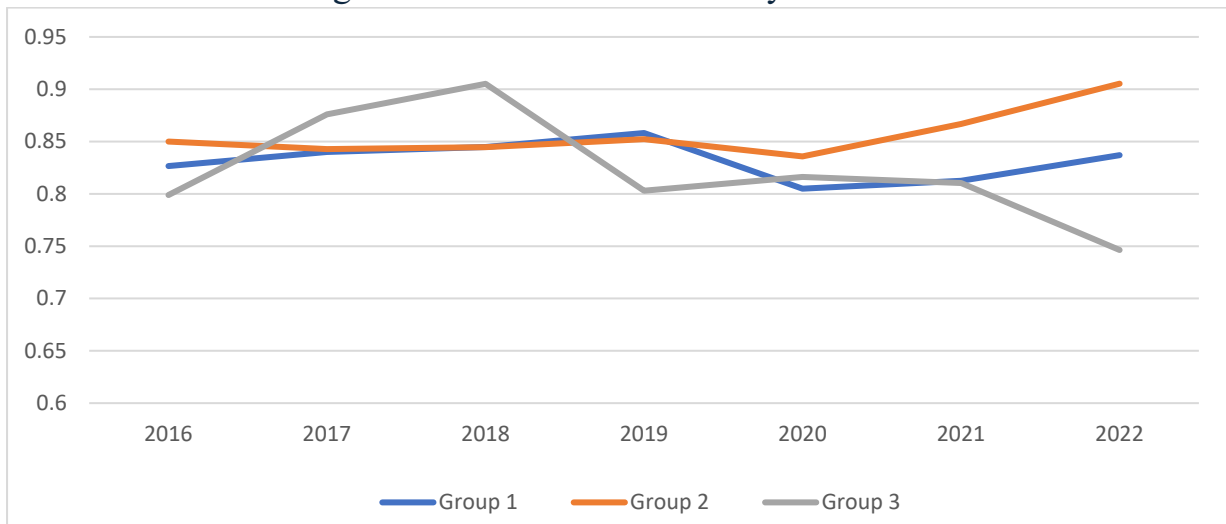
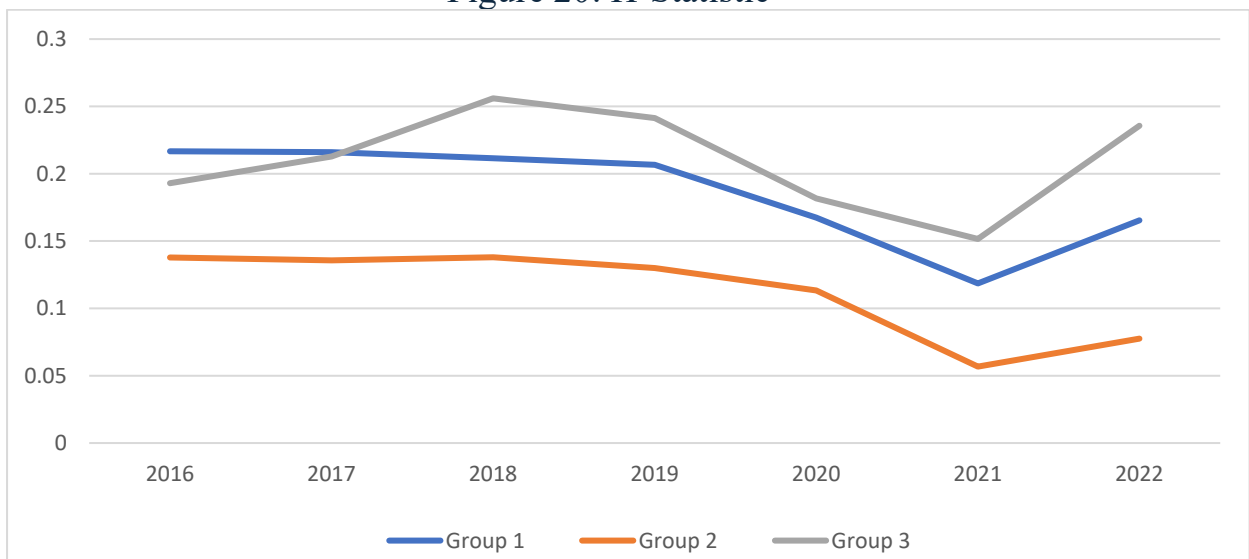


Figure 20: H-Statistic



B. A Four Distinct Categories of New Zealand Banks

The banks in New Zealand are grouped into four distinct categories in this section. In this classification, Kiwibank is singled out from other local banks to highlight its distinct status as a government-owned entity.

