Nowcasting Inflation in New Zealand

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Abstract

Inflation is a crucial statistic for Kiwis to know. However, Kiwis do not regularly receive official updates on New Zealand's (NZ's) inflation levels. Statistics on some components of inflation are published monthly. Despite this, statistics on the overall inflation rate in New Zealand are only published quarterly. As a result, it is not easy for Kiwis to know the current inflation levels in New Zealand (NZ). The inflation rate is calculated using the New Zealand Consumer Price Index, referred to as the NZ CPI or CPI.

In my research, I look at how best to nowcast inflation in New Zealand. I create model nowcasts from six different models and adjusted them for various situations. I also source professionals and household nowcasts of inflation from nine data sources and compare them with model nowcasts.

My research finds that univariate models such as ARIMA (autoregressive integrated moving average) and the RBNZ (Reserve Bank of New Zealand) Target model have similar root mean squared errors (RMSEs) compared to multivariate models. The best multivariate model in my research depends on the month of the nowcast. Specifying the models with a rolling window results in a higher root mean square error (RMSE) value than using a recursive approach. This could be because of the quarterly nature of the NZ CPI, which meant means there is not enough data available to the rolling window models to create a good nowcast.

Models that used all the data I had available had access to 16 independent variables. From these independent variables, models are created using only a portion of the data. Specifically, models were made using only soft, economic activity, price, financial, and Phillips curve data. The RMSEs from these models are, on average, similar to or better than when all 16 variables were used. This result may be because adding all the variables into one model may result in parameter proliferation.

Models in my sample generally have a lower RMSE value in quarters where the New Zealand inflation rate was between 0% and 1%. This result may be because many models exclusively produce nowcasts within this range. When the published quarterly inflation rate is outside this range, the RMSE value, on

average, increases by around 150%. Generally speaking, nowcasts for my six models perform best during quarter 1 and worst in quarter 4.

The mean nowcast of inflation by Kiwi households has an RMSE value significantly higher than the best performing univariate benchmark in my sample, the ARIMA model. This finding is consistent with the literature. Meanwhile, the nowcasts of most professionals beat the ARIMA model's nowcasts. However, the one-quarter-ahead forecasts of four out of the seven professionals have a higher RMSE than the ARIMA model nowcasts. The best nowcasts for the NZ inflation rate have a relative RMSE value of around 60% lower than the ARIMA model nowcasts.

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Attestation of Ownership

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

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Of course, a thesis is not the result of one individual but a whole group. I hope to acknowledge the contributions of as many of these people towards my research.

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Chapter 1: Introduction

Inflation is an important statistic for Kiwis to know. Unfortunately for New Zealanders, official statistics on it are not published frequently. New Zealand is the only OECD country where inflation figures are published quarterly (Brockett, 2022).

In New Zealand, inflation can be calculated by using the All Groups New Zealand Consumer Price Index (NZ CPI, or simply CPI). The NZ CPI is an index used to measure inflation. It is the most commonly used index for estimating inflation in New Zealand and is published by Statistics New Zealand, or Stats NZ (Statistics New Zealand, 2022a). Percentage changes in the NZ CPI are referred to as the inflation rate and act as a measure of inflation. The NZ CPI is released with a lag of around 12 working days (Stats NZ DataInfo+, 2022). Over time, the NZ CPI measures the changes in the price of goods and services that Kiwi households buy.

Inflation significantly impacts people worldwide, including Kiwis (Faust & Wright, 2013). As prices change, inflation affects how much New Zealand consumers and businesses spend on expenses. As a result, this may influence whether people choose to spend or save their money. Inflation rates may also influence the choices of businesses on where they set their prices. Labour contracts and mortgage rates are also negotiated with inflation in mind (Faust & Wright, 2013).

Over the past year, inflation has become a more topical issue in New Zealand. In 2022, many examples of a “cost of living” crisis were mentioned in the media (e.g., Dann, 2022; Radio New Zealand, 2022). Inflation exceeded the RBNZ’s mandated target band of 1 to 3 per cent annual inflation ("Reserve Bank of New Zealand (Replacement of Remit for Monetary Policy Committee) Order 2021,") throughout 2022. In the second quarter of 2022, the annual percentage change of the NZ CPI reached a 32-year high (Statistics New Zealand, 2022b). These inflation levels have been the highest since the inflation-targeting era. With such high inflation levels relative to previous years, it is not surprising that Kiwis have started to pay attention to inflation.

Overseas countries have not avoided high levels of inflation either. The United Kingdom reported an annual increase in their consumer price index of 10.1 per cent in the year ending September 2022 (Office for National Statistics (UK), 2022). Additionally, the United States of America experienced inflation levels of 8.2 per cent in the year ending September 2022 (Bureau of Labor Statistics (USA), 2022). Inflation has also been a widely reported topic in the media worldwide (Hart, 2022; Lopez, 2022).

Understanding the current level of inflation in New Zealand could interest households, the Reserve Bank of New Zealand (RBNZ), and the financial sector. This appetite may be why many commercial banks, such as ANZ, produce estimates of the New Zealand inflation rate figure a few days before the official CPI figure is released. The RBNZ also publishes nowcasts every quarter in their monetary policy statement. In this thesis, we see some examples of organisations that publish nowcasts.

Official NZ CPI statistics are published less frequently compared to OECD counterparts. The rest of the OECD countries report inflation levels at least monthly (Brockett, 2022). NZ CPI figures are also published around 12 working days after the end of most quarters (Stats NZ DataInfo+, 2022). As a result, when trying to gain an accurate picture of inflation, nowcasts of inflation may be more critical in New Zealand than in other countries.

With such infrequent official statistics on inflation, it is difficult for Kiwis to get a picture of current inflation levels. People cannot realistically look at thousands of prices simultaneously, do complex mathematics, and then “calculate” current inflation levels. Additionally, infrequent inflation statistics may make it difficult for the RBNZ to achieve their inflation mandate. The RBNZ monetary policy committee aims to keep annual inflation between one and three per cent over the medium term ("Reserve Bank of New Zealand (Replacement of Remit for Monetary Policy Committee) Order 2021,"). They meet seven times a year to discuss how to do this (Reserve Bank of New Zealand, 2022a). When CPI figures are only published four times a year, it may become harder for the committee to know what is happening with inflation. As a result, it could become more difficult for the RBNZ monetary policy committee to control inflation effectively. Considering how impactful inflation is on our daily lives, this is likely, not ideal.

Fortunately, Kiwis may not be at the mercy of Stats NZ if they wish to know what is happening with the New Zealand inflation rate. This is because researchers can try to nowcast inflation. Nowcasting refers to predicting "the present, the very near future, and the very recent past" (Bańbura et al., 2013, p. 196). The predictions from nowcasting are called "nowcasts".

For several years, economic researchers have researched models that have been used to predict inflation levels well into the future. However, the academic literature on nowcasting inflation has only developed recently. Researchers have published most nowcasting inflation literature over the past ten years. The literature on nowcasting inflation is relatively sparse compared to the literature on forecasting inflation. This may make it more difficult to nowcast inflation accurately.

As far as I am aware, researchers have published no research on nowcasting New Zealand inflation. Therefore, to give accurate inflation estimates in real-time, we need to know what methods work best for nowcasting the NZ inflation rate. To solve this problem, I have three questions I wish to answer through my research:

1. Which models and data could be best suited to nowcast the New Zealand inflation rate (the percentage change in the NZ CPI)?
2. Are there situations where nowcasting models perform better or worse than usual?
3. Can a model nowcast outperform New Zealand professional forecasters and Kiwi household forecasts?

The novelty of my research is twofold. The first is its contribution to New Zealand's nowcasting inflation literature. To my knowledge, I have not found any research on nowcasting inflation in New Zealand. However, there is at least one paper that does have strong similarities. Matheson (2005) paper is such a paper. It focuses on creating short-term forecasts for the New Zealand inflation rate, GDP (Gross Domestic Product) growth, interest rates (90-day bank bill), and the nominal trade-weighted exchange rate. While similarities may exist between Matheson (2005) and my thesis, Matheson (2005) is a paper on short-term forecasting, not nowcasting.

The second novelty is the use of more recent data and techniques. Some papers have looked at predicting inflation levels using older data (e.g., Matheson, 2005). However, this research is one of the first that incorporates NZ CPI data from the past few years, including data from the COVID-19 pandemic. I specifically examine how the COVID-19 pandemic has impacted the ability to estimate the real-time inflation rate in New Zealand. My research also looks to implement more modern trends in the forecasting and nowcasting literature. For example, I use a neural network in my thesis to examine its effectiveness in nowcasting New Zealand inflation.

My thesis is structured as follows. Chapters 2 to 6 are related to my literature review. These chapters review fundamental concepts, the state of the nowcasting inflation literature, and the models and techniques I use. I also look at factors that can influence the accuracy of inflation nowcasts. Lastly, in these chapters, I will examine papers about professional and household inflation predictions. Chapters 7 and 8 explain the methodology I use in my research. Chapter 9 is where I explain my results and findings. Chapter 10 concludes this thesis. I will discuss limitations and future directions in Chapter 10. An Appendix at the end of the thesis supplements my methodology and results.

Chapter 2: Definitions and Basic Concepts

2.1 General Definitions

It is essential to clarify the definitions of some key terms in this thesis. This is because different papers use these terms differently. The definitions below are general and broad. In Chapter 7, I slightly adjust some of these definitions to be more specific to my research.

Inflation is a rise in the average price of goods and services over a specific timeframe. Inflation is generally measured by tracking the prices of various goods and services over time. If the price of these goods generally rises over time, this is considered inflation. If one or two goods rise in value, this is not automatically considered inflation. This is because inflation tracks the prices of a diverse range of goods, not just one or two. In many countries, such as New Zealand, it is typical to measure inflation using a consumer price index (CPI). Consumer price indices, such as New Zealand's, measure the change in the price of goods and services that consumers buy (Stats NZ DataInfo+, 2022). The percentage change in a consumer price index, such as the NZ CPI, over a certain time period, is called the inflation rate. It is usually expressed as a percentage.

Nowcasting refers to predicting "the present, the very near future, and the very recent past" (Bańbura et al., 2013, p. 196). In other words, nowcasting generally involves predicting the outcome of something that is currently happening, that happened very recently, or that will happen very soon. The results that someone gets from nowcasting are called "nowcasts".

Forecasting involves predicting the outcome of something that has not happened yet (Hyndman & Athanasopoulos, 2018). Forecasting generally involves anticipating what will happen beyond the immediate future. Forecasting could involve foretelling what will happen in only a few months. Alternatively, forecasting could involve predicting what may happen in several years. The results that someone gets from forecasting are called "forecasts".

2.2 Forecasting and Nowcasting in General

Forecasting and nowcasting likely have a history spanning thousands of years. For example, when humans looked at the weather outside and said, "It will rain in 10 minutes", they would have been nowcasting the weather. Or, when humans estimated how many years they might have left to live, they would be making a forecast. We still forecast and nowcast things today. For example, if we are in the shower and estimate how much water we are using, we are making a nowcast. Additionally, we are making a forecast when we predict how much money we will spend over the next year. Forecasting and nowcasting appear all the time in our lives.

In the academic literature, there are many papers on nowcasting and forecasting. For example, in New Zealand, nowcasting literature has been published on housing construction (Holmes et al., 2009), rainfall in New Zealand (Gray et al., 2005; Larsen & Gray, 2003), and flight planning (Eckermann et al., 2019). Nowcasting and forecasting are techniques found heavily in Economics literature as well. For example, many papers have been written on nowcasting economic variables such as GDP and interest rates (e.g., Eickmeier & Ng, 2011; Matheson, 2005; Richardson et al., 2021).

It is essential to know how accurately we can forecast or nowcast something (Hyndman & Athanasopoulos, 2018). As a result, I will later discuss how useful different models have been in nowcasting and forecasting inflation. In some situations, it is easier to nowcast or forecast something than in others (Hyndman & Athanasopoulos, 2018). For example, if we have a job with a fixed salary, it is not difficult to predict how much money we will make in the next month. However, this is much more difficult for a business owner with variable income. Without knowing how easy it is to project something, we may waste our time trying to nowcast or forecast a variable.

2.3 Evaluating the Forecasting and Nowcasting Potential of a Model

When forecasting a variable, we may wish to see how well our models perform. To do this, we can implement a procedure that I refer to as pseudo-forecasting. Pseudo-forecasting involves simulating the experience of a model doing forecasting in real-time (Rünstler et al., 2009 is one of many examples of psuedo-forecasting in practice). The difference between "pseudo-forecasting" and "forecasting" is that when pseudo-forecasting, the modeller is not technically forecasting in real-time. This is because pseudo-forecasting does not involve predicting something that will actually happen in the future. For example, a model may simulate forecasting GDP for the first quarter of the year 2000, but in reality, it may be the year 2023.

To successfully pseudo-forecast, we can only use data available at the time we are "forecasting" for (Petropoulos et al., 2022). For example, suppose we were pseudo-forecasting the value of milk exports sent to Australia in the first quarter of 2000. Presume that I am making this pseudo-forecast as if today were 1 January 1998. In such a case, I am only supposed to use data that would have been available on 1 January 1998. I can use data published before or on 1 January 1998. However, I should not use data published after the 1st of January 1998.

When available, vintage datasets help us only use data available at the time that we are "predicting" for. Vintage datasets are available for some large countries such as the USA (e.g., Federal Reserve Bank of Philadelphia, n.d.). A vintage dataset contains the data available for a particular variable at a particular time. If possible, academics should use a vintage dataset because data is subject to revisions. For example, as of October 2022, Statistics New Zealand said that GDP grew 1.7% in the quarter ending June 2022 (Statistics New Zealand, 2022c). However, as Stats NZ gains extra information, they may revise this figure. Using this more accurate and more updated information may give someone an unfair advantage when pseudo-forecasting (Petropoulos et al., 2022).