Table 3: A four distinct categories of New Zealand banks

Group	Banks
1	ANZ, ASB-BK, BNZ, WNZL
2	Kiwibank
3	TSB, SBS, CO-OP, HEART
4	BOC, CCB, CITI-BK, HSBC, ICBC, MUFG, RABO-NZ

Figure 21: Net Interest Margin

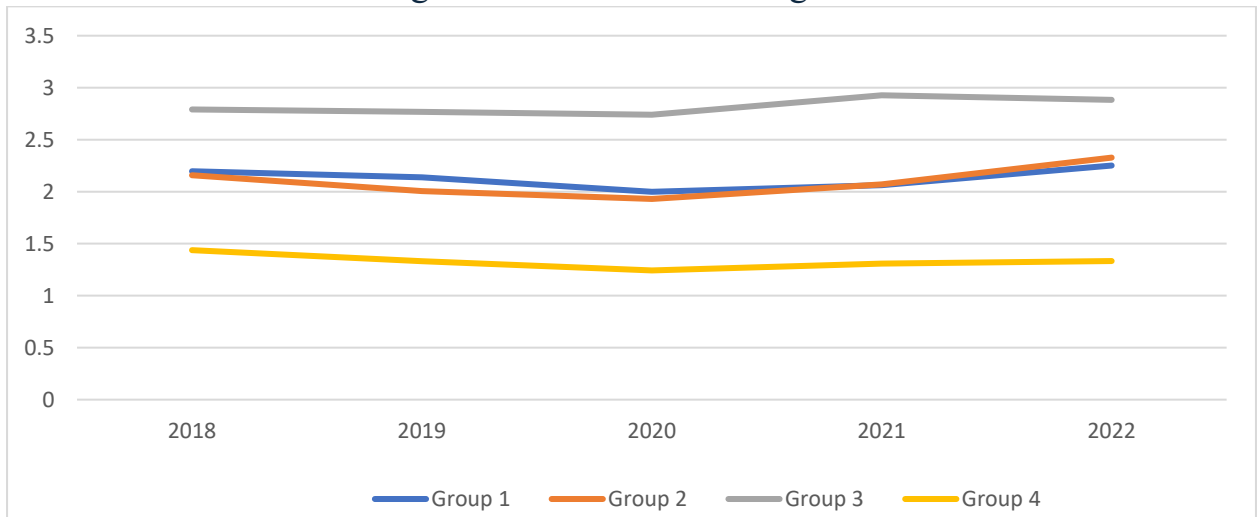


Figure 22: Return on Assets

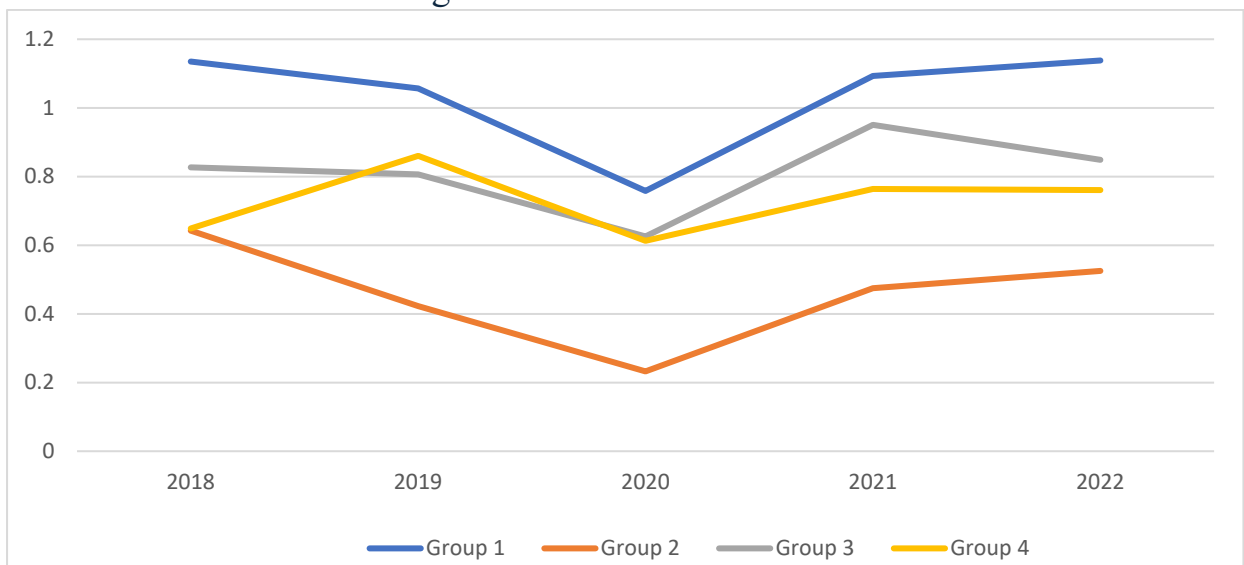


Figure 23: Return on Equity

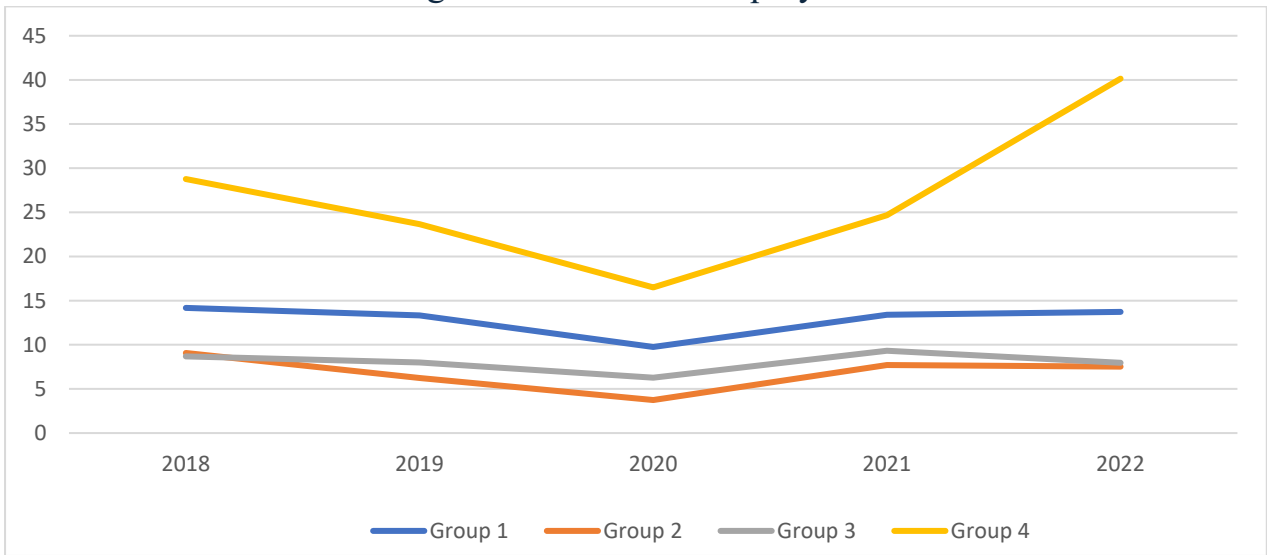


Figure 24: Profit Efficiency

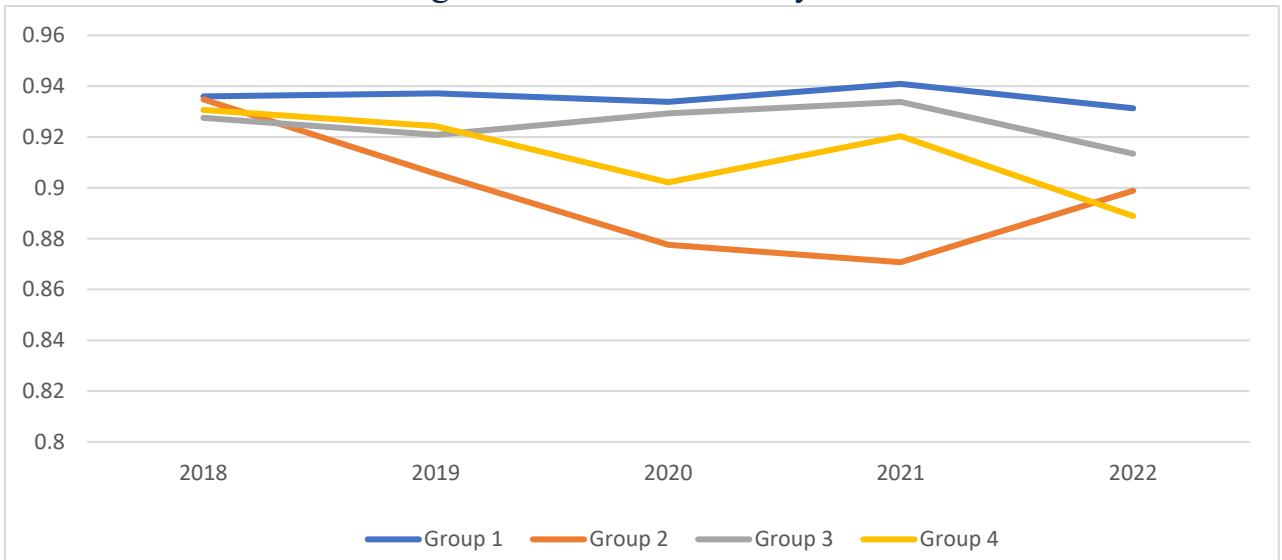


Figure 25: Cost Efficiency

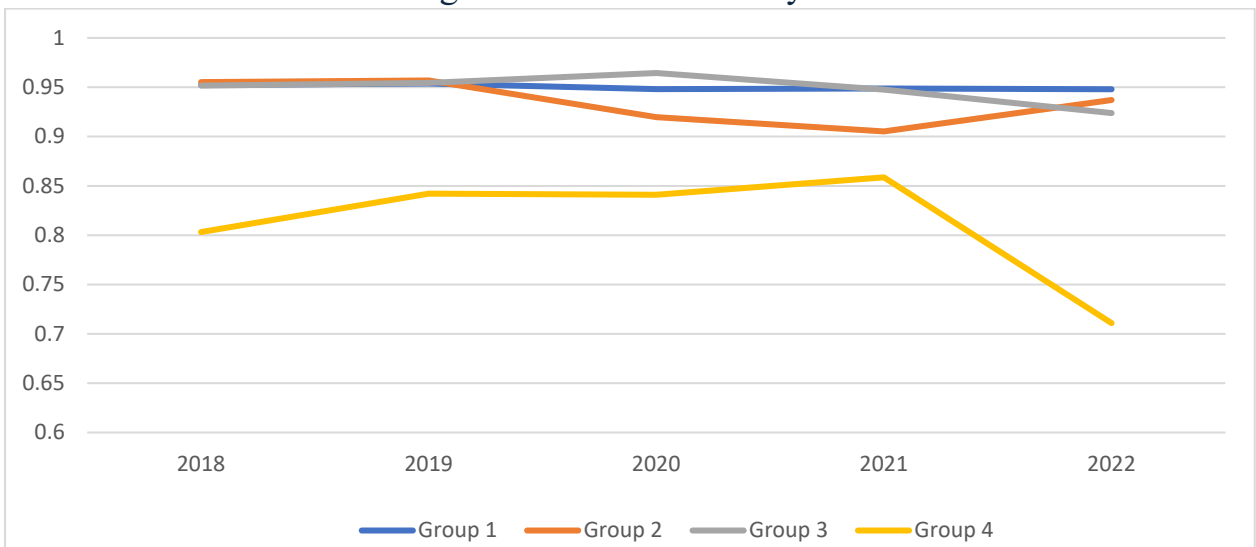


Figure 26: Loan Lerner Index

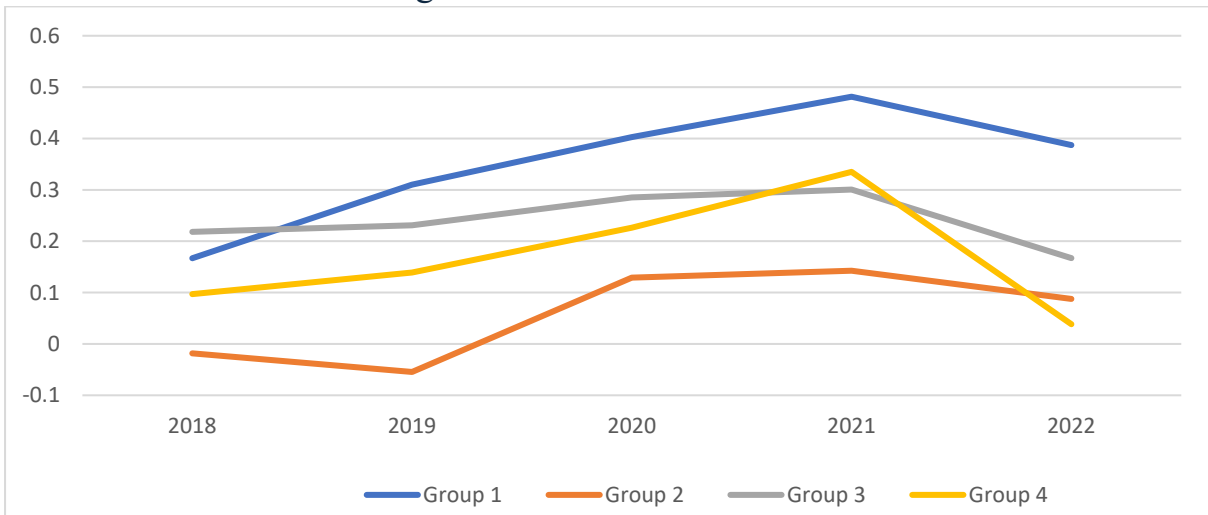


Figure 27: Cost Elasticity of Loans

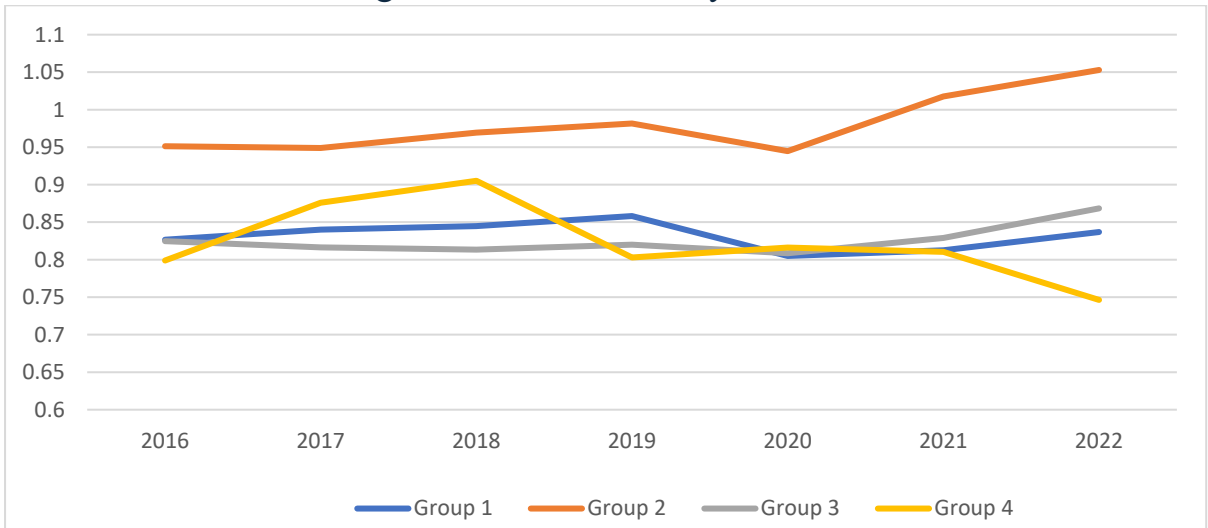
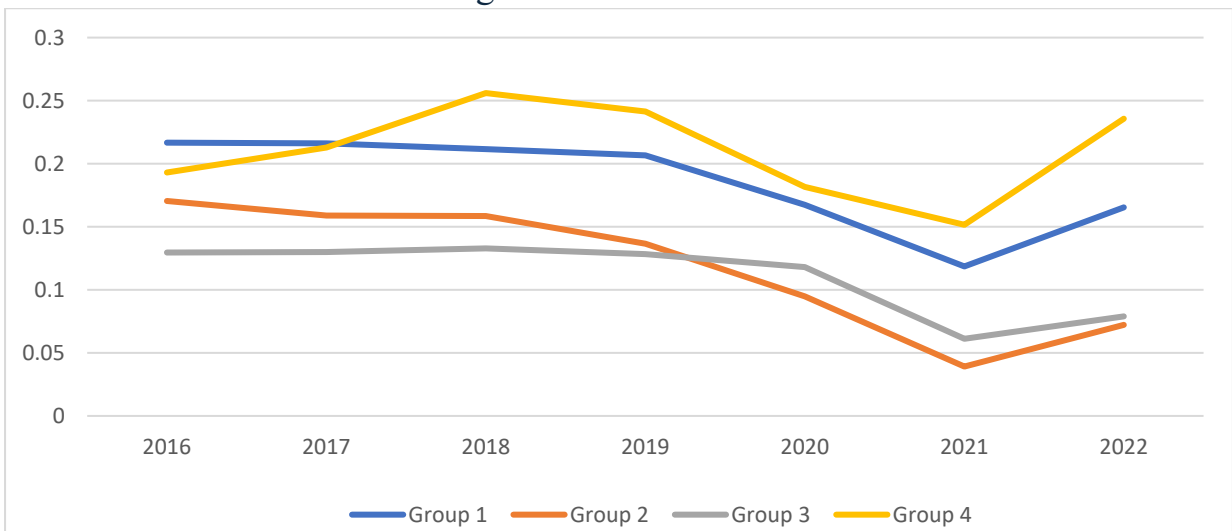


Figure 28: H-Statistic



11. Concluding Remarks

An issue that often makes headline news in New Zealand, especially around the time the Big-4 Australian-owned banks announce earnings from their operations in the country, is whether they earn excess profits. Banks are in the business of taking risks and are expected to be profitable for the risks they take. From a regulator's perspective concerns arise when banks take excessive risks or earn excessive profits or both. Even more concerning are situations where banks are no longer deemed to be profitable.