Unfortunately, vintage datasets may be hard to come by for small countries. In such cases, we may not be able to confidently say that we are only using data available at the time they are "predicting" for. If there is no vintage dataset, we would need to download the most up-to-date version of our data and use it. However, we should know that these values may have been adjusted since they were first published (Petropoulos et al., 2022). As a result, what we are using is not a vintage dataset.

Using this approach in the previous paragraphs means that one will also have to estimate when a specific variable was previously released. The problem is that this is not easy. For example, it is difficult for someone to prove when the unemployment rate was released 30 years ago. As a result, a practical approach could be to find out when the variable is being released currently and then presume this holds for all periods.

I was not aware of an available vintage dataset I could have used when doing my research, so I use the approaches mentioned in the previous paragraph in the later chapters of my thesis. However, it has come to my attention after completing my research that a vintage dataset does exist for the NZ CPI (Federal Reserve Bank of St. Louis, n.d.). I acknowledge that it could have been ideal to incorporate this vintage dataset in my research. This would have made sure that I was only using data available at the timeframes that I was "predicting" for.

If we want to evaluate nowcasts with a similar procedure as pseudo-forecasting, we would use pseudo-nowcasting instead. Pseudo-nowcasting involves simulating the experience of someone nowcasting in real-time. Pseudo-nowcasting uses the same process as pseudo-forecasting with one difference. Instead of forecasting, we are now nowcasting.

We need to split the data into a training set and a test set to pseudo-forecast or pseudo-nowcast successfully. A training set is the data used to create a model which forecasts or nowcasts a variable (Hyndman & Athanasopoulos, 2018). Training sets are also known as estimation samples. There should be enough training set data to calibrate the model accurately. However, we still need to leave some data to test the model when pseudo-forecasting or pseudo-nowcasting. This data used to test the model is called a test set (Hyndman & Athanasopoulos, 2018). A test set can also be referred to as an evaluation sample. To test for accuracy, we should compare how well their model predicts that variable during the test set period.

2.4 RMSE as a Measure of Accuracy

Imagine we have created our model predictions and calculated nowcasts for a model. Now, we need a measure of accuracy to determine our models' performance. The root-mean-square-error, or RMSE, can help us do this. The most common metric to evaluate a model's forecasting or nowcasting accuracy in economics literature seems to be the RMSE. This is despite critiques being levelled at the use of it in the past (e.g., Armstrong & Collopy, 1992). RMSE can be calculated using the formula

$$RMSE = \sqrt{\frac{1}{n}\left(\sum_{i=1}^{n} {\varepsilon_t}^2\right)}$$

where ε_t represents the forecast error at time t (Hyndman & Koehler, 2006). The lower the RMSE, the more accurate the forecasts are.

A related measure called the relative RMSE can also be used to compare models (Hyndman & Koehler, 2006). The relative RMSE is calculated using the formula,

$$Relative\ RMSE = \frac{Model\ of\ Interest\ RMSE}{Benchmark\ Model\ RMSE}$$

where the benchmark model can be any model we wish to compare the projections to. In Chapter 4, I will discuss some standard benchmarks for comparing inflation predictions.

The relative RMSE can be used to compare the RMSEs of different models more quickly. The relative RMSE has been used in many forecasting and nowcasting papers (e.g., Faust & Wright, 2013; Fulton & Hubrich, 2021; Jaworski, 2021). This is because the RMSE of one model is not so informative unless we have something else to compare it to. It is difficult to ascertain whether an RMSE of 0.5, for example, is “good” or “bad” without context.

We can interpret the relative RMSEs as follows. A relative RMSE of 1 means that the model of interest is as accurate as the benchmark model. A relative RMSE of less than 1 means the model of interest creates better predictions than the benchmark model. Meanwhile, a relative RMSE of more than 1 means the model of interest creates less precise projections than the benchmark model.

The RMSE is sensitive to outliers (Hyndman & Koehler, 2006). This is because the errors are squared. If ε_t is abnormally large at one point in time, then ${\varepsilon_t}^2$ will increase the impact of this abnormality. As a result, $mean({\varepsilon_t}^2)$ will experience a dramatic increase, meaning that $\sqrt{mean(\varepsilon_t{}^2)} = \sqrt{\frac{1}{n}(\sum_{i=1}^{n} \varepsilon_t{}^2)}$, or the RMSE, will increase significantly. As a result of this, RMSE rewards consistently accurate models with few large outliers.

2.5 Statistical Significance Tests

In the past, researchers have used statistical significance tests to determine whether one set of projections is better than another set. One famous example is the Diebold-Mariano test (Diebold & Mariano, 2002). However, statistical significance tests have recently been criticised in various papers. When forecasting, the results of statistical significance tests can be misinterpreted, and the test themselves could be misapplied (Kostenko & Hyndman, 2008). Besides this, these tests require a good number of observations to prove statistical significance (Ashley, 2003). If a statistical significance test was applied to NZ inflation rate nowcasts, it may be more difficult to gain enough observations so that these tests will produce a statistically significant result. This is because the NZ CPI is a variable released only four times a year.

Chapter 3: State of the Nowcasting Inflation Literature

This chapter gives an overview of the different strands of literature related to nowcasting inflation. Despite the long-standing interest in forecasting inflation and nowcasting other economic variables, the academic literature on nowcasting inflation has only developed recently. Most literature on this subject seems to have been published in the past ten years.

3.1 Strands of Literature in the Nowcasting Inflation Area

The academic papers on nowcasting inflation can be categorised into four main strands. Despite this, some papers could be placed into more than one of these strands.

The first strand consists of literature that tests different nowcasting approaches. There are a variety of methods that could be used for nowcasting. However, while some may be appropriate for nowcasting one type of economic variable, they may not be as appropriate for nowcasting other economic variables. For example, a Phillips curve may be appropriate for nowcasting inflation but is probably not for forecasting unemployment rates. As a result, it is necessary to examine the suitability of different methods for our intended purpose.

Many approaches below have been used to nowcast inflation or food price inflation (changes in the price of food). These include[1]:

- AR models (Goshima et al., 2021; Knotek & Zaman, 2017; Marsilli, 2017)
- ARIMA models or variations of an ARIMA (Macias & Stelmasiak, 2019; Macias et al., 2022)
- Random walk model (Macias & Stelmasiak, 2019; Macias et al., 2022; Modugno, 2013)
- Phillips curve (Marsilli, 2017)
- Neural networks and machine learning (Goshima et al., 2021)
- Dynamic factor models (Funke et al., 2015; Giannone et al., 2006; Knotek & Zaman, 2017; Mariano & Ozmucur, 2021; Modugno, 2013; Yadav & Das, 2021)
- Vector autoregressions (VAR) and variations of a VAR (Beber et al., 2015; Clements & Galvão, 2013; Mariano & Ozmucur, 2021)

[1] Note that some of these models will be discussed in more detail in Chapter 4.

- MIDAS-R (Knotek & Zaman, 2017; Mariano & Ozmucur, 2021)
- MIDAS-U (Rufino, 2017)
- Model averaging (combination nowcasts) (Mariano & Ozmucur, 2021)

The results of this literature are generally mixed. While some papers find positive results for these models, other papers find that some other benchmark manages to beat these models.

Some of the models mentioned above can take on different specifications. For example, take the Phillips curve model. Marsilli (2017) implemented a MIDAS augmented Phillips curve, extending the triangle model of Gordon (1990) to nowcast inflation. Meanwhile, Goshima et al. (2021) use a Phillips curve framework similar to Stock and Watson (1999). In the same way, neural networks can be used in many ways. For example, Goshima et al. (2021) used news articles and processed them through a neural network to help nowcast inflation. The approach of Goshima et al. (2021) is a different nowcasting approach to other typical approaches.

The second strand of literature on nowcasting inflation looks at a related area: food price inflation. Food price inflation is the average change in the cost of food over a specific timeframe. A few papers have been published on this topic over the past few years (Jaworski, 2021; Macias & Stelmasiak, 2019; Macias et al., 2022).

Nowcasting food price inflation may have recently become a lot easier. This becomes easier because researchers can now web-scrape food price data online from places such as supermarkets (Macias & Stelmasiak, 2019 is an example of this). Web scraping involves extracting data from a website, usually done by a bot (Dogucu & Çetinkaya-Rundel, 2021). The discovery of web scraping may be why more literature has recently appeared on this topic in the past couple of years.

The literature on food price inflation has two main findings. First, food price inflation estimates can be obtained through web scraping without requiring official statistics (Jaworski, 2021). These estimates can sometimes outperform benchmark models, judgemental methods, and model combinations (Macias & Stelmasiak, 2019). The second finding is that these accurate food price inflation estimates can be provided before the official statistics on food price inflation are published (Jaworski, 2021).

At first sight, nowcasting food price inflation may seem like an insignificant area of literature. However, 19.29% of the NZ CPI is weighted towards food (Statistics New Zealand, 2020). Additionally, food price inflation statistics in New Zealand are released monthly (Stats NZ DataInfo+, 2022). But unfortunately for nowcasters, recent months suggest these statistics are only released around two weeks after the reference month (Statistics New Zealand, 2022d). If we can create timely and accurate nowcasts of food price inflation, then it may be easier for us to create timely and accurate nowcasts of the New Zealand inflation rate.

The third strand of literature looks at what happens when different data types are used. As the literature is relatively new, it may not be fully established what data are best to use to nowcast inflation.

Many papers in this area look at more novel methods of nowcasting inflation. For example, Rambaccussing and Kwiatkowski (2020) and Goshima et al. (2021) use the content of local newspapers to help estimate inflation. They find that the content of UK and Japanese newspapers can be helpful for nowcasting inflation. Goshima et al. (2021) found that their news-based business cycle index could discover Japan's economic activity changes. The web scraping literature that nowcasts food price inflation also falls under this category.

The fourth strand of literature looks to nowcast inflation in different countries. Different countries have different data available for nowcasting purposes. Each country also has differences in how its economy operates. As a result, the approach of researchers for nowcasting inflation may need to differ between countries.

Research has been published for multiple parts of the world. This includes larger areas such as the USA (Beber et al., 2015; Giannone et al., 2006; Knotek & Zaman, 2017; Marsilli, 2017; Modugno, 2013) and the Euro area (Modugno, 2013). These areas tend to have more literature on inflation than other areas. Additionally, papers on nowcasting inflation have also been published for the United Kingdom (Rambaccussing & Kwiatkowski, 2020), China (Funke et al., 2015), India (Yadav & Das, 2021), Philippines (Mariano & Ozmucur, 2021), and Japan (Goshima et al., 2021). From this literature, it is unclear whether the best approach for nowcasting inflation depends on the country one is trying to nowcast for.

3.2 New Zealand Literature

As far as I am aware, there is no existing literature on nowcasting inflation for New Zealand. However, one paper looks at short-term forecasting of inflation and has some similarities to my research (Matheson, 2005). Matheson (2005) is a discussion paper from the RBNZ. It focused on predicting the New Zealand inflation rate, GDP growth, interest rate (90-day bank bill), and the nominal trade-weighted exchange rate. The findings of Matheson (2005) are significant for my research because they are specific to New Zealand.

The time that the paper looked to predict these values was between one and eight quarters ahead. In other words, Matheson (2005) looked to produce short-term inflation forecasts and compare these with the RBNZ's forecasts.

Importantly, this paper has three key differences compared to my thesis. Firstly, and most importantly, this paper only looks to forecast inflation; it does not look at nowcasting inflation. Secondly, my thesis uses a broader variety of forecasting methods than Matheson (2005). Thirdly, my thesis uses more recent data to estimate my model. My thesis can enrich academic literature in these three areas.

To create forecasts, Matheson (2005) used four different models: autoregressive models, bivariate regressions, factor models, and vector autoregressions. Then, it compared these forecasts to the RBNZ's forecasts. Matheson used 386 indicators in their models, including a variety of "forward-looking and backward-looking indicators" (Matheson, 2005, p. 6). All indicators were aggregated to a quarterly level when needed.

Matheson made two critical findings. Firstly, Matheson found that the RBNZ's inflation forecasts outperformed all the models when predicting future inflation values between one quarter and four quarters ahead. However, some models outperformed the RBNZ's inflation forecasts beyond four quarters. These models that outperformed the RBNZ's forecasts were either "factor models with one or two factors, or the mean/median of a range of bivariate forecasts" (Matheson, 2005, p. 17). These models also contained a large number of indicators. Secondly, Matheson found that for short-term inflation forecasting, allowing a factor model to use all the indicators available is best. It is not as clear whether this is the case in the longer term.

Chapter 4: Models and Techniques for Nowcasting/Forecasting

This chapter overviews the models and techniques used in the methodology and results chapters (Chapters 7 to 9). As a general guideline, reliable models for predicting future inflation levels are scarce. Inflation forecasting models become unstable as time passes, meaning their accuracy decreases (Stock & Watson, 2010). This phenomenon has been documented in the past (e.g., Cogley & Sargent, 2005; Stock & Watson, 2007). The Covid-19 pandemic may also have contributed to models becoming less accurate for predicting inflation.

Most papers I cite in Chapters 4 and 5 are related to forecasting inflation. This is because there is much more literature on the topics below regarding forecasting than nowcasting inflation. Many of the findings in this literature review are still relevant, even if they come from papers that forecast inflation.

Firstly, it is essential to look at benchmarks. Imagine we conduct a pseudo-nowcasting exercise. After we implement our pseudo-nowcasting exercise, we will have our nowcasts. If we wish to determine how useful a set of forecasts or nowcasts are, we should compare our predictions to a benchmark. A benchmark is a point of reference to which we can compare our model's results. This benchmark can be predictions from one or more models of our choice, or professional forecasters/nowcasters.

We could theoretically pick a variety of models for a benchmark. There are some common choices for a benchmark, of which I cover four in the following pages: the random walk model, autoregressive models, the ARIMA model, and a target forecast/nowcast.