Do small and large banks earn excess profits in New Zealand for the risks they take? Quoting former finance minister Grant Robertson announcing an inquiry into the sector in June 2023, he stated "there have been long-standing concerns that the market is not working well for New Zealanders. Banks have consistently made high profits over a number of years and their returns have outperformed their peers in other countries." An answer to these questions requires a thorough investigation of market structure involving detailed empirical analysis that the Commerce Commission is currently undertaking. The present study covers certain aspects of this analysis focussing on a quantitative assessment of bank efficiencies, measures of market power, and economies of scale. In a nutshell, from the perspective of our analysis, the response to the question above would be that high profits are a concern if they are largely made by inefficient firms extracting large consumer rents.

At stake is the question of contestability. The New Zealand banking market is moderate to highly concentrated depending on the measure used (e.g., HHI vs. C5) but is it contestable? If it is contestable then it would resemble a competitive market, and we would not expect banks to earn excessive profits. Determining whether the banking market in New Zealand is contestable requires assessing various factors that influence market competitiveness and the ability of new entrants to compete effectively. The findings of this study indicate the presence of moderate pricing power in the market albeit one that is accompanied by relatively high cost and profit efficiency.

Specifically, our findings are aligned with the efficiency structure hypothesis that claims that competitive pressures lead firms to operate at their most efficient levels, as they seek to gain market share and maximise profits. In competitive markets, inefficient firms are typically driven out, leading to concentrated market structures populated by more efficient firms. In this

sense, causality is more likely to run from efficiency to market structure than the other way around. Consistent with this observation, we provide, in **Section 9** above, further analysis by associating bank-specific metrics to our estimates of market power. Further evidence on market structure points to the presence of cost economies of scale, thereby suggesting that the incumbents, even the larger banks, are efficient firms operating under constant or increasing returns to scale.

Arguably, high and sustained profits among existing banks could indicate barriers to entry or limited competition. Conversely, lower and perhaps more volatile profits might indicate greater contestability and competitive pressures. From our perspective, the main interest is on the nexus between market power and bank efficiency. If a concentrated market dominated by a few large banks is not contestable, and barriers to entry exist then it is open to excessive rent seeking, inefficient governance and management practices, and low service quality to paraphrase the Hicksian “Quiet Life Hypothesis”.

Barriers to entry are influenced by factors such as regulatory requirements, capital requirements, economies of scale, and access to technology. Customer switching costs, namely the easiness with which customers can switch between banks influences competitive dynamics. High switching costs, such as fees for closing accounts, switching fixed to floating mortgages, or transferring funds, could inhibit customer mobility and limit competition.

The regulatory environment also plays an important role in promoting competition and consumer choice that enhance contestability. Advancements in technology and digital banking platforms can lower barriers to entry and facilitate the emergence of new competitors. Banks that leverage innovative technologies to offer competitive products and services could enhance market contestability.

What we observe so far is that banks in New Zealand are very slow or reluctant to adopt banking platforms that are widely used in many other countries and are highly sought after by bank customers. Innovative New Zealand companies such as Youtap have to market their digital banking platforms and digital wallet solutions with great success in other countries as banks here tend to keep away from leading edge consumer focussed innovation. Do slow adoption or reluctance reflect the marks of market power as in the “Quiet Life Hypothesis”?

Such questions are expected to be part of the broader market study undertaken by the Commerce Commission.

Some caveats are important. We have confined our analysis to the New Zealand banking industry. Determining whether large Australian banks earn excess profits in New Zealand would probably require further analysis involving the banking industries of both countries, including factors such as market structure, competitive dynamics, regulatory environment, and profitability of individual banks. This is a subject of future research.

Appendix 1. The sample of banks

In this report we have considered 19 registered banks in New Zealand as follows:

ANZ, ASB-BK, BARODA, BNZ, BOC, BOI-NZ, CCB, CITI-BK, CO-OP, HEART-BK, HSBC, ICBC, KIWI, KOOK, MUFG, RABO-NZ, SBS-Bk, TSB, WNZL.

The inputs and outputs as well as their prices we have considered are as follows:

Table A1: Variables Definition

Outputs	Total loans (LOANS)
	Debt securities (SEC)
	Total Other Income (OTH_INC)
Price of outputs	Price Loans = Interest Income on Loans / Total Loans
	Price Securities = Total Debt Securities Income / Total Debt Securities
	Price Other Income = Total Other Income / Total Assets
Inputs	Personnel expenses
	Fixed Assets
	Borrowed funds
Price of Inputs	Price Employees = Personnel Expenses / Total assets; (P_EMP)
	Price Fixed Assets = Total Other Expenses / Total Assets; (P_FA)
	Price Borrowed funds = Interest Exp / (Total Deposits + Other Borrowed Funds) = Interest Exp / Total Borrowed Funds; (P_BF)

RABO-NZ	Min	9,675.54	344.18	-2.30	10.00	3.31	26.23	0	0.0017	-0.0002	0.0009	0.0003	0.0023
	Max	13,000	892.94	1.33	21.02	6.43	160.02	0.0184	0.0081	0.0001	0.0017	0.0005	0.0122
	Mean	11,200	636.86	0.34	14.92	4.6493	67.93	0.009	0.0046	0	0.0012	0.0004	0.0062
	p50	11,300	635.94	0.56	15.14	4.49	72.35	0.0101	0.0051	0	0.0012	0.0003	0.0068
	SD	1,027.49	95.50	0.82	3.58	0.9191	29.99	0.0055	0.0019	0.0001	0.0002	0.0001	0.0024
SBS-Bk	Min	3,260.25	345.73	6.35	10.63	7.17	11.49	0	0.0047	0.0012	0.0022	0.0017	0.0028
	Max	5,199.76	574.98	10.61	16.34	12.76	63.60	0.0147	0.0105	0.0023	0.0029	0.0027	0.0129
	Mean	4,133.06	513.57	8.67	12.75	10.4048	28.22	0.0094	0.007	0.0018	0.0026	0.0022	0.0069
	p50	4,079.84	539.65	8.50	12.70	10.66	28.96	0.0115	0.0073	0.0019	0.0027	0.0022	0.0079
	SD	459.42	62.86	0.93	1.31	1.3812	11.65	0.0055	0.0017	0.0003	0.0002	0.0002	0.0024
TSB	Min	4,467.01	1,342.35	2.36	9.16	7.48	16.03	0	0.0032	0.0003	0.0012	0.0011	0.002
	Max	7,106.55	2,059.54	14.00	21.34	36.34	57.28	0.0128	0.0106	0.002	0.0023	0.004	0.0069
	Mean	6,019.77	1,769.65	5.85	13.19	14.3678	35.45	0.0077	0.0058	0.0007	0.0016	0.0017	0.0049
	p50	6,164.80	1,827.81	5.20	11.51	12.94	39.01	0.0092	0.0058	0.0007	0.0015	0.0016	0.0056
	SD	748.98	227.29	2.58	3.54	5.7644	11.10	0.0045	0.0019	0.0004	0.0003	0.0006	0.0017
WNZL	Min	77,400	4,961.18	38.04	108.50	75.41	211.00	0	0.0027	0.0003	0.0012	0.0006	0.0026
	Max	98,700	9,058.17	109.15	191.07	94.66	1,028.73	0.0142	0.0104	0.0012	0.0016	0.001	0.0121
	Mean	87,100	6,678.58	76.67	137.00	84.5637	469.73	0.0076	0.0062	0.0008	0.0013	0.0008	0.0066
	p50	86,900	6,648.43	70.72	125.25	83.55	497.89	0.0087	0.0062	0.0007	0.0013	0.0009	0.0074
	SD	7,358.68	1,175.83	19.37	25.26	5.5606	188.94	0.0046	0.0023	0.0003	0.0001	0.0001	0.0024

Appendix 3. Time-Series Analysis

We adopt the Shin, Yu, and [Shin, Yu and Greenwood-Nimmo \(2014\)](#) nonlinear ARDL (NARDL) framework in which short-run and long-run nonlinearities are modeled as positive and negative partial sum decompositions of the explanatory variables. The Shin et al. model is based on a conditional error correction (EC) representation of the more familiar autoregressive distributed-lag (ARDL) model with the added, albeit important, complexity of allowing nonlinearities in long-run and short-run responses of the model's dependent variable to regressors. The conditional error correction model shown in **Table A3** allows for asymmetries in both the short-run dynamics and in the long-run equilibrium relationship.

Specifically, we estimate a NARDL(2,4,4,1) model of floating mortgage rates (R_HH) on the OCR, the 6m deposit rate (DEP), and the 10-year and 2-year Government bond spread (R_10Y-R_90), over the period 1999M04 to 2023M11. We treat the OCR as an asymmetric variable in both the short-run and the long-run, the 6m deposit rate as an asymmetric variable only in the short-run, and the interest rate spread as a symmetric variable. Optimal lag orders are determined using the Schwarz Information Criterion (SIC) with a max set at 8 lags. The estimated NARDL(2,4,4,1) model is given by:

Table A3: ARDL Model 1999:M07-2023M11

Variable	Coefficient	Std. Error	t-Stat.
R_HH(-1)	-0.173***	0.032	-5.399
R_10Y(-1)-R_90(-1)	-0.054***	0.009	-5.936
DEP(-1)	0.074***	0.015	4.784
@CUMDP(OCR(-1))	0.047**	0.022	2.126
@CUMDN(OCR(-1))	0.045**	0.019	2.367
Const.	0.902***	0.193	4.685
D(R_HH(-1))	-0.206***	0.052	-3.949
D(R_10Y-R_90)	-0.006	0.026	-0.224
D(R_10Y(-1)-R_90(-1))	0.005	0.027	0.196
D(R_10Y(-2)-R_90(-2))	0.013	0.027	0.499
D(R_10Y(-3)-R_90(-3))	0.108***	0.025	4.375
@DCUMDP(OCR)	0.119**	0.051	2.358
@DCUMDN(OCR)	0.060	0.039	1.560
@DCUMDP(OCR(-1))	0.403***	0.053	7.640
@DCUMDN(OCR(-1))	0.390***	0.046	8.430
@DCUMDP(OCR(-2))	0.275***	0.056	4.879
@DCUMDN(OCR(-2))	0.201***	0.045	4.519
@DCUMDP(OCR(-3))	0.346***	0.050	6.981
@DCUMDN(OCR(-3))	0.082**	0.037	2.224
@DCUMDP(DEP)	0.178**	0.073	2.422
@DCUMDN(DEP)	0.374***	0.066	5.700
DUM08	0.095***	0.027	3.543
Adj. R-squared	0.793	Durbin-Watson	1.971

Notice the OCR is split into four variables corresponding to the positive and negative cumulative sums and cumulative difference sums using the labels “@CUMDP(OCR(-1))” and “@CUMDN(OCR(-1))” for the long-term effects, and the labels “@DCUMDP(OCR)” and “@DCUMDN(OCR)” for the short-term effects. The 6m deposit rate (DEP) is split into two variables corresponding to the positive and negative cumulative difference sums using the labels “@DCUMDP(DEP)” and “@DCUMDN(DE)” for the short-term effects. There was no evidence of long-run asymmetry for the deposit rate. DUM08 is a dummy variable for the GFC.

The NARDL model embeds a long-run equilibrium (co-integrating) relationship into the dynamic Error-Correction (EC) model. The model also allows for the presence of stationary and non-stationary variables in the relationship. Cointegration is a mechanism that keeps the variables in the long-run relationship together, an important statistical property for model involving non-stationary series, and in this sense it represents the statistical counterpart of an economic equilibrium relationship. The existence of cointegration in the levels of variables is affirmed by the Pesaran, Shin and Smith (2001) bounds test. The error correction mechanism is a mean reverting mechanism that corrects gradually, at a pace determined by the EC coefficient, the presence of disequilibrium in the relationship between the variables of interest. **Table A3** shows the estimate of the error correction coefficient is -0.173, meaning that about 17% of the deviation from equilibrium is corrected in one period. It is important that this coefficient is negative, otherwise there is no mean reversion. The estimated long-run model is given by:

Table A4: Long-Run Model 1999:M07-2023M11

Variable	Coefficient	Std. Error	t-Stat.
R_10Y(-1)-R_90(-1)	-0.310***	0.049	-6.374
DEP(-1)	0.425***	0.081	5.246
@CUMDP(OCR(-1))	0.271***	0.095	2.864
@CUMDN(OCR(-1))	0.262***	0.079	3.302
C	5.203***	0.365	14.249

Hence, the estimated cointegrating equation is given by:

$$\begin{aligned}
 CE = & R_{HH}(-1) - (-0.310 \times (R_{10Y} - R_{90}) + 0.425 \times DEP(-1) \\
 & + 0.271 \times @CUMDP(OCR(-1), "1999M03") \\
 & + 0.262 \times @CUMDN(OCR(-1), "1999M03") + 5.203).
 \end{aligned}$$

Since the OCR is a fully asymmetric variable, it is tested for symmetry along both the long-run and short-run dimensions, while DEP is tested only in the short-run dimension. **Table A5** shows that we can reject symmetry for OCR and DEP at conventional significance levels in the short-run but not in the long-run for the OCR.

Table A5: Coefficient Symmetry Tests

Coefficient symmetry tests		
Null hypothesis: Coefficient is symmetric		
Degrees of freedom (simple tests): F(1,271), Chi-square(1)		
Degrees of freedom (joint tests): F(2,271), Chi-square(2)		
Variable	F-statistic	Chi-square
Long-run		
OCR	0.182	0.182
Short-run		
DEP	3.523*	3.523*
OCR	12.727***	12.727***
Joint (Long-Run and Short-Run)		
OCR	6.933***	13.867***

We can gain further insights into how the OCR and DEP contribute to the dynamics of the mortgage rate by looking at their response curves. **Figures A1** and **A2** below show the banks' floating mortgage rate response to one-time change in the OCR and DEP, respectively, distinguishing between the response to a positive change (grey line) and negative change (yellow line). The figures display the cumulative 12-month dynamic multiplier (CDM) curves demonstrating the short-run asymmetry in the effects of OCR and 6m-deposit rate, respectively, on the floating mortgage rate.

Since the OCR is asymmetric in the short-run but not in the long-run, we expect the dynamic multiplier curves to differ in the short-run but to approach the same absolute value level in the long-run. This relationship is seen in the fact that the absolute difference between these paths (the red line within the shaded CI interval) in **Figure A1** approaches zero gradually. The remaining lines display the CDMs for the positive and negative changes starting off at different values indicative of the contemporaneous asymmetry in short-run response (stronger in absolute value terms for increases than decreases in the OCR).