4.1 Random-Walk (Naïve) Model

A random walk or naïve model predicts future the inflation rate to be the same as the last known inflation rate value. For example, imagine the most recent quarterly inflation rate was 1.4%. The nowcast and forecast for all other future inflation rates would be 1.4%. Mathematically, this means that

$$\hat{y}_{T+h|T} = y_T$$

where $\hat{y}_{T+h|T}$ is the estimate of y_{T+h} given value y_T (Hyndman & Athanasopoulos, 2018). Many papers have used a naïve forecast as a benchmark for evaluating forecasts (e.g., Altug & Çakmaklı, 2016; Aparicio & Bertolotto, 2020; Aron & Muellbauer, 2013; Faust & Wright, 2009; Groen et al., 2009; Ülke et al., 2018) and nowcasts (e.g., Knotek & Zaman, 2017; Modugno, 2013).

Despite how basic this model is, a naive forecast can perform very well in some circumstances. For example, Atkeson and Ohanian (2001) famously reported that random walk forecasts did better than a set of NAIRU Phillips curves. However, it was later found that such a result depended on the sample period and forecast horizon (Stock & Watson, 2008).

4.2 Autoregression (AR) and ARIMA Models

A second group of benchmark models consists of autoregressions (AR) and autoregressive integrated moving average (or ARIMA) models. These are two forms of a univariate model. Univariate models only use one variable to create forecasts and nowcasts. Generally, this variable is past values of the variable being predicted.

AR and ARIMA models are typically used for stationary time series data only (Hyndman & Athanasopoulos, 2018). Stationary datasets have constant mean and variance, and the covariance of the dataset is independent of time. Stationary time series data should hold the same characteristics over time, no matter when we observe the dataset (Hyndman & Athanasopoulos, 2018).

Not all time series data are stationary. However, data must be made stationary before using an ARIMA model. One way to do this is to calculate the difference in values between consecutive observations in the dataset and use this data instead (Hyndman & Athanasopoulos, 2018). The process of doing this is called differencing. Differencing helps to reduce or eliminate trends and cycles in the dataset. Sometimes, a dataset will not be stationary after differencing the data once. In this case, we could repeat the differencing process with the already differenced data as needed until the data is stationary. We can determine whether a time series is stationary using stationarity tests, such as the KPSS test (Kwiatkowski et al., 1992).

Autoregressions predict future values of a variable by using a linear regression. The x-variables of this linear regression are past values of the variable being forecasted or nowcasted. AR models can be written as

$$y_t = c + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \cdots + \phi_p y_{t-p} + \varepsilon_t$$

where y_t is the value of the variable at time t, ϕ represents the coefficients, ε_t is the error term at time t, and c is a constant (Hyndman & Athanasopoulos, 2018). We can refer to an autoregression model as an $AR(p)$ model, where p is the number of past variables of the variable being used.

Meanwhile, ARIMA models combine an autoregression model (AR), a moving average (MA) model, and some differencing of the dataset. The “integration” (I) part of ARIMA refers to the number of differences needed to make the dataset stationary.

An MA model also predicts future values of a variable by using a linear regression. Despite this, the difference between an AR and MA model is that the x-variables of the MA model are past forecast errors. Moving average models can be written as

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_p \varepsilon_{t-q}$$

where y_t is the value of the variable at time t, θ represents the coefficients, ε_t is the error term at time t, and c is a constant (Hyndman & Athanasopoulos, 2018). We can refer to a moving average model as an $MA(q)$ model, where q is the number of past error terms of the variable being used.

A non-seasonal ARIMA model can be specified as

$$y'_t = c + \phi_1 y'_{t-1} + \phi_2 y'_{t-2} + \cdots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \cdots + \theta_p \varepsilon_{t-q} + \varepsilon_t$$

where y'_t is a dataset that has been differenced at least once (Hyndman & Athanasopoulos, 2018). We can refer to ARIMA models as an $ARIMA(p, d, q)$, where p is the number of lags of the y-variable, d is the number of differences required to make the dataset stationary, and q is the number of past error terms of the y-variable used. A small numbers of papers in the inflation literature have also used variations of an ARIMA model, such as a seasonal ARIMA model (e.g., Macias et al., 2022).

Before forecasting or nowcasting with an ARIMA model, we must choose the best model. Specifically, we need to choose the number of AR and MA terms and how many times the series needs to be differentiated. There are numerous specifications of an ARIMA model that could be chosen. So, to pick the best one, researchers generally use an information criterion. The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are two information criteria that could do this task. The AIC and BIC examine how well a model fits a data set but will penalise models as the number of parameters increases. For an ARIMA model, the formulas for the AIC and BIC are as follows.

$$AIC = -\ 2log(L) + 2(p + q + k + 1)$$

$$BIC = AIC + [\log(T) - 2](p + q + k + 1)$$

where L is the data's likelihood, $k = 1$ when $c \neq 0$ (constant does not equal zero) and $k = 0$ when $c = 0$ (Hyndman & Athanasopoulos, 2018). T represents how many observations were used for estimating the model (Hyndman & Athanasopoulos, 2018).

Many times, AIC and BIC agree on which model is best. When using AIC or BIC, the "best" model is the one with the lowest AIC or BIC value. Generally, the best information criterion to use depends on the context (Emiliano et al., 2014).

Many papers have used AR and ARIMA models to compare their inflation forecasts (e.g., Ang et al., 2007; Moser et al., 2007; Stock & Watson, 2008). Nowcasting papers have also used AR, ARIMA, or slight variations on these models (e.g., Goshima et al., 2021; Knotek & Zaman, 2017; Macias & Stelmasiak, 2019; Richardson et al., 2021). Generally, most of these papers mention how the models they are testing outperform the AR or ARIMA benchmark. This is not surprising because of the positive publication bias in the academic literature.

4.3 Inflation Target Forecasts/Nowcasts

Inflation target models are another type of benchmark. They are helpful in countries where the reserve bank has a target band that they need to keep inflation in between. For example, the Reserve Bank of Australia aims to keep Australian inflation levels between a target band of two to three per cent (Reserve Bank of Australia, n.d.). Many economies, such as emerging economies, have successfully pushed inflation near their inflation targets (Agarwal & Ghosh, 2021). As a result, simply predicting that inflation will stay within the target band area for a particular country could be a good idea.

There are a few papers in this space of literature. Diron and Mojon (2008) found that inflation targets can be used as a good forecasting benchmark. Using a dataset of inflation-targeting countries, Diron and Mojon (2008) found that inflation target forecasts perform better than some forecasting models and professional forecasters. Similar results have been found in Diron and Mojon (2005). Beechey and Österholm (2010) found that incorporating information about a country's inflation target could improve the forecasting performance of a Bayesian autoregressive model. All studies mentioned above include New Zealand as one of the countries used in their study.

The following few pages will look at some techniques that are not generally used as benchmark models. Specifically, I will look at neural networks and machine learning, MIDAS models, and temporal aggregation.

4.4 Neural Networks and Machine Learning

As computer software advances further, new developments occur in the literature. Two of these developments include neural networks and machine learning. Neural networks and machine learning can be used to predict inflation. Machine learning refers to computer systems that can learn from experience through computational methods (Zhou, 2021). Machine learning can be applied in many different forms. So can neural networks, a type of machine learning. They can produce forecasting/nowcasting methods that mimic the human brain (Hyndman & Athanasopoulos, 2018). This way, neural networks use training data to "learn" how to specify a model best.

Neural networks and machine learning have been a positive development in the literature. Some results have been promising, as most papers seem to have found these tools as good as, or better than, traditional models for forecasting inflation (Araujo & Gaglianone, 2020; Baybuza, 2018; Medeiros et al., 2021). Despite this, some literature has found that machine learning models work better in some circumstances and not in others (e.g., Ülke et al., 2018).

A few pieces of New Zealand literature on nowcasting have used these tools for nowcasting economic variables. One thesis (Fan, 2019) used machine learning methods to nowcast New Zealand GDP. Specifically, Fan (2019) used machine learning methods such as Xgboost, Lightgbm, Ridge Regression, KNearest Neighbors, Lasso, Adaboost and Support Vector Machine. Fan (2019) found that a combination nowcast of nine machine learning methods outperformed a random walk model and ARIMA model for nowcasting New Zealand GDP. An RBNZ working paper (Richardson et al., 2021) found that machine learning models could create more accurate forecasts when nowcasting New Zealand GDP than AR and dynamic factor models. They also suggest that machine learning methods could improve the RBNZ's forecast accuracy.

4.5 MIDAS Models (MIDAS-R and MIDAS-U)

Mixed-data sampling models, or MIDAS models, are another type of model that can be used to nowcast inflation. MIDAS models can potentially use data of different frequencies if the data is aligned correctly. By using all the data available, we avoid potentially losing information that could be useful for nowcasting the variable of interest (Giannone et al., 2006). As a result, predictions using MIDAS may become more accurate (Andreou et al., 2013; Yadav & Das, 2021). MIDAS models were introduced in Ghysels et al. (2004) and have been used widely for nowcasting.

To get a flavour of the MIDAS regression, I will use an example from Asimakopoulos et al. (2013). Imagine that it is currently time t. We wish to predict future values of variable Y. It is an annual variable, so we can denote this as Y^A. Time t is the date of release of the last known variable, so we will only use data released at or before time t. If we wish to estimate Y^A at time $t+1$, then we are looking to predict Y^A_{t+1}. To predict variable Y^A_{t+1}, the example from Asimakopoulos et al. (2013) used lags of variable X. Variable X is a quarterly variable (X^Q). In a similar fashion to Asimakopoulos et al. (2013), we can write the regression below.

$$Y^A_{t+1} = \beta_0 + \sum_{i=0}^{N_Q-1} \beta_j X^Q_{N_Q-i,t} + u_{t+1}$$

In the regression above, N_Q equals the number of quarters in a year (four). However, a MIDAS model can be specified with more data than just the last four quarters of data available. In this regression, β_j represents the coefficient for each lag of X^Q. The value of j changes depending on the value of i, as shown in the next equation below.

Another way of representing the previous equation is as follows.

$$Y_{t+1}^A = \beta_0 + \beta_1 X_{N_Q,t}^Q + \beta_2 X_{N_Q-1,t}^Q + \beta_3 X_{N_Q-2,t}^Q + \beta_4 X_{N_Q-3,t}^Q + u_{t+1}$$

The specification of the model above can be estimated using OLS. There are no restrictions on the parameters of an OLS model. Using OLS would be indicative of a MIDAS-U (unrestricted MIDAS) regression. A MIDAS-U regression can be estimated using simple linear regression.

Unfortunately, this approach runs into problems when there are more variables and lags. For example, imagine we were predicting the value of the same yearly variable, but the quarterly variable was now available daily. Including daily data could quickly result in too many parameters being added to the model, or parameter proliferation. Parameter proliferation caused by too many variables and lags may be problematic from a theoretical point of view.

MIDAS-R (restricted MIDAS) solves this problem. In the case of Asimakopoulos et al. (2013), the model above estimated as a restricted MIDAS (MIDAS-R) is below,

$$Y_{t+1}^A = \mu + \beta \sum_{j=0}^{q_X^Q - 1} W(L^{N_Q};\theta)\, X_{t-j}^Q + \ \varepsilon_t$$

where $W(L^{N_Q};\theta)$ is a weighting function that assigns weights to each lag in the data. L^{N_Q} is a quarterly lag operator, and θ helps to determine the shape of the weighting function. q_X^Q is the "number of lags of the high frequency variable after it has been transformed to low frequency using the lag polynomial" (Asimakopoulos et al., 2013). The weighting function encapsulates the relationship between the high-frequency data (x-variable) and the lower-frequency yearly data (y-variable) (Karagedikli & Özbilgin, 2019).

The presence of the weighting function can significantly reduce the number of parameters that need to be estimated. This is because an additional beta parameter is not added for each additional lag of X^Q, unlike when using MIDAS-U. Only one beta is needed because the weighting function is there to help appropriately weight each lag of X^Q. The weighting function sums to one, so therefore, β is there to change the magnitude of the coefficients as needed. This is needed, for example, if a researcher is nowcasting a variable with a large value, such as American GDP.

With fewer parameters to estimate, there is less chance of running into parameter proliferation problems. However, if enough variables are added to a MIDAS-R model, then there is always still the possibility of overfitting the model.

The weighting function used is not fixed and can be chosen. Examples of potential weighting schemes are exponential Almon lag, Beta, Gompertz, Log-Cauchy, and Nakagami (Ghysels et al., 2016). One of the literature's most commonly used weighting schemes seems to be the exponential Almon lag polynomial (as found in Karagedikli & Özbilgin, 2019; Schumacher, 2016). Ghysels et al. (2007) found that the exponential Almon lag polynomial can take on various shapes even with only a few parameters. As a result of this flexibility, using the exponential Almon lag polynomial should help to model many variables appropriately.

Asimakopoulos et al. (2013) mention that $W(L^{N_Q};\theta)\,X_t^Q$, or the distributed lag polynomial from the previous equation, can be given as:

$$W(L^{N_Q};\theta)\,X_t^Q = \sum_{i=0}^{N_Q-1} \omega_j\,(\theta_X^Q)\,X_{t-j}^Q$$

In my research, I use the exponential Almon lag polynomial to replace $\omega_j\,(\theta_X^Q)$. It is a flexible and common weighting scheme that can take on various specifications (Ghysels et al., 2007). It only requires two parameters, $\theta = (\theta_1, \theta_2)$, to estimate the regression. In the example from Asimakopoulos et al. (2013), the exponential Almon lag would be defined as follows:

$$\omega_j\,(\theta_X^Q) = \omega_j(\theta_1, \theta_2) = \frac{\exp\,(\theta_1 j + \theta_2 j^2)}{\sum_{j=1}^{m} \exp\,(\theta_1 j + \theta_2 j^2)}$$

We must provide starting values for the model's parameters to estimate a MIDAS-R regression. After choosing these starting values, the MIDAS-R regression will use an optimisation algorithm to pick the most appropriate parameter values, using the initial values as a starting point. Various optimisation methods can be chosen, such as non-linear least squares and the Broyden–Fletcher–Goldfarb–Shanno algorithm, also known as BFGS (Ghysels et al., 2016).

The starting values for the MIDAS-R regressions can affect the regression results (Ghysels et al., 2004). As a result, we need to choose appropriate starting values. To choose starting values, we can estimate what we think the appropriate starting values are. We could also use multiple optimisation methods. Specifically, Ghysels et al. (2004) suggest using the parameter values given by a previous optimisation algorithm as starting values for the next optimisation algorithm. Next, we would repeat this process. The values given from the penultimate optimisation method would then be used to run the final MIDAS-R regression. The final regression will become the regression used for nowcasting or forecasting the y-variable. Alternatively, we could start with the idea that all parameters have equal weights and no impact, which could deliver good empirical results (Libonatti, 2018).

MIDAS models have enjoyed a large share of the spotlight in the nowcasting literature. Additionally, MIDAS models have also been used in the forecasting literature. Some papers find good results for MIDAS (e.g., Clements & Galvão, 2008). Kuzin et al. (2011) found that MIDAS produced better-performing forecasts for short-term horizons (until four to five months) but not as well-performing forecasts over longer-term horizons (until nine months) compared to a mixed-frequency vector autoregression. On the flip side, other papers have found mixed results for MIDAS (e.g., Mariano & Ozmucur, 2021).

Some papers have examined which MIDAS model performs best: a MIDAS-U model or a MIDAS-R model. Foroni et al. (2015) found that when the sampling frequencies are close (e.g., the dependent variable is quarterly and the independent variable is monthly), a MIDAS-U model performs better than a MIDAS-R model. However, when the sampling frequencies are further away (e.g., the dependent variable is quarterly, but the independent variable is daily), MIDAS-U's performance deteriorates compared to MIDAS-R.

MIDAS-U and MIDAS-R models are regressions. The data used in these regressions should be stationary to avoid spurious results. Making the data stationary is a practice present in the MIDAS literature (Asimakopoulos et al., 2013).

4.6 Temporal Aggregation

According to Bańbura et al. (2013), one of the critical elements of nowcasting arises when a nowcaster uses data of different frequencies. Not all data is released simultaneously and at the same frequency. In other words, data is of mixed frequency. Some models can be easily specified with mixed-frequency data, but this is not always the case. Therefore, sometimes, we may need to manipulate our data to use it.

Additionally, we may feel that it is best to use a large amount of data to produce our nowcast. If this is the case, it can become quite cumbersome to create nowcasts using some models, such as MIDAS-U. For example, with MIDAS-U, we can run out of degrees of freedom if we add too many variables to our model. Also, adding more variables to a model increases the chance of overfitting, resulting in poor forecast or nowcast accuracy (Hyndman & Athanasopoulos, 2018).

One of the techniques available to researchers to solve these problems is called temporal aggregation, which involves turning a dataset from one frequency into another. For example, presume we were to forecast quarterly GDP in Australia and had quarterly, weekly, monthly, and daily data for our independent variables. It may be easier for us to turn all those variables into ones with one frequency only (e.g., quarterly) to make it easier to estimate our model. The disadvantage of this is that by doing this, information is lost about the independent variables (Giannone et al., 2006).

Chapter 5: Factors That Can Influence The Accuracy of a Nowcast or Forecast

This chapter aims to discuss how the accuracy of models and professionals is affected by different factors not already discussed yet. Factors that will be discussed include data level of aggregation, time period, seasonality, the dataset used, and the use of a rolling window. Like the last chapter, many papers cited here are related to forecasting inflation. Again, this is because there is less relevant literature on nowcasting inflation than forecasting inflation.

5.1 Data Level of Aggregation

When forecasting or nowcasting a variable, it is necessary to consider what aggregation of variables to use to avoid parameter proliferation. In theory, having data with a very detailed breakdown of data could improve a model's accuracy. However, the extent that this is the case depends on the paper. For example, Ibarra (2012) found that using disaggregated CPI data helped improve the accuracy of inflation forecasts in Mexico. Despite this, not all papers forecasting or nowcasting macroeconomic variables find significant benefits in disaggregating data. Some papers, for example, found only a marginal benefit to having disaggregated data (e.g., Bańbura & Modugno, 2014).

5.2 Time Period

There is evidence that the accuracy of models can change over time. A well-known example comes from Atkeson and Ohanian (2001). They found a result suggesting that random walk forecasts did better than a set of NAIRU Phillips curves. However, it was later shown that this result depended partially on the time the forecasts were being evaluated (Stock & Watson, 2008).

Faust and Wright (2013) found four elements of a good inflation forecast. One of these elements was that inflation forecasts should be able to adapt as the mean level of inflation can change over time. Shocks such as the COVID-19 pandemic and the Global Financial Crisis may have impacted the prediction ability of professionals and models. For example, take the Eurosystem and European Central Bank (ECB) staff. Chahad et al. (2022) say that Eurosystem and ECB staff "substantially underestimated" the rapid increase in inflation levels that occurred in late 2021. Interestingly, Chahad et al. (2022) mention that their COVID-19 inflation projections were more accurate than the predictions during the Global Financial Crisis.

There is good evidence that a macroeconomic forecast or nowcast is more accurate over a short-term horizon than a long-term horizon (e.g., Bańbura et al., 2013; Giannone et al., 2006). One explanation for this finding is that as the time horizon of the prediction decreases, there is less time for economic conditions to deviate significantly from the expected path. Evidence also supports this result for inflation predictions by New Zealand professionals (Ranchhod, 2002).

5.3 Seasonality

Inflation possesses seasonal traits in many countries. This includes countries such as Turkey (Altug & Çakmaklı, 2016), Brazil (Altug & Çakmaklı, 2016), and New Zealand (Stats NZ DataInfo+, 2022). Many countries, such as the USA (U.S. Bureau of Labor Statistics, 2022) and New Zealand (Stats NZ DataInfo+, 2022), publish seasonally adjusted CPI values. Researchers have tried to capture inflation seasonality using models such as a Bayesian VAR (Stelmasiak & Szafrański, 2016). To the best of my knowledge, I have not found significant research on the accuracy of models depending on the month/quarter of the year.

5.4 Type of Data Used

The types of data used when nowcasting or forecasting inflation are also vital. For accurate macroeconomic predictions, Marcellino et al. (2003) suggest researchers should use country-specific information instead of area information (e.g., German data instead of European Union data).

Fassas et al. (2022) found that survey-based forecasts are biased but can efficiently predict certain macroeconomic variables. For inflation specifically, past literature shows the usefulness of survey forecasts. For example, Ang et al. (2007) found that survey data is regularly given the highest weights when forecasting US inflation. Ang et al. (2007) also found that survey data helps to forecast inflation better than macro variables and term structure data. They found that term structure data often produces worse forecasts than models that only use aggregate activity measures. Faust and Wright (2013) found that judgemental forecasts for inflation frequently outperform model-based forecasts by a large margin. Fassas et al. (2022) report that this is a consistent finding across the literature.

Price data is also helpful in predicting inflation. Price data has also been used over the past few years to predict food price inflation, a sizeable component of CPI, with good results (Jaworski, 2021; Macias & Stelmasiak, 2019; Macias et al., 2022).

Investigating the effectiveness of Phillips curve data (and Philips curve specifications) is another area of research in this space. The Phillips curve suggests that unemployment and inflation negatively correlate with each other (Phillips, 1958). Phillips curve data is any data used to create a Phillips curve-related model.

The results from the Phillips curve literature have been mixed. At first, similar findings to Phillips (1958) were reported (e.g., Samuelson & Solow, 1960). Many of these results were found before the Phillips curve was used to predict inflation. However, as the years went by, some authors expressed scepticism over some of this literature. Many variations of the Phillips curve were examined, such as generalised Phillips curves (Koop & Korobilis, 2012), backward and forward-looking Phillips curves (Altug & Çakmaklı, 2016), and MIDAS augmented Phillips curves (Marsilli, 2017).

Some literature has supported using the Phillips curve for inflation forecasting (e.g., Stock & Watson, 1999). Despite this, some literature has mentioned that the Phillips curve has not helped forecast inflation or has produced mixed results (e.g., Atkeson & Ohanian, 2001; Gabrielyan, 2019). Some literature has mentioned how Phillips curves produce worse forecasts than other models or methods of forecasting inflation (Faust & Wright, 2013). A few papers have also tried to nowcast inflation using a Phillips curve specification (Goshima et al., 2021; Marsilli, 2017).

5.5 Rolling Window vs Recursive

As mentioned earlier, good forecasts need to consider that the average level of inflation changes over time (Faust & Wright, 2013). As the average level of inflation changes over time, older data may become less relevant for predicting future inflation levels. Due to this, it may be best to phase out such data when creating a forecasting or nowcasting model. This way, extra weight will be put on more recent data. Because phasing out old data can account for the idea that inflation changes over time, this may help improve a model's predictive accuracy.

One method to phase out older data is to use a rolling window. A rolling window involves using the last “x” observations available to create future projections for a variable. The number of observations used in a rolling window, or “x”, can be chosen to be any reasonable value. As time passes, new observations will be added, meaning that the values of the last “x” observations will change too. As a result, this process phases out past data in favour of more recent data. However, a rolling window limits the number of observations used in the training set. If the omitted data happens to be helpful, then this is problematic. A rolling window approach has been used to predict inflation in the past (e.g., Stock & Watson, 2008).

Alternatively, we might think using all the available data is better. In such a case, we may choose to use a recursive window. A recursive window uses all observations available at the time of the prediction. A potential advantage of this approach is that it uses all the data available to the researcher. This could be especially useful when there is not a lot of data available. Contrary to this, the added data could be so old that it is counterproductive for creating reasonable projections. Some papers that predict inflation use this recursive approach (Araujo & Gaglianone, 2020)

Chapter 6: Inflation Predictions of Professionals and Households

This chapter examines the literature that discusses the inflation nowcasts and forecasts of professionals and households.

Professionals use a variety of inputs, such as their judgement, economic models, and other information, to create their estimates. These predictions from professionals are supposed to have high accuracy compared to other models (Faust & Wright, 2009, 2013). As a result, professionals could potentially be an excellent benchmark for nowcasters.

Professional forecasters have advantages compared to economic models. Firstly, professionals can use a combination of any models they wish to generate their estimates. Secondly, professionals can exercise their judgement, which can help finetune inaccurate forecasts and nowcasts. This judgement is especially beneficial when professionals can see things that their models cannot. For example, when GST increased in New Zealand from 12.5% to 15%, causing an increase in the prices of goods and services, professionals could adjust their forecasts for this. Meanwhile, many economic models may not have known that GST increased, meaning they could not capitalise on this information.

Economic literature has investigated which organisations produce the best judgemental forecasts for New Zealand. Baghestani and Kaya (2013) found that when used to forecast inflation, the RBNZ's survey of expectations outperformed a naïve forecast. Additionally, forecasts could accurately ascertain whether future inflation levels would increase or decrease. Turner (2006) found that when forecasting the New Zealand inflation rate, the RBNZ's forecasts "performed slightly better than the average of other forecasters." Labbé and Pepper (2009) used data from multiple external forecasters. Their results suggested that the RBNZ's macroeconomic forecasts are more accurate than most. However, the results of Labbé and Pepper (2009) also suggest that some external forecasting agencies produce accurate enough forecasts to help formulate monetary policy. To the best of my knowledge, I have found no work specifically on evaluating judgemental nowcasts in New Zealand.

On average, households consistently overestimate real-time levels of inflation (Hayo & Neumeier, 2022; Leung, 2009). Specifically, results from Leung (2009) suggest that New Zealand households consistently overestimate inflation levels.

Chapter 7: Modelling Methodology (For Subchapters 9.1 Until 9.6)

Before discussing the methodology in more detail, it is necessary to note a few specific adjustments I am making to some definitions. From now onwards, inflation refers to a percentage change in the All Groups New Zealand Consumer Price Index (NZ CPI) over a given time period. Forecasting refers explicitly to predicting future values of inflation that are due to be published in more than three months. In other words, forecasting inflation means estimating the inflation rate of any quarter beyond the next-to-be-released inflation value.

Meanwhile, nowcasting refers explicitly to predicting the next NZ inflation rate value to be published. In other words, a nowcast predicts an NZ inflation rate value that will be released within three months. For example, imagine the inflation value for the first quarter of 2023 (Q1 2023) is the latest released value and that it is the middle of February 2023. So, in two months, the CPI value for Q2 2023 will be released, with future NZ CPI values published every three months after that. Therefore, predicting the Q2 2023 inflation rate will be a nowcast. Meanwhile, predicting any inflation rate value from Q3 2023 onwards will be a forecast.

In my research, I use six models to calculate nowcasts for four different points in time. These periods are called Month 1, Month 2, Month 3, and Month 4.

Table 1 – Months in Methodology

Month	Time	Description
Month 1	Mid-January, mid-April, mid-July, and mid-October	Nowcast is made the day the previous CPI figure is released.
Month 2	Mid-February, mid-May, mid-August, and mid-November	Nowcast is made two months before the next CPI release date
Month 3	Mid-March, mid-June, mid-September, and mid-December	Nowcast is made one month before the next CPI release date
Month 4	Early-to-mid-April, early-to-mid-July, early-to-mid-October, and early-to-mid-January	Nowcast is made one week before the next CPI release date

7.1 How Inflation in New Zealand is Calculated

The NZ CPI figure is published by Statistics New Zealand (Stats NZ) every quarter. This figure is usually released 12 working days after the end of most quarters (Stats NZ DataInfo+, 2022). The percentage change in the CPI over a certain time period represents the inflation rate.

Stats NZ DataInfo+ (2022) mentions that the NZ CPI figure measures the change in the price of a basket of goods over time. The basket of goods measured is meant to be representative of the goods and services bought by Kiwi households. The NZ CPI has far-reaching implications, from helping to set monetary policy, changing the amount of New Zealand Superannuation payments, and helping to set wages (Stats NZ DataInfo+, 2022).