Since DEP is asymmetric in the short-run, but symmetric in the long-run, the absolute asymmetry graph shown by the red line in **Figure A2** is below zero at the start of the evolution, but then settles to zero as we approach the long-run. We surmise differences in the response of floating rates to changes in the OCR and the 6m deposit rate reflect attempts by banks to balance changes in retail and wholesale funding cost components.

Figure A1: Cumulative Dynamic Multiplier: OCR on R_HH

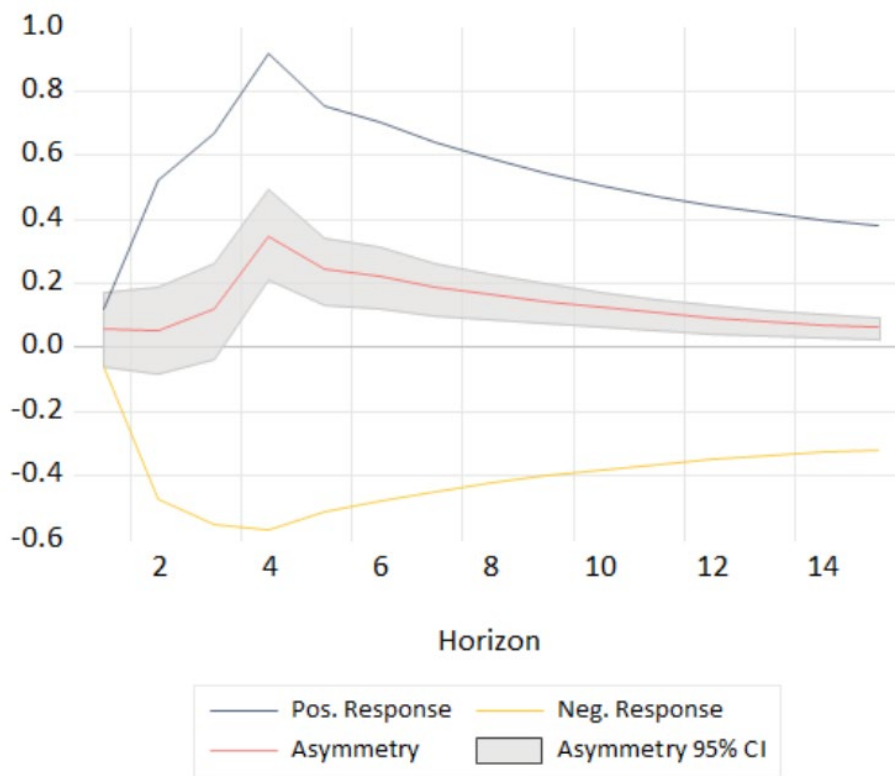
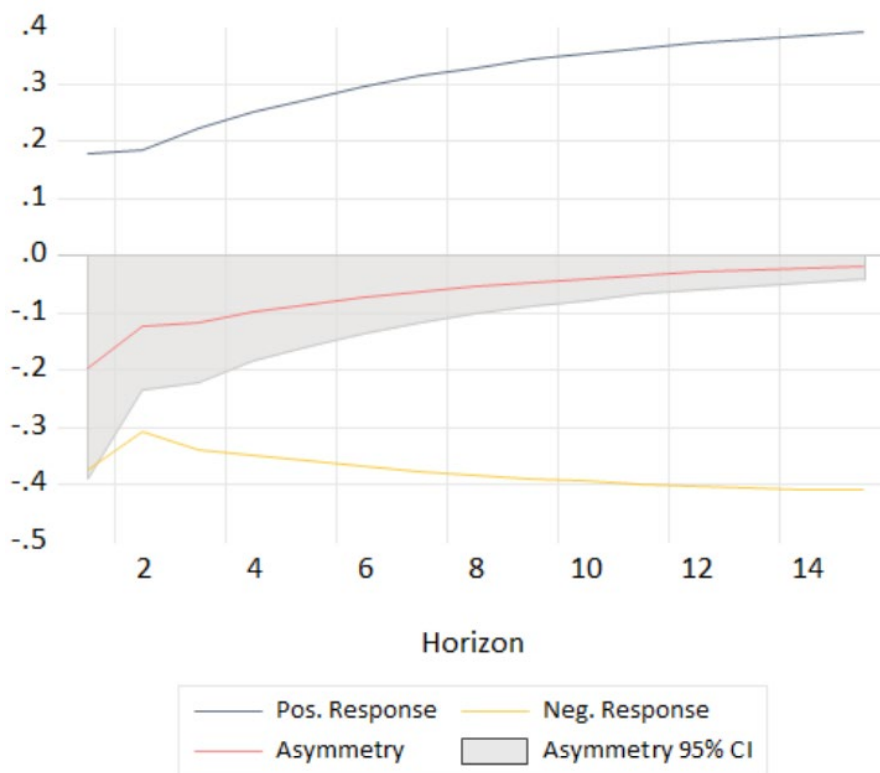


Figure A2: Cumulative Dynamic Multiplier: DEP on R_HH



Appendix 4. Efficiency Measurement

A4.1. Cost Efficiency

The functional form (translog) used to estimate cost efficiency is as follows:

$$\ln TC_{it} = \alpha + \sum_{n=1}^3 \alpha_n \ln Y_{n,it} + \frac{1}{2} \sum_{n=1}^3 \sum_{k=1}^3 \alpha_{kn} \ln Y_{k,it} \ln Y_{n,it} + \sum_{n=1}^3 \beta_n \ln P_{n,it} + \frac{1}{2} \sum_{n=1}^3 \sum_{k=1}^3 \beta_{kn} \ln P_{k,it} \ln P_{n,it} + \sum_{n=1}^3 \sum_{k=1}^3 \delta_{kn} \ln P_{k,it} \ln Y_{n,it} + \lambda t + v_{c,it} + u_{c,it} \quad (1)$$

Subject to:

1. Symmetry

$$\begin{aligned} \ln Y_{k,it} \ln Y_{n,it} &= \ln Y_{n,it} \ln Y_{k,it} & k = 1,2, \text{ and } 3, \quad n = 1,2,3. \\ \ln P_{k,it} \ln P_{n,it} &= \ln P_{n,it} \ln P_{k,it} & k = 1,2, \text{ and } 3, \quad n = 1,2,3. \end{aligned}$$

2. Homogeneity:

$$\sum_{n=1}^3 \beta_n = 1,$$

$$\sum_{k=1}^3 \delta_{kn} = 0,$$

$$\sum_{k=1}^3 \beta_{kn} = 0.$$

Where:

TC_{it} = Total operating and interest expenses for each bank i at time t ;

$Y_{n,it}$ = The value of the n^{th} output variable, shown in **Table 1**, at time t ;

$P_{n,it}$ = The price of the n^{th} input variable, shown in **Table 1**, at time t ;

z_{1it} = The value of (log) Total Assets for each bank i at time t ;

z_{2it} = The ratio of Equity over Total Assets for each bank i at time t ;

z_{3it} = The ratio of interest income to total income;

$v_{c,it}$ = is the two-sided normally distributed error term;

$u_{c,it}$ = is the (log) cost inefficiency term following a one-sided truncated normal distribution with

$$\text{mean} = \theta_1 z_{1it} + \theta_2 z_{2it} + \theta_3 z_{3it}.^3$$

³ We use the Battese and Coelli (1995) conditional mean frontier model, in which the mean of the truncated normal distribution is expressed as a linear function of the covariates specified here as z_{1it} and z_{2it} . Other bank-specific covariates such as the ratio of provisions for non-performing loans to total loans or the ratio of debt securities to total assets were not statistically significant and have been omitted.