The steps stated by Stats NZ Infoshare (2022) to calculate the NZ CPI are below. Stats NZ collects price data through surveys, online data collection, web scraping, using administrative data, and going directly to retail outlets. Around 100,000 prices and 1,700 surveys are collected for each quarter. Adjustments are made for goods and services that are no longer sold or have changed in size or quantity. A review of the methodology to measure the NZ CPI is conducted every three years to ensure accuracy. Table 2, derived from Stats NZ DataInfo+ (2022), shows the weighting given to each item category in the NZ CPI calculations (data is only given to two decimal places).

Table 2 – New Zealand Consumer Price Index Weighting

Group	Base expenditure weight	
	September 2017 quarter	June 2020 quarter
	Per cent	
Food	19.25	18.72
Alcoholic Beverages and Tobacco	7.11	7.49
Clothing and Footwear	4.36	4.10
Housing and Household Utilities	24.51	28.00
Household Contents and Services	4.38	4.30
Health	3.78	4.24
Transport	13.97	11.93
Communication	3.20	3.11
Recreation and Culture	9.40	8.46
Education	2.01	1.80
Miscellaneous Goods and Services	8.02	7.85
All groups	100.00	100.00

7.2 Modelling Methodology

In my thesis, I create economic models to nowcast inflation and compare their performance across different situations. Firstly, I complete recursive nowcasts for six models and compute the RMSE values. Then I calculate the RMSE values of these models for different scenarios. One area I look at is how the RMSE changes over time and in quarters. I also examine how the accuracy of my models change as the NZ inflation rate changes in value. I discuss how supplying the models with different data types affects each model's nowcasting potential. Lastly, I look at how using a rolling window impacts the accuracy of my NZ inflation rate nowcasts.

Such a comprehensive analysis helps to gain a broader view of nowcasting inflation in New Zealand. From this analysis, we can find out what models may be suitable for nowcasting inflation and when. We can also better understand what is necessary for making a good nowcast of the NZ inflation rate.

7.2.1 General Notes

I use three benchmark models: the random walk model, the ARIMA model, and a target model based on the Reserve Bank of New Zealand's inflation target (RBNZ Target model). I use these models because these three models have been used previously in the literature to benchmark inflation nowcasts.

In terms of the non-benchmark models, an ideal approach would be to include all models that exist and nowcast the NZ inflation rate using all of them. Unfortunately, this is impractical, given the dozens of models that exist. As a result, I limit the number of models I choose.

The non-benchmark models I use are a neural network autoregression (NNAR), MIDAS-R, and MIDAS-U model. I use an NNAR to examine whether using a neural network can increase the accuracy of my nowcasts. Using an NNAR model also involves using a modern addition to the nowcasting inflation literature, a neural network. I use both MIDAS-R and MIDAS-U because MIDAS models are a popular tool in the inflation prediction space for projecting inflation values.

For all the variables I have, I mostly use data published from 1992-2021. The one exception occurs when specifying the MIDAS model data. As some data is not published promptly, I must use lags. So, for example, when specifying the data available to a model nowcasting the NZ inflation rate for Q1 1992, I need to use some values published in Q4 1991. I choose the 1992-2021 timeframe because I wanted to use the most data I could for this exercise while avoiding data published before the RBNZ's mandate came into effect in the late 1980s ("Banking (Prudential Supervision) Act 1989,"). The RBNZ's mandate may have caused a structural change in inflation that, if included, may affect the accuracy of my models.

With this data, I create pseudo-nowcasts for 2002-2021. Provided all the data available is used, there are 40 NZ inflation rate observations from 1992 to 2001 that can be used to estimate all my models. This arrangement gives me enough observations to estimate all the models and leaves enough data points to test my data (80 observations).

The amount of data given to each model depends on the circumstance. When pseudo-nowcasting, I always ensure that I align the timing of the variables correctly. I make sure that for the time I am making the pseudo-nowcast, I only give the model the data that would have been "published" at that time. When using the recursive window approach, the data used to pseudo-nowcast at a specific timeframe will be all data I have until the day the pseudo-nowcast is made.

In the results chapter (Chapter 9), I also use a five, eight, and ten-year rolling window. In such a case, I only use the observations from the last five, eight, and ten years for these models. I choose these rolling window sizes to try to optimise between having a large enough training set and a large enough test set. If I have too small of a rolling window, I may not have enough data to train the model. Alternatively, if I have too large of a rolling window, I may not have enough data to test my models.

I nowcast the quarter-on-quarter inflation rate (which I also refer to as CPI (Q/Q%) or Q/Q% inflation rate) when creating my pseudo-nowcasts. The CPI Q/Q% inflation rate can be calculated as follows, where variable y is the NZ CPI index, and the Q/Q% inflation rate at quarter t is π_t^Q.

$$\pi_t^Q = \frac{y_t}{y_{t-1}}$$

The reason for nowcasting the Q/Q% inflation rate is twofold. Firstly, it is more prevalent in the literature to nowcast the inflation rate between release dates. For example, with many countries publishing monthly inflation data, many researchers nowcast the month-on-month (M/M%) inflation rate (e.g., Knotek & Zaman, 2017; Marsilli, 2017; Yadav & Das, 2021). Similarly, because NZ CPI data is quarterly, I choose to nowcast the NZ CPI Q/Q% inflation rate. Secondly, turning the Q/Q% inflation rate nowcast into a year-on-year inflation rate (Y/Y%) pseudo-nowcast is not tricky. When we make a Q/Q% nowcast, we also know the Q/Q% inflation rates for the three preceding quarters. Of course, as there are four quarters in a year, we can use the last three-quarters of Q/Q% inflation rate values, plus the nowcast for the current quarter, to create a Y/Y% inflation rate pseudo-nowcast.

I follow the pseudo-nowcasting steps mentioned in Chapter 2 for all models. Further details on the data used are available in Appendix A1, Tables A1 and A2.

7.2.2 Variables Used in the Modelling

Below are some summary tables regarding the data used in this thesis. All the data mentioned in the tables, except for the dependent variable, are independent variables. Before using this data, I make sure that it is stationary. This is because, as mentioned in the literature review, the multivariate models I use are generally best implemented with stationary data.

The variables I use have been put into different groups. This is because, in the results chapter of my thesis (Chapter 9), I look to see if using different data types improves the nowcasts' accuracy. As seen in Subchapter 5.4, the type of data used to predict inflation can influence the accuracy of that prediction. Ignoring the NZ inflation rate lag variable (CPI QoQ Lag), I split the independent variables into different groups – soft, economic activity, financial, price, and Phillips curve data. Some data, namely the WTI Cushing and UE Rate Data, are in multiple groups as they can be plausibly classified under multiple groups.

When using multivariate models, I ensure that the data I use is stationary. If it is not stationary, I differentiate the data as needed until it is stationary. I use the KPSS test (Kwiatkowski et al., 1992) for all multivariate models to ensure that the data is stationary before using it.

Table 3 – Dependent Variable Information (Modelling Chapters)

Variable	Unit	Source
All Groups New Zealand Consumer Price Index (CPI QoQ Dep)	Per cent Change Per Quarter	Stats NZ

Table 4 – Inflation Rate Lag Information

Variable	Unit	Source
1-Quarter Lag of All Groups New Zealand Consumer Price Index (CPI QoQ Lag)	Per cent Change Per Quarter	Stats NZ

Table 5 – Soft Data Information

Variable	Unit	Source
Survey of Expectations - Annual CPI Growth 1 Year Out Forecast (CPI 1Y)	Per cent Change Per Year	RBNZ
Survey of Expectations – Unemployment Rate 1 Year Out Forecast (UE Rate 1Y)	Per cent	RBNZ
Survey of Expectations – GDP 1 Year Out Forecast (GDP 1Y)	Per cent Change Per Year	RBNZ
Perception of monetary conditions (net) - end of the current quarter (PMC)	Per cent	RBNZ

Table 6 – Economic Activity Data Information

Variable	Unit	Source
Unemployment Rate for People Between 15-64 (UE Rate)	Per cent	Stats NZ
Real Expenditure-based Gross Domestic Product (GDP)	Per cent Change Per Quarter	Stats NZ

Table 7 – Financial Data Information

Variable	Unit	Source
Yield Spread: 10-year secondary market government bond yields minus 90-day bank bill (YS)	Per cent	RBNZ
Trade-weighted index (TWI)	Per cent Change Per Month (converted from an index)	RBNZ

Table 8 – Price Data Information

Variable	Unit	Source
Food price index (FPI)	Per cent Change Per Month	Stats NZ
Meat, skins and wool price index (MSW)	Per cent Change Per Month (converted from an index)	ANZ Bank New Zealand Limited
Forestry products index (FP)	Per cent Change Per Month (converted from an index)	ANZ Bank New Zealand Limited
Aluminium price index (Aluminium)	Per cent Change Per Month (converted from an index)	ANZ Bank New Zealand Limited
Monthly Average Close Price of Gold in NZD (Gold)	Per cent Change Per Month	Refinitiv Workspace
Monthly Average Close Price of Silver in NZD (Silver)	Per cent Change Per Month	Refinitiv Workspace
Monthly Average Close Price of Crude Oil WTI Cushing Commodity Spot Rate in NZD (WTI Cushing)	Per cent Change Per Month	Refinitiv Workspace

Table 9 – Phillips Curve Data Information

Variable	Unit	Source
1-Quarter Lag of All Groups New Zealand Consumer Price Index (CPI QoQ LagI)	Per cent Change Per Quarter	Stats NZ
Unemployment Rate for People Between 15-64 (UE Rate)	Per cent	Stats NZ
Monthly Average Close Price of Crude Oil WTI Cushing Commodity Spot Rate in NZD (WTI Cushing)	Per cent Change Per Month	Refinitiv Workspace

This data specification for the Phillips curve is inspired by Marsilli (2017). They use a MIDAS augmented Phillips curve, extending the triangle model of Gordon (1990) to nowcasting inflation. The augmented Phillips curve of Marsilli (2017) consists of three variables; a monthly unemployment gap (changed to quarterly in my research), inflation, and oil price month-on-month returns.

Table 10 summarises the variables using data from Q1 1992 to Q4 2021. This data was not adjusted or made stationary when calculating the statistics below. Due to data revisions, the figures below may change slightly in the future.

Table 10 – Statistics for Independent and Dependent Variables

Variable	Frequency	Count	Mean	Standard Deviation	Correlation to CPI QoQ Dep
CPI QoQ Dep	Quarterly	120	0.525	0.509	1.000
CPI QoQ Lag	Quarterly	120	0.513	0.506	0.300
PF CPI 1Y	Quarterly	120	2.126	0.633	0.512
PF UE Rate 1Y	Quarterly	120	6.081	1.752	-0.237
PF GDP 1Y	Quarterly	120	2.400	1.019	0.229
PF PMC	Quarterly	120	-5.686	50.796	0.207
UE Rate	Quarterly	120	5.941	1.789	-0.196
GDP	Quarterly	120	0.763	1.894	-0.132
YS	Monthly	360	0.354	1.352	-0.103
TWI	Monthly	360	0.094	1.832	0.004
FPI	Monthly	360	0.180	0.757	0.314
MSW	Monthly	360	0.304	3.003	0.262
FP	Monthly	360	0.117	3.726	-0.028
Aluminium	Monthly	360	0.256	4.325	0.134
Gold	Monthly	360	0.458	3.766	0.057
Silver	Monthly	360	0.615	6.220	0.074
WTI Cushing	Monthly	360	0.690	8.676	0.188

Correlation refers to a variable's contemporaneous correlation to CPI QoQ Dep. In other words, the correlation statistic looks at how the movement of one variable is related to the NZ inflation rate movement at the same time period. Any monthly variables are aggregated using temporal aggregation to a quarterly frequency before calculating this correlation statistic. Appendix A1, Tables A1 and A2, has information on the release timing of each of the variables.

7.2.3 Random Walk Implementation

The random walk model is calculated by making the nowcast equal to the last NZ inflation rate Q/Q% observation. Note that the nowcasts of the random walk model are the same across Months 1, 2, 3, and 4. This is because, by definition, new values of the NZ CPI are only published in Month 1. In other words, no new data is published in Months 2, 3, and 4 that the random walk model can use. See Chapter 4 for more details.

7.2.4 ARIMA Implementation

For each quarter, the ARIMA nowcasts are calculated in three steps. I repeat these steps separately for each quarter. The first step is to evaluate the ARIMA model that is best to use. I do this by minimising the Bayesian Information Criterion (BIC). Depending on the quarter, the BIC suggested that either the $ARIMA(1,0,0)$, $ARIMA(0,0,1)$, or $ARIMA(0,0,0)$ was best. The second step is to use the model suggested by the BIC to nowcast inflation. The third step is to check the residuals of each ARIMA model used to see if they are uncorrelated and have zero mean. I check this to determine whether the model uses all the available information and whether the forecasts are biased. There were no problems found when implementing the third step. For similar reasons as the random walk model, the nowcasts of this model are the same for all four quarters.

7.2.5 RBNZ Target Implementation

Since 2002, the RBNZ has had an annual inflation target between 1 and 3 per cent (Williams et al., 2020). An explicit focus on an annual inflation level of 2 per cent was added in 2012 (Williams et al., 2020).

To create the RBNZ Target nowcast, I take the middle ground between 1 and 3 per cent, which was 2 per cent per annum. Then I divide 2 per cent by four to gain a quarterly value of 0.5 per cent per quarter. As a result, every Q/Q% inflation RBNZ Target nowcast equals 0.5 per cent. This approach has some similarities with Diron and Mojon (2005). Their RBNZ Target model assumed inflation from 2004 onwards was 2% per annum and 1.5% per annum between 2002 and 2003. However, I choose my approach as it is more straightforward and consistent. Because this model nowcasts inflation as a constant, the RBNZ Target model nowcasts are equal across all four quarters.

The RBNZ’s annual inflation target has not changed from 2003 to 2021, which is why the nowcasts remain the same across this period. However, the RBNZ annual inflation target changed from 1992-2001. If we include 1992-2001 as part of the test set, we will see more variation in the RBNZ Target nowcasts.

7.2.6 Neural Network Autoregression (NNAR) Implementation

I implement this model in three steps. My first step is to test for non-stationarity in the NZ inflation rate Q/Q% values. I check for non-stationarity in my data using the KPSS unit root test (Kwiatkowski et al., 1992). I find no evidence of non-stationary when implementing this test in my sample. The second step of this process is to choose the specification of the neural network autoregression (NNAR). The Akaike Information Criterion (AIC) chooses the optimal number of non-seasonal lags, seasonal lags, and neurons. Once the model specification is chosen, the third step is to forecast one quarter ahead using the NNAR model chosen. I repeat this process for each quarter that I am nowcasting for. For similar reasons as the random walk model, the nowcasts of this model are the same for all four quarters.

No papers, to my knowledge, use a neural network autoregression to nowcast inflation. Despite this, the use of autoregressions to nowcast inflation is not unfamiliar to the literature. Using an NNAR felt like a natural step to extend the literature.

7.2.7 MIDAS-R Model Implementation

MIDAS models are regressions. I only have four observations of the NZ inflation rate value per year. As a result, I aim to be careful with the number of parameters I include in the MIDAS models. If I gave the MIDAS models all the data possible, I would quickly run out of degrees of freedom.

So, as a result, for quarterly variables, the MIDAS models only use the last available value of a variable. For example, if the last value of GDP were published in Q4 2021, then the MIDAS models would only use the Q4 2021 GDP value. For monthly variables, the MIDAS models only use the values related to the quarter being nowcasted. For example, presume it is Q1 2002, and we are using food price inflation data, which is monthly. In this case, I should only use food price inflation data for January 2002, February 2002, and March 2002.

In the results, we will see that Months 1 and 2 do not have any MIDAS-R results. We see this because there need to be multiple lags of at least one variable so the exponential Almon lag can be used. In Months 1 and 2, there are no variables where this is the case. Only in Months 3 and 4 will this be the case (where there will be at least two observations for each monthly variable). As a result, the MIDAS-R values for Months 1 and 2 are replaced with NAs.

One may argue that I should add lags from previous quarters to run the MIDAS-R model for Months 1 and 2. However, adding in extra lags creates another problem. To fairly compare all the multivariate models with each other, I need to give them all the same data. Otherwise, one model may have an unfair advantage. Following this logic, if I add extra lags to the MIDAS-R model, I should also add extra lags to the MIDAS-U models. Unfortunately, by doing this, the MIDAS-U model could have more parameters to estimate than observations of the NZ inflation rate. This may cause poor nowcasting performance. For example, suppose I added one extra lag of all the quarterly variables. In that case, the MIDAS-U model would have 42 parameters to estimate. However, MIDAS-U would only have 40 observations available when implementing a ten-year rolling window.

I use the exponential Almon lag for the MIDAS-R models. I implement this because of its popularity in the literature. I use BFGS (Broyden–Fletcher–Goldfarb–Shanno algorithm) as my optimisation method, in line with Ghysels et al. (2016). The starting values are chosen in line with Libonatti (2018). Libonatti (2018) assumes that all parameters have equal weights and are null impact parameters.

7.2.8 MIDAS-U Model Implementation

OLS (ordinary least squares) is used to calculate the MIDAS-U model, in line with what was mentioned in Chapter 4. Note that a MIDAS-U model is similar to a time series linear regression. The data specified in the MIDAS-U model is the same as in the MIDAS-R model.

Chapter 8: Methodology for Comparing Professional and Household Predictions (For Subchapter 9.7)

8.1 Data and Methodology

In this thesis, I also calculate the RMSEs of different professional and household predictions. Then, I compare these RMSEs to the best-performing benchmark model (random walk, ARIMA, or RBNZ Target) using the relative RMSE benchmark.

When comparing professional and household inflation predictions, I use nowcasts from these groups. With the motivation of this thesis being to nowcast inflation accurately, it is a natural step to look at how well people can nowcast inflation. However, I also look at one-step-ahead forecasts (also known as one-quarter-ahead forecasts). This is because I wish to see whether one-quarter-ahead inflation forecasts can beat my inflation benchmark models. Some data sources, namely the ANZ Preview and RBNZ Household predictions, only have data available for nowcasts and not one-step-ahead forecasts.

Presume that we are nowcasting inflation, but we also want to make a one-step-ahead forecast. A one-step-ahead forecast is made when we predict the inflation value for the quarter after the nowcast. For example, if we are nowcasting for Q1 2023 and want to produce a one-step-ahead forecast, their one-step-ahead forecast would be for Q2 2023.

For most datasets, the number of nowcast and forecast observations are limited. When modelling inflation using six different models in Chapter 9, I have 80 observations that I can use to calculate RMSEs (2002 Q1-2021 Q4). However, only the RBNZ Household Inflation Expectations dataset has nowcasts for all of 2002 Q1 until 2021 Q4. So, to expand the available data, I use data from 2002 Q1 until 2022 Q3 for this exercise.

Where it was practical, I drop a small number of observations to ensure that the forecasts for each organisation in my dataset were published around the same time each quarter. However, numerous forecasters (e.g., The Treasury) publish their predictions at irregular periods. In such cases, dropping observations to ensure my dataset was published around the same time each quarter would significantly reduce my dataset. I do not have many observations to start with. Therefore, when dropping observations would significantly reduce the dataset available, I include all data I have available. In the tables below, I mention when each dataset is published.

Some organisations, such as The Treasury, changed the presentation of their economic projections over time. For example, The Treasury published Q/Q% inflation rate predictions between 2003 and 2019 but only published Y/Y% inflation rate predictions between 2020 and 2022. In such cases, I use the data format that was most common over the timeframe to maximise the amount of data available.

My analysis will not be as broad as in Chapter 7. If I were to replicate much of the analysis I mentioned in Chapter 7, there would be significant drawbacks. Firstly, there would be problems due to the lack of observations in my dataset. Even without this problem, many datasets do not have the appropriate data for this analysis. For example, around half of the datasets have no pandemic-related data, and The Treasury datasets are not published in all quarters of the year. Due to these problems, my ability to analyse the inflation predictions of households and professionals is limited.

Additional information on the release timing of the data used is given in Appendix B1, Table B1.

Table 11 – Professional Forecasters Used

Variable	Unit	Source	General Comments
ANZ CPI Preview (ANZ Preview)	Per cent Change Per Quarter	ANZ Bank New Zealand Limited	The ANZ CPI Preview predicts each NZ inflation rate value one week before Stats NZ officially releases the NZ inflation rate figure. Only produces nowcasts.
ANZ Quarterly Economic Forecast and Quarterly Economic Outlook Series (ANZ QEF + QEO)	Per cent Change Per Quarter	ANZ Bank New Zealand Limited	The ANZ Quarterly Economic Forecasts were renamed the ANZ Quarterly Economic Outlook in 2014.
ASB Quarterly Economic Forecasts (ASB)	Per cent Change Per Year	ASB	
BERL Forecasts (BERL)	Per cent Change Per Year	Business and Economic Research Limited	
New Zealand Institute of Economic Research Consensus Forecasts – Mean (NZIER Mean)	Per cent Change Per Quarter	New Zealand Institute of Economic Research	
RBNZ Household Inflation Expectations – Perception of Current Inflation Mean (RBNZ Household)	Per cent Change Per Year	RBNZ	Only nowcasts are available from this data source.
RBNZ Monetary Policy Statement Economic Forecasts (RBNZ MPS)	Per cent Change Per Year	RBNZ	Data is from the supplementary Excel files for each RBNZ MPS.
The Treasury Economic and Fiscal Updates (Treasury EFU)	Per cent Change Per Quarter	The Treasury	Combines the Treasury Budget Economic and Fiscal Updates (BEFU) and the Half-Year Economic and Fiscal Updates (HYEFU)
Westpac Economic Overview (Westpac)	Per cent Change Per Quarter	Westpac	

8.2 Comparing Year-on-Year and Quarter-on-Quarter Projections

Note that some inflation predictions are in the Y/Y% format, and some are in the Q/Q% format. My benchmarks are calculated in a Q/Q% format. Therefore, it is essential to note that the RMSEs of the Y/Y% and Q/Q% predictions cannot be directly compared to each other without making some adjustments. This is because the predictions are not in the same unit (Hyndman & Athanasopoulos, 2018). As a result, I make sure to change the Q/Q% benchmarks into a Y/Y% format, as Appendix C explains. I also give more details on how the RMSE changes depending on the format of the inflation rate predictions in Appendix C.

It is important to note that the benchmark RMSE changes depending on the timeframe that predictions are available for. For example, suppose that nowcasts are only available for 2002 Q1 until 2010 Q4. In this case, the ARIMA, RBNZ Target, and random walk models have their RMSEs calculated only for 2002 Q1 until 2010 Q4. This calculation is redone for each model as needed.

Chapter 9: Results

Most of this chapter (from subchapters 9.1 until 9.6) presents results for recursive nowcasts for the NZ inflation rate for six models (random walk, ARIMA, RBNZ Target, NNAR, MIDAS-R, MIDAS-U) at four different time points. To do this, I use the process detailed in Chapter 7.

I interchangeably use some terms when referring to the results from my six models. For example, I use terms such as “nowcast” instead of “pseudo-nowcast”, “forecasting” instead of “pseudo-forecasting”, and so forth. This practice is typical in the literature (Bańbura et al., 2013).

9.1 Recursive Nowcast Results

In this subchapter, I create recursive nowcasts for the NZ inflation rate using the process detailed in the methodology. For tables that use the standard RMSE value instead of the relative RMSE value, I underline which models have the lowest RMSE for each month, quarter, or timeframe. The graphs from these recursive nowcasts can be found in Appendix A2. Below are my results from doing this.

Table 12 - Recursive Nowcasts RMSE Table

Recursive Model RMSE	Month 1	Month 2	Month 3	Month 4
Random Walk	0.638	0.638	0.638	0.638
ARIMA	0.533	0.533	0.533	0.533
RBNZ Target	0.535	0.535	0.535	0.535
NNAR	<u>0.529</u>	0.529	<u>0.529</u>	<u>0.529</u>
MIDAS-R	NA	NA	0.580	0.626
MIDAS-U	0.540	<u>0.494</u>	0.559	0.648

Literature such as Bańbura et al. (2013) has shown that nowcasts of macroeconomic variables such as GDP and inflation generally get better as more information is available. Therefore, it may be surprising that this does not hold with the multivariate models in my research. During Months 3 and 4, the MIDAS models have an RMSE value higher than Month 1 and Month 2 of MIDAS-U. The RMSE for Months 3 and 4 of both MIDAS models is higher than the ARIMA and RBNZ Target models.

One hypothesis for why this finding is true relates to the fact that most developed countries use monthly inflation data. As a result, researchers nowcasting in these countries have three times as many observations to work with, compared to New Zealand. As a result, the number of degrees of freedom in models in most developed countries would be higher, all other things equal. Having too few degrees of freedom may result in overfitting. New Zealand, the only country with quarterly inflation rate data in the OECD (Brockett, 2022), does not comprise much of the literature on inflation forecasting and nowcasting. Therefore, this problem may not be encountered as much in the academic literature.

Having fewer degrees of freedom can result in overfitting, which may cause the result seen in Table 12. Overfitting can become a problem in Months 3 and 4, where the number of parameters in the MIDAS models increases dramatically. Overfitting occurs because new monthly variables are released and get added to these models. These new variables can be a hindrance if they add more noise than predictive information to the model. The overfitting problem may be felt most during the early 2000s, where the fewest observations of the NZ inflation rate are available. As the recursive approach uses all available data, the number of observations grows during the later years (e.g., the 2010s). With more observations come more degrees of freedom, which may make the models less prone to overfitting. In the *RMSE Split by Year* subchapter, we will see evidence to support this hypothesis.

Random walk, ARIMA, and NNAR are univariate models. Of course, the inflation rate nowcasted by these models is, by definition, released the day that the Month 1 nowcast is made. As a result, there is no new information for these univariate models to process as Months 2, 3, and 4 go by. Due to this, their nowcasts and RMSE values remain static throughout all four months. Additionally, because the RBNZ Target nowcast is constant, the RBNZ Target's RMSE stays the same across the quarter. Out of the three benchmark models, the ARIMA model has the lowest RMSE value at 0.533. The RBNZ Target has a similar RMSE value to ARIMA at 0.535. The random walk model is the worst-performing benchmark. It has an RMSE value 19.7% higher than the ARIMA model.

9.2 RMSE Split by Actual NZ Inflation Rate Value

Subchapter 5.2 showed that past literature suggests that the accuracy of inflation predictions can change during different periods. One potential reason for this is that the characteristics of the economy which influence inflation change over time (Odendahl et al., 2022). As a result, a model can forecast better in some periods, but worse in others. In other words, inflation may become a state dependent variable (Odendahl et al., 2022). As a result of this phenomenon, my NZ CPI inflation rate nowcasts may nowcast better in some periods than in others.

When actual inflation is significantly outside the zero to one percent band, it generally coincides with a change in the economy such as the Global Financial Crisis, a GST increase, or the COVID-19 pandemic. This suggests that New Zealand inflation may be a state dependent variable. I notice that the Q/Q% nowcasts of many of the models lie between zero to one percent. The models that primarily nowcast Q/Q% inflation between zero and one percent are the RBNZ Target, ARIMA, and NNAR models. All of this supports the idea that my NZ inflation rate nowcasts could perform better if the actual value of the NZ inflation rate ends up being between zero and one percent.