We specify three output measures, loans, total securities, and non-interest income, and three input prices, labour, premises and fixed assets, and deposits and other borrowed funds. We include total equity as a quasi-fixed input to control in part for differences in risk across banks (Berger and Mester, 2003), and covariates (z_{it}) in the specification of the inefficiency term. We also introduce a time variable to control for changes in regulation, technological change, and the pandemic crisis. Cost efficiency is calculated as $\exp(-u_{c,it})$ using the Jondrow et al. (1982) estimator.

A4.2. Profit Efficiency

The profit differences across banks can be measured as the “mark-up” ratio of operating revenue over operating cost. The functional form used to estimate profit efficiency is as follows:

$$\ln \frac{Rev_{it}}{TC_{it}} = \alpha + \sum_{n=1}^3 \alpha_n \ln Y_{n,it} + \frac{1}{2} \sum_{n=1}^3 \sum_{k=1}^3 \alpha_{kn} \ln Y_{k,it} \ln Y_{n,it} + \sum_{n=1}^3 \beta_n \ln P_{n,it} + \frac{1}{2} \sum_{n=1}^3 \sum_{k=1}^3 \beta_{kn} \ln P_{k,it} \ln P_{n,it} + \sum_{n=1}^3 \sum_{k=1}^3 \delta_{kn} \ln P_{k,it} \ln Y_{n,it} + \lambda t + v_{P,it} + u_{P,it} \quad (2)$$

Where:

TC_{it} = Total operating and interest expenses for each bank i at time t ;

Rev_{it} = Total operating revenue for each bank i at time t ;

$Y_{n,it}$ = The value of the n^{th} output variable, shown in **Table 1**, at time t ;

$P_{n,it}$ = The price of the n^{th} input variable, shown in **Table 1**, at time t ;

z_{1it} = The value of (log) Total Assets for each bank i at time t ;

$v_{P,it}$ = is the two-sided normally distributed error term;

$u_{P,it}$ = is the (log) cost inefficiency term following a one-sided truncated normal distribution with mean = $\theta_1 z_{1it}$.

Profit efficiency is then calculated as $\exp(-u_{P,it})$ using the Jondrow et al. (1982) estimator.

Appendix 5

A5.1. Cost Elasticity of Scale

The cost elasticity for loans cost is calculated as:

$$\varepsilon_{Y_{1it}} = \frac{\partial \ln TC_{it}}{\partial \ln Y_{1it}}$$

Where:

$\varepsilon_{Y_{1it}}$ = The loan cost elasticity of the i^{th} bank at time t ;

$\frac{\partial \ln TC_{it}}{\partial \ln Y_{1it}}$ = the derivative of the log of total cost obtained from (1) with respect to log of loans (Y_{1it}). It

is calculated as below:

$$\frac{\partial \ln TC_{it}}{\partial \ln Y_{1it}} = \alpha_1 + \alpha_{11} \ln Y_{1it} + \alpha_{12} \ln Y_{2it} + \alpha_{13} \ln Y_{3it} + \delta_{11} \ln P_{1it} + \delta_{12} \ln P_{2it} + \delta_{13} \ln P_{3it} \quad (3)$$

A5.2. Lerner Index

To assess market power, we use the Lerner index, a measure widely applied in the literature.

Specifically, we define the Lerner index of market power for loans as follows:

$$L_{1it} = \frac{P_{1it} - \frac{\partial TC_{it}}{\partial Y_{1it}}}{P_{1it}} \quad (4)$$

Where L_{1it} = the Loan Lerner index for i^{th} bank at time t ; and $\frac{\partial TC_{it}}{\partial Y_{1it}}$ is the marginal cost of loans, calculated as:

$$\frac{\partial TC_{it}}{\partial Y_{1it}} = \frac{\partial \ln TC_{it}}{\partial \ln Y_{1it}} \times \frac{TC_{it}}{Y_{1it}} \quad (5)$$

The first component of the above formula, $\frac{\partial \ln TC_{it}}{\partial \ln Y_{1it}}$, is obtained from (3) above. Note that covariates in the error term of (2) above are used to control for bank-specific effects that may relate to efficiency but may cloud the interpretation of the Lerner index. For example, large or more productive banks may appear more competitive by passing on scale or productivity related cost savings to their clients in the form of lower output prices.

A5.3. Panzar-Rosse H-Statistic

The Panzar-Rosse H-statistic is obtained by estimating a revenue function specified here in a translog form as a function of input prices and control variables:

$$\ln Rev_{it} = \alpha_i + \sum_{n=1}^3 \beta_n \ln P_{n,it} + \frac{1}{2} \sum_{n=1}^3 \sum_{k=1}^3 \beta_{kn} \ln P_{k,it} \ln P_{n,it} + \sum_{n=1}^3 \sum_{k=1}^3 \delta_{kn} \ln P_{k,it} \ln Y_{n,it} \\ + \text{control variables} + \text{time effects} + \varepsilon_{it} \quad (6)$$

Rosse and Panzar (1977) show that this measure is negative for a neoclassical monopolist or collusive oligopolist, between 0 and 1 for a monopolistic competitor, and equal to unity for a competitive price-taking bank in long-run competitive equilibrium. Table A6 report the estimates for the Panzar-Rosse H-statistic using equation (6) estimated as a panel regression with fixed- and time-effects, profit efficiency using equation (2), and cost efficiency using equation (1) estimated via SFA.

Table A6: Model Estimation 2016:Q4 – 2023:Q3

Revenue Function		Profit Function		Cost Function	
LnRev	Coeff	LnRev/TC	Coeff	LnTC	Coeff
PEmp	-1.336***	Loans	0.490**	Loans	0.109
PFA	0.093	Sec	-0.536***	Sec	0.729***
PBF	0.837***	OthInc	-0.376***	OthInc	0.351***
PEmp ²	-0.084***	Loans ²	-0.025**	Loans ²	0.140***
PFA ²	-0.016	Sec ²	-0.039***	Sec ²	0.093***
PBF ²	0.062***	OthInc ²	0.014***	OthInc ²	0.004
PEmp × PFA	0.047	Loans × Sec	0.042*	Loans × Sec	-0.237***
PEmp × PBF	-0.046**	Loans × OthInc	-0.029***	Loans × OthInc	-0.068***
PFA × PBF	0	Sec × OthInc	0.016	Sec × OthInc	0.048***
Loans/TA	0.220*	PEmp	-0.309	PEmp	0
Loans/Dep	-0.040**	PFA	0.052	PFA	0.717***
Equity/TA	-2.279***	PBF	0.014	PBF	0.283***
Year		PEmp ²	-0.081***	PEmp ²	-0.009
2017	0.078**	PFA ²	-0.086***	PFA ²	0
2018	0.176***	PBF ²	-0.025***	PBF ²	0.046***
2019	0.206***	PEmp × PFA	0.108***	PEmp × PFA	0.027***
2020	0.262***	PEmp × PBF	0.025	PEmp × PBF	-0.018***
2021	0.411***	PFA × PBF	0.048***	PFA × PBF	-0.027***
2022	0.475***	Loans × PEmp	0.100***	Loans × PEmp	-0.073***
2023	0.501***	Loans × PFA	-0.064***	Loans × PFA	0.068***
Const.	2.843***	Loans × PBF	0.024*	Loans × PBF	0.005
sigma_w	1.626	Sec × PEmp	-0.095***	Sec × PEmp	0.095***
sigma_e	0.108	Sec × PFA	0.015	Sec × PFA	-0.163***
rho	0.996	Sec × PBF	-0.012	Sec × PBF	0.068***
		OthInc × PEmp	-0.071***	OthInc × PEmp	0.035***
		OthInc × PFA	0.005	OthInc × PFA	0.006
		OthInc × PBF	-0.025**	OthInc × PBF	-0.041***
		LnEquity	0.091***	year quarter	0.002**
		Const.	-1.423	Const.	1.734***
		Mu		Mu	
		LnTA	-0.704***	LnTA	-0.260***
				Equity/TA	-22.512***
				IntInc/Inc	0.851***
		Usigma		Usigma	
		Const.	-1.315	Const.	-0.985***
		Vsigma		Vsigma	
		Const.	-5.127***	Const.	-7.185***
		sigma_u	0.518***	sigma_u	0.611***
		sigma_v	0.077***	sigma_v	0.028***
		lambda	6.726***	lambda	22.195***