Figure 1 – RBNZ Target Recursive Nowcasts

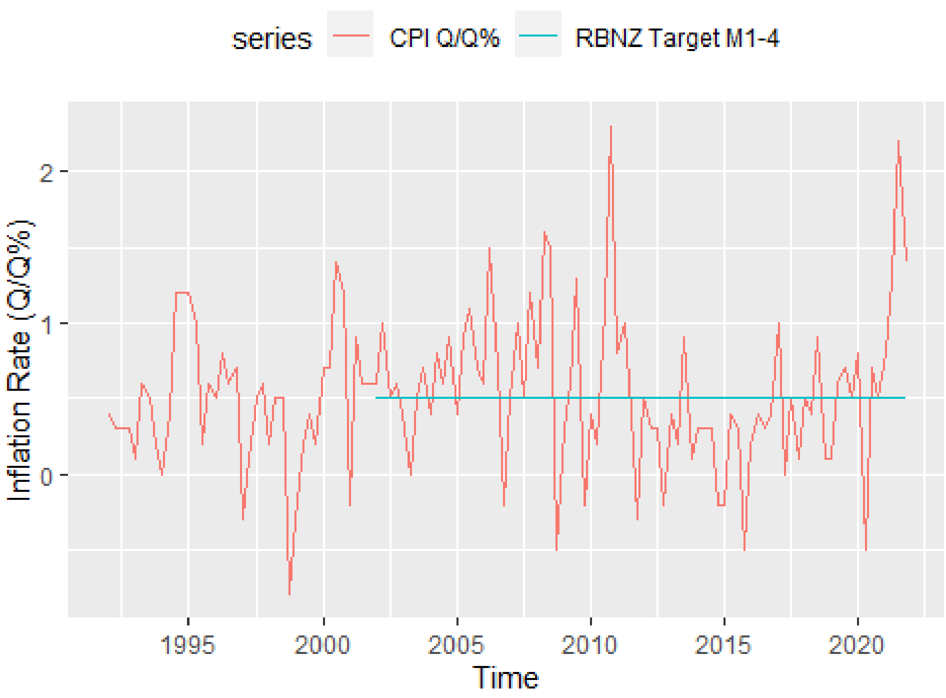


Figure 2 – ARIMA Model Recursive Nowcasts

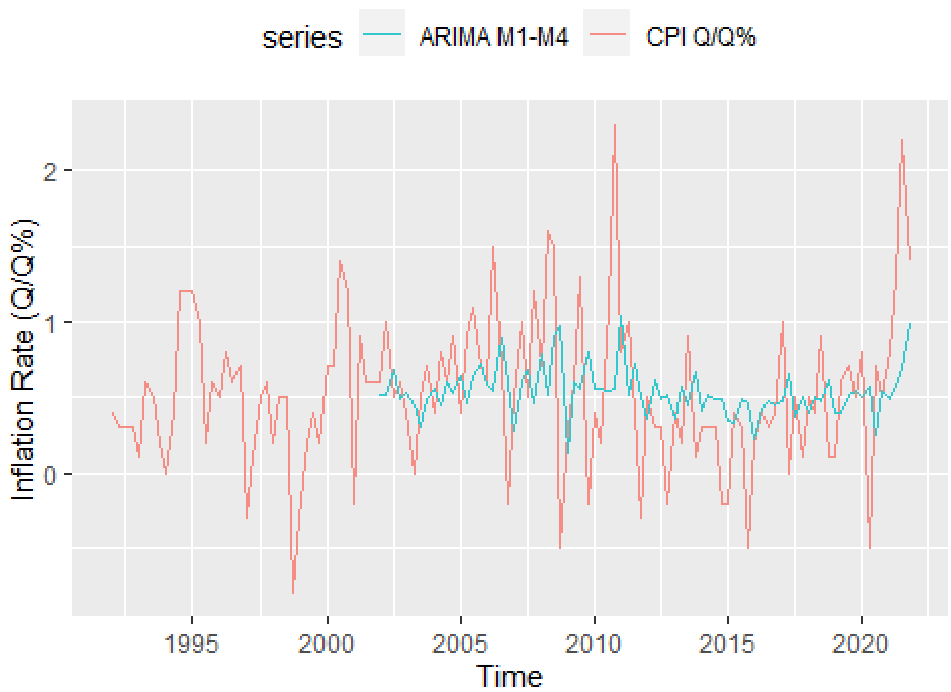
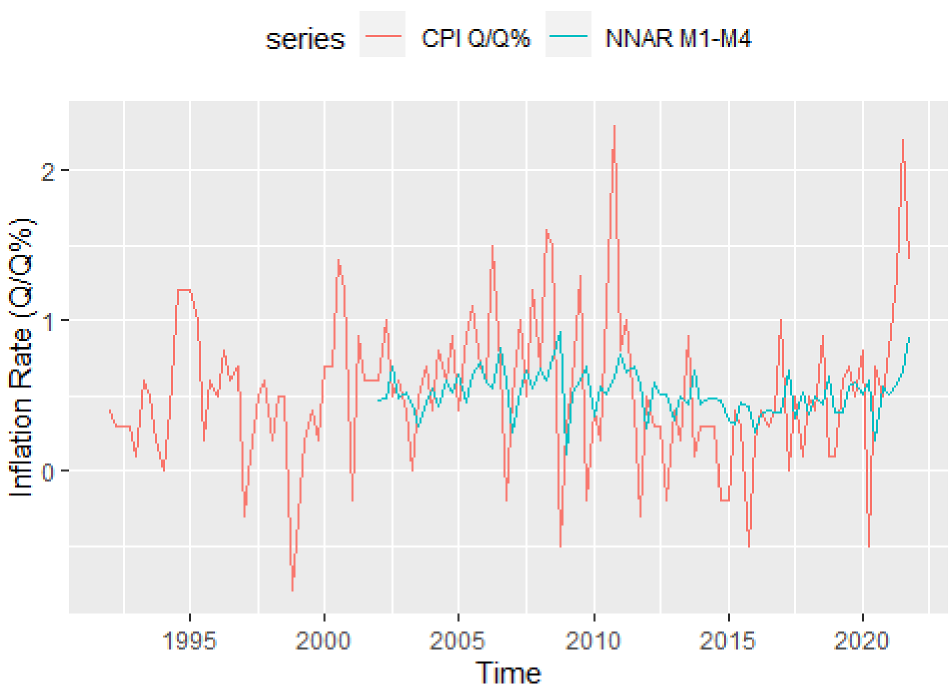


Figure 3 – Neural Network Autoregression (NNAR) Recursive Nowcasts



To test how state dependence could influence the accuracy of my inflation nowcasts, I split my recursive nowcasting data into two portions. The first portion is where the actual inflation rate value published by Stats NZ was between zero and one percent, including zero and one percent. The second portion is when the actual inflation rate value released by Stats NZ is outside of this range.

Between 2002 to 2021, there were 60 quarters where Q/Q% inflation was between zero and one percent inclusive. There were 20 quarters where Q/Q% inflation was outside of this range. Figure 4 below helps to show the quarters that inflation was outside of the zero to one per cent band. Table 13 below shows the results of my analysis.

Figure 4 – NZ Inflation Rate Graph 1992-2021 With 0% to 1% Band

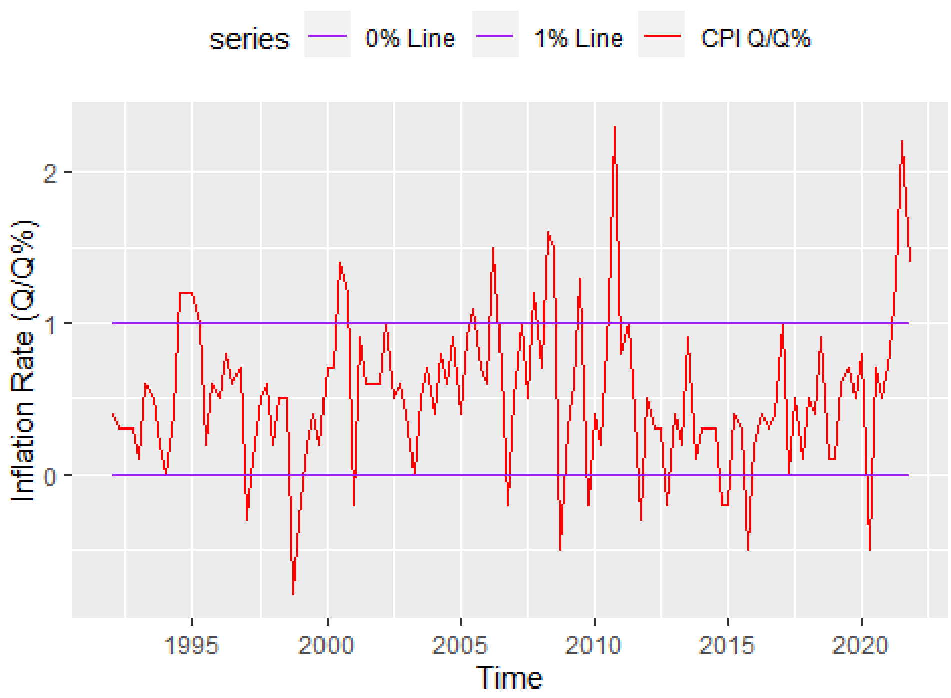


Table 13 – 0% to 1% Split Recursive Nowcasts RMSE Table

Recursive Model RMSE	0% to 1% Inclusive	Outside 0% to 1%
Random Walk	0.510	0.921
ARIMA	0.284	0.946
RBNZ Target	<u>0.262</u>	0.968
NNAR	0.287	0.934
MIDAS-R M3	0.436	0.880
MIDAS-R M4	0.542	0.828
MIDAS-U M1	0.312	0.935
MIDAS-U M2	0.362	<u>0.763</u>
MIDAS-U M3	0.412	0.860
MIDAS-U M4	0.573	0.832
Average RMSE	0.398	0.887

The last row of Table 13 shows the average of the RMSEs for each model. "M" refers to which month it is. For example, M3 is a Month 3 nowcast.

All the models have a lower RMSE for quarters where the Q/Q% NZ inflation rate stays between the 0% to 1% inclusive band. The RBNZ Target model has the lowest RMSE value when the Q/Q% inflation rate is between zero and one percent. The ARIMA and NNAR models follow closely behind in RMSE. This result is not surprising because the nowcasts of these models largely stay between the 0% to 1% band.

What may be more surprising are the results in the quarters when the published inflation rate has been outside the 0% to 1% band. In these quarters, the MIDAS-R and MIDAS-U models generally have an RMSE lower than the rest of the models. This outcome may be because the projections of these models are more volatile as they attempt to follow the data. For example, when Q/Q% inflation is not inside the 0% to 1% area, the nowcasts of the MIDAS-R and MIDAS-U models generally tend to exit the 0% to 1% band. With that logic in mind, it is unclear why the RMSE of the random walk model is as high as it is when it is outside of the 0% to 1% band. Maybe this is because when inflation levels are outside this band, the persistence of the Q/Q% NZ inflation rate could become lower. I say this because Figure 4 suggests that when the inflation rate exits this band, it quickly returns within the 0% to 1% area. As a result, the last observation may become less helpful in projecting future inflation rate values.

9.3 RMSE Split by Year

As discussed in the literature review, some models do better than others, depending on the year (Stock & Watson, 2008). As a result, it is natural to look at how the RMSE values of models change over time. In this subchapter, I look to answer two questions:

1. How has the RMSE of my six models changed over the past 20 years?
2. How has the RMSE of my six models changed during the pandemic years (2020 and 2021)?

In this subchapter, I use the recursive models from earlier. Understanding what was occurring during each period is necessary to contextualise the results. Usually, significant events coincided with the quarterly NZ inflation rate going outside the boundaries of zero and one percent.

During the late 1980s, the government gave the RBNZ an inflation-targeting mandate ("Banking (Prudential Supervision) Act 1989,"). The RBNZ aimed to keep annual inflation between 0 and 2 per cent, per their mandate. In 1996, this target was revised to between 0 and 3 per cent (Williams et al., 2020). During the 90s and early 2000s, the RBNZ succeeded in pushing down the inflation rate compared to where it was previously. Shocks similar to the Dotcom Bubble pushed inflation outside this target band. In 1999, the RBNZ was asked to "seek to avoid unnecessary instability in output, interest rates, and the exchange rate" ("Reserve Bank of New Zealand (Replacement of Remit for Monetary Policy Committee) Order 2021,").

2002 to 2006 was a relatively calm period for inflation. In 2002, the RBNZ's annual inflation target was revised to 1 and 3 per cent (Williams et al., 2020). Additionally, it was made more explicit in legislation that this target range was for inflation levels in the medium term.

For at least two reasons, Kiwis saw more volatile inflation levels during 2007-2011. Firstly, between 2007-2009, the Global Financial Crisis struck the world. Secondly, in 2010, Goods and Services Tax (GST) in New Zealand was increased from 12.5% to 15%.

Inflation returned to more stable levels in the early-to-mid 2010s. This trend continued for the rest of the decade. Then, the COVID-19 pandemic hit in 2020.

The pandemic and its effects have contributed to unstable and record inflation in the past few years. We can see through the inflation graph that, in 2020, Q/Q% inflation levels dipped into negative territory. Shortly after, prices rapidly increased from then onwards. In 2022, annual inflation levels hovered around 7 per cent (Statistics New Zealand, 2022a).

Table 14 – Recursive Nowcasts RMSE Table Split by Timeframe

Recursive Model RMSE	**2002-2006**	**2007-2011**	**2012-2016**	**2017-2021**	**2020-2021**
Random Walk	0.462	0.889	0.464	0.640	0.795
ARIMA	0.382	0.728	0.400	0.549	0.753
RBNZ Target	0.384	0.702	0.406	0.581	0.834
NNAR	0.386	0.703	0.392	0.569	0.773
MIDAS-R M3	0.504	0.699	0.455	0.629	0.831
MIDAS-R M4	0.769	0.681	<u>0.291</u>	0.654	0.870
MIDAS-U M1	0.384	0.731	0.409	0.564	0.780
MIDAS-U M2	<u>0.358</u>	0.707	0.354	<u>0.471</u>	<u>0.562</u>
MIDAS-U M3	0.372	0.715	0.361	0.684	0.862
MIDAS-U M4	0.644	<u>0.674</u>	0.473	0.764	0.974
Average RMSE	0.465	0.723	0.401	0.611	0.803

The last row of Table 14 shows the average of the RMSEs for each model. “M” refers to which month it is. For example, M3 is a Month 3 nowcast.

Table 14 shows an interesting story. 2020-2021 was the period in Table 14 where the RMSE was highest, on average. This outcome could be for two reasons. Firstly, the pandemic was a unique event that created unique consequences. Many of the variables in the models exhibited unusual characteristics. For example, the absolute price of oil went negative. Real expenditure-based GDP in 2020 Q2 decreased by 9.5% compared to the previous quarter. Then, this variable increased by 14.3% in 2020 Q3 compared to 2020 Q2. In the RBNZ professional forecasters survey (Reserve Bank of New Zealand, 2022b), economists predicted that a year from 2020 Q2, Y/Y% GDP growth would be -4.87%. Shortly afterwards, they quickly changed tack, predicting that one year from 2020 Q3, Y/Y% GDP growth would be 4.24%. The multivariate and univariate models were not trained to predict the NZ inflation rate in such a unique environment. Secondly, half of the quarters from 2020 to

2021 had a published inflation rate value outside the 0% to 1% range. As shown in the previous subchapter, this generally correlates with a higher RMSE value on average. With this in mind, it is also unsurprising that the RMSE values from 2017 to 2021 are higher than average.

In the table, the average RMSE of the models are lowest between 2012 and 2016. The reason for this may be because of the stable level of inflation during this timeframe. The nowcasting method with the lowest RMSE during 2012 and 2016 was MIDAS-R using the data from Month 4. Meanwhile, the nowcasting method with the highest RMSE between 2012 and 2016 was MIDAS-U using data from Month 4. Both the MIDAS-R and MIDAS-U models are given the same data. I think this result helps show how estimating a model differently can change a model's accuracy.

The RMSE of my models is lower than average between 2002 and 2006. This is not surprising, given that inflation levels were less volatile than from 2007 to 2011 and 2017 to 2021. The RMSEs of the MIDAS-R and MIDAS-U models using Month 4 data were the highest out of all prediction methods for the 2002 to 2006 period. This outcome is consistent with the hypothesis that these models were overfitting due to fewer degrees of freedom. The MIDAS results for Months 3 and 4 align more with the rest of the models from 2007-2021. This result supports this overfitting hypothesis, as the number of degrees of freedom increased as time went on. If the MIDAS-R and MIDAS-U Month 4 models were not included, 2002-2006 would be the period with the lowest average RMSE.

2007 to 2011 has the highest RMSE on average of all the five-year periods. The impacts of the Global Financial Crisis and a GST increase in 2010 may not have been recognised by the inflation rate nowcasts. A volatile inflation rate and many published inflation rate values outside the 0% to 1% band would not have helped the univariate and multivariate models to nowcast well.

The ARIMA, RBNZ Target, and NNAR models have somewhat similar RMSEs over time. This result is unsurprising as all these prediction methods nowcast inflation around the 0% to 1% band. I find it interesting that the accuracy of the MIDAS models during a given timeframe can change significantly depending on what data is given to the model. Additionally, it is not always the case that giving the model more data results in a lower RMSE.

9.4 Split by Quarter

In this subchapter, I look at how the RMSE of each model changes over each quarter. For this subchapter, I use the recursive models from Subchapter 9.1.

Table 15 – RMSE Results Split by Quarter Recursive Nowcasts

Recursive Model RMSE	**Q1**	**Q2**	**Q3**	**Q4**
Random Walk	0.575	0.568	0.566	0.809
ARIMA	<u>0.241</u>	0.539	0.486	0.743
RBNZ Target	0.269	0.532	0.542	0.703
NNAR	0.247	<u>0.529</u>	0.499	0.728
MIDAS-R M3	0.456	0.68	0.47	0.674
MIDAS-R M4	0.412	0.816	0.645	<u>0.563</u>
MIDAS-U M1	0.266	0.566	0.526	0.706
MIDAS-U M2	0.335	0.537	0.462	0.601
MIDAS-U M3	0.385	0.72	<u>0.431</u>	0.629
MIDAS-U M4	0.54	0.851	0.519	0.626
Average RMSE	0.373	0.634	0.515	0.678

"Q" refers to which quarter it is. For example, Q3 is a Quarter 3 nowcast.

On average, the RMSE for my nowcasts are lowest for quarter one. The next lowest average RMSE values are in quarter three, followed by quarters two and four. Table 16 can help us understand the reason for this seasonal trend. From 2002 to 2021, Table 16 shows the number of times each quarter where the Q/Q% inflation rate was outside the 0% to 1% band. Generally speaking, the RMSE of a model seems to correlate positively with the number of values outside this band. However, 20 years is not a large sample size for this analysis. Therefore, this result may be a coincidence.

Table 16 – NZ Inflation Rate Values Not Between 0% to 1% Inclusive (2002-2021)

Number of Values	Q1	Q2	Q3	Q4
Inflation Rate Values Outside of 0% to 1% Inclusive Range in 2002-2021	1	4	5	10

The order of lowest to highest RMSE (Q1, Q3, Q2, then Q4) generally holds for most models, but there are a few exceptions. For example, for months 3 and 4 of the MIDAS-R and MIDAS-U models, this rule-of-thumb does not apply. It may be helpful to extend this research to other countries to see how the seasonality of inflation affects the accuracy of nowcasting models.

9.5 Split by Data

In this subchapter, I aim to find out which data helps the most in predicting inflation. Specifically, I wish to see how soft data, economic activity data, financial data, price data, and Phillips' curve specifications help predict the NZ inflation rate. I follow the same strategy as the recursive nowcast subchapter (Subchapter 9.1). The only difference is that I will only give the model the corresponding data it needs and nothing else. For example, when calculating soft data models, I only give the model soft data and previous NZ inflation rate values.

The relative RMSE benchmarks for Tables 17 to 21 are the RMSE values in Subchapter 9.1. For example, the MIDAS-U Month 4 Soft Data benchmark is the MIDAS-U Month 4 model RMSE in Subchapter 9.1 ($RMSE = 0.648$). Some months and models have NAs next to them. This is because the models cannot be applied to those months with the relevant set of data. In other words, some, or all, of the needed data does not exist for that particular month.

For example, there are no values for MIDAS-R Soft Data because MIDAS-R cannot be calculated because the soft data is all quarterly data. I only use the last quarterly value available for soft data for reasons mentioned in Chapter 7. However, MIDAS-R can only be calculated when multiple lags of a variable exist.

Table 17 – Soft Data Recursive Nowcasts Relative RMSE Table

Model Relative RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Soft Data	NA	NA	NA	NA
MIDAS-U Soft Data	1.060	0.985	0.870	0.751

Table 18 – Economic Activity Data Recursive Nowcasts Relative RMSE Table

Model Relative RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Economic Activity Data	NA	NA	NA	NA
MIDAS-U Economic Activity Data	0.995	1.080	0.960	0.828

Table 19 – Financial Data Recursive Nowcasts Relative RMSE Table

Model Relative RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Financial Data	NA	NA	0.962	0.902
MIDAS-U Financial Data	NA	1.107	0.992	0.862

Table 20 – Price Data Recursive Nowcasts Relative RMSE Table

Model Relative RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Price Data	NA	NA	0.951	0.877
MIDAS-U Price Data	NA	0.978	0.913	0.862

Table 21 – Phillips Curve Recursive Nowcasts Relative RMSE Table

Model Relative RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Phillips Curve	NA	NA	0.923	0.912
MIDAS-U Phillips Curve	NA	1.016	0.919	0.800

Generally, the relative RMSEs of Tables 17 to 21 are near one. However, this is not as much the case for the MIDAS-U model, especially in Months 3 and 4.

We saw in previous subchapters in Chapter 9 that the RBNZ Target model had a comparable RMSE value to the other models, despite having little information available to it. Similarly, many models in this subchapter nowcasted a Q/Q%

inflation rate around 0.5%, potentially because they did not have much information. The intercept for many MIDAS models was near 0.5%, and the coefficients were not large. There were some exceptions to this trend. There was generally more variance in the inflation rate predictions over time when using price, soft data, or a Phillips curve specification. Despite the increased variance, the RMSE values of these data specifications are generally not better than the economic activity or financial data specifications.

The lowest absolute RMSE value from this exercise came from the MIDAS-U price data from Month 2 ($RMSE = 0.483$) and MIDAS-U soft data from Months 2-4 ($RMSE = 0.486$). The RMSE of these models is around 10 per cent smaller than the ARIMA and RBNZ Target RMSE. This result is consistent with the findings from the literature review that soft data and price data help predict inflation. A future direction may involve combining soft and price data and seeing how this performs. The absolute RMSE tables for each model are available in Appendix A1, Tables A3 until A7.

9.6 Rolling Window

This subchapter covers results for five models when a rolling window is used. Note that a rolling window is not presented for the random walk and RBNZ Target models. The reason is that the nowcasts of these models remain the same regardless of how large the rolling window is. The rolling windows are used to nowcast inflation between 2002 and 2021. The rolling window models use the same methodology as the recursive nowcasts with one difference; rolling windows use a rolling window instead of a recursive window.

I choose not to present a five-year rolling window for MIDAS-R. I also chose not to present results for a five and eight-year rolling window for MIDAS-U. If I included these values in the RMSE table, I would include models with more parameters to estimate than observations. Not surprisingly, this causes significant problems, as mentioned in Chapter 7.

Table 22 – RMSE Table with Rolling Windows and Recursive Results

Model RMSE	5-Year RW	8-Year RW	10-Year RW	Recursive
ARIMA	<u>0.562</u>	<u>0.567</u>	0.598	0.533
NNAR	0.707	0.735	0.755	0.529
MIDAS-R M3	NA	0.756	0.736	0.580
MIDAS-R M4	NA	0.816	0.834	0.626
MIDAS-U M1	NA	NA	0.598	0.540
MIDAS-U M2	NA	NA	<u>0.594</u>	<u>0.494</u>
MIDAS-U M3	NA	NA	0.736	0.559
MIDAS-U M4	NA	NA	1.269	0.648

No average RMSE is given for this table. The reason is that the lack of data for the five and eight-year rolling window MIDAS models may bias the average RMSE calculation.

The significant finding from Table 22 is that none of the rolling window models has a lower RMSE than their recursive counterparts. One potential reason for this result is the infrequency of inflation rate data. The five-year, eight-year, and ten-year rolling windows in countries with monthly inflation data would represent 60, 96, and 120 inflation rate observations. However, because New Zealand's CPI data is published quarterly, there are only 20, 32, and 40 inflation rate observations in each respective rolling window period. As a result, the models may not have enough observations to model inflation better than the recursive models. One may argue that I should increase the rolling window size. If I did this, our sample would require a fifteen-year, twenty-four-year, and thirty-year rolling window to have 60, 96, and 120 inflation rate observations, respectively. However, such large rolling windows would substantially decrease or eliminate the test set.

Another potential reason for these results is parameter proliferation, as discussed earlier. The potential problems with parameter proliferation become apparent when looking at the MIDAS-U model's ten-year rolling window. As more data and variables are added to the model, the RMSE of MIDAS-U increases dramatically. This increase primarily occurs in Months 3 and 4.

The RMSEs of the ARIMA model are around 5.4-12.2% higher than the recursive model counterparts, depending on the rolling window and timeframe.

The NNAR RMSEs are abnormally high because of the nowcast for 2021 Q4. In all three rolling windows, the NNAR model gives a nowcast of around 5% for 2021 Q4. This nowcast may have occurred because the data used to make this nowcast would not include previous shocks such as the Global Financial Crisis and the Dotcom Bubble. As a result, the NNAR model may not have been trained on appropriate data to forecast high inflation levels, like was present in 2021 Q4. I conducted some extra analysis after discovering this. I found that increasing the rolling window size to twelve years gave a much more reasonable nowcast for 2021 Q4.

9.7 Comparing Inflation Rate Predictions from Professionals and Households

We have seen in Subsections 9.1 until 9.6 how different model nowcasts compare to univariate benchmarks. In addition, it is also interesting to look at how professional and household inflation rate predictions compare to the univariate benchmarks.

In this subchapter, I compare the nowcasts of professionals and households to the ARIMA model. In other words, the benchmark model that I compare the professionals and households to is the ARIMA model. I choose ARIMA because ARIMA was the best-performing benchmark in the *Recursive Nowcast Results* subchapter. As a result, I am interested in seeing whether these organisations and individuals can outperform my best-performing benchmark model in my sample.

The results from the random walk and RBNZ Target benchmarks have strong similarities with the ARIMA results. However, the professional and household predictions may generally have a higher relative RMSE when compared to the ARIMA benchmark. When the benchmark is the random walk or RBNZ Target models, the relative RMSEs are generally lower. This outcome is not surprising because the ARIMA model had a lower RMSE than these models in the *Recursive Nowcasts Results* subchapter. Appendix B1, Tables B3 and B4, show how professional and household predictions compare to the random walk and RBNZ Target models. Additionally, Appendix B2 shows graphs of all the data that I used for Subchapter 9.7.

The ASB, BERL, RBNZ Household, and RBNZ MPS produce Y/Y% inflation rate predictions, which I have used in this thesis. The rest of the NZ inflation rate predictions are in Q/Q% format. It is important also to remember that a 1Q Ahead Forecast is made between three to six months before the predicted inflation rate value would be released. Meanwhile, a nowcast is made less than three months before the predicted inflation rate value is released. For example, suppose that it was February 2022 and we wanted to predict the NZ inflation rate value. The next two NZ CPI