Notes: LnREV, LnREV/TC and LnTC denote natural logarithms of revenue, revenue to cost, and cost, respectively; PEMP, PFA, PBF represent natural logarithms of input prices as defined in Appendix 1; Loans, SEC, OthInc are also natural logarithms of outputs as defined in Appendix 1; LnTA is the log of total assets; INTINC/INC is the interest income to total income ratio. The definition of the other variables is given in Appendix 1. The Lambda statistic is a test of the influence of the inefficiency in the model defined as the ratio of the standard deviation of the inefficiency term (u) to the standard deviation of the random error (v) shown in Appendix (4); mu denotes mean inefficiency; and LnTA, Equity/TA, and IntInc/Inc are the inefficiency covariates as shown in Appendix 4.

Table A7 reports the descriptive statistics of the two efficiency measures, the two market power measures, and cost elasticity of loans.

Table A7: Descriptive Statistics 2016Q4-2023Q3

Variable	Obs	Mean	Std. dev.	Min	Max
Cost Efficiency	410	0.883	0.129	0.349	0.994
Profit Efficiency	410	0.923	0.039	0.696	0.982
Lerner Index	328	0.211	0.230	-1.199	0.999
Cost Elasticity of Scale	410	0.838	0.209	0.000	1.412
H-statistic	434	0.177	0.104	-0.135	0.657

Note: The Lerner Index is calculated using data on bank output prices starting in 2018Q3. Output price data prior to 2018Q3 was not available.

References

- Battese, G.E., and Coelli, T.J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics*, 20, 325-332.
- Berger, A. N., Demirgüç-Kunt, A., Levine, R., and Haubrich, J. G. (2004). Bank concentration and competition: An evolution in the making. *Journal of Money, Credit and Banking*, 433-451.
- Berger, A. N., and Mester, L. J. (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? *Journal of Banking & Finance*, 21(7), 895-947.
- Berger, A. N., and Hannan, T. H. (1998). The efficiency cost of market power in the banking industry: A test of the “quiet life” and related hypotheses. *Review of Economics and Statistics*, 80(3), 454-465.
- Berger, A. N., Klapper, L. F., and Turk-Ariss, R. (2009). Bank competition and financial stability. *Journal of Financial Services Research*, 35, 99-118
- Bikker, J. A., Shaffer, S., and Spierdijk, L. (2012). Assessing competition with the Panzar-Rosse model: The role of scale, costs, and equilibrium. *Review of Economics and Statistics*, 94(4), 1025-1044.
- Bolt, W., and Humphrey, D. (2015). A frontier measure of US banking competition. *European Journal of Operational Research*, 246(2), 450-461.
- Elzinga, K. G., and Mills, D. E. (2011). The Lerner index of monopoly power: Origins and uses. *The American Economic Review*, 101(3), 558-564.
- Färe, R., Grosskopf, S., and Margaritis, D. (2024). *Market Power, Economic Efficiency, and the Lerner Index*. Now Publishers and World Scientific Publishing Company.
- Färe, R., and Karagiannis, G. (2017). The denominator rule for share-weighting aggregation. *European Journal of Operational Research*, 260(3), 1175–1180.
- Hicks, J. R. (1935). Annual survey of economic theory: The theory of monopoly. *Econometrica*, 1-20.
- Hughes, J. P., and Mester, L. J. (2013). Who said large banks don't experience scale economies? Evidence from a risk-return-driven cost function. *Journal of Financial Intermediation*, 22(4), 559-585.
- Jondrow, J., Lovell, C. K., Materov, I. S., & Schmidt, P. (1982). On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics*, 19(2-3), 233-238.
- Keeley, M. C. (1990). Deposit insurance, risk, and market power in banking. *The American Economic Review*, 80(5), 1183-1200.
- Koetter, M., Kolari, J. W., and Spierdijk, L. (2012). Enjoying the quiet life under deregulation? Evidence from adjusted Lerner indices for US banks. *Review of Economics and Statistics*, 94(2), 462-480.
- Koutsomanoli-Filippaki, A., Margaritis, D., Staikouras, C. (2009a). Efficiency and productivity growth in the banking industry of Central and Eastern Europe. *Journal of Banking and Finance*, 33(3), 557-567.
- Koutsomanoli-Filippaki, A., Margaritis, D., Staikouras, C. (2009b). Profit efficiency under a directional technology distance function approach. *Managerial Finance*, 35(3), 276-296.
- Kumbhakar, S. C. (2006). Specification and estimation of nonstandard profit functions. *Empirical Economics* 31, 243–260.

- Lerner, A. (1934), The concept of monopoly and the measurement of monopoly power. *Review of Economic Studies*, 1, 157–175.
- Liu, M. H., Margaritis, D., and Tourani-Rad, A. (2008). Monetary policy transparency and pass-through of retail interest rates. *Journal of Banking & Finance*, 32(4), 501-511.
- Panzar, J. C., and Rosse, J. N. (1987). Testing for " monopoly" equilibrium. *The Journal of Industrial Economics*, 443-456.
- Panzar, J. C., and Rosse, J. N. (1982). Structure, conduct, and comparative statistics. Bell Telephone Laboratories.
- Pesaran, M. H., Shin, Y., and Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289-326.
- Rosse, J. N., and Panzar, J. C. (1977). Chamberlin vs. Robinson: An empirical test for monopoly rents. Bell Laboratories.
- Shaffer, S. and Spierdijk, L. (2015). The Panzar–Rosse revenue test and market power in banking. *Journal of Banking & Finance*, 61, 340-347.
- Shin, Y., Yu, B., and Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. Festschrift in honor of Peter Schmidt: *Econometric Methods and Applications*, Springer, 281-314.
- Spierdijk, L., and Zaourasa, M. (2018). Measuring banks' market power in the presence of economies of scale: A scale-corrected Lerner index. *Journal of Banking & Finance*, 87, 40-48.
- Tsionas, E. G., Malikov, E., and Kumbhakar, S. C. (2018). An internally consistent approach to the estimation of market power and cost efficiency with an application to US banking. *European Journal of Operational Research*, 270(2), 747-760.
- Wheelock, D. C., and Wilson, P. W. (2012). Do large banks have lower costs? New estimates of returns to scale for US banks. *Journal of Money, Credit and Banking*, 44(1), 171-199.
- Wheelock, D. C., and Wilson, P. W. (2018). The evolution of scale economies in US banking. *Journal of Applied Econometrics*, 33(1), 16-28.
- Wheelock, D. C., and Wilson, P. W. (2019). New estimates of the Lerner index of market power for US banks. FRB St. Louis Working Paper, (2019-012D).
- Wilson, P. W. (2021). US banking in the post-crisis era: New results from new methods. In *Advances in Efficiency and Productivity Analysis* (pp. 233-264). Springer International Publishing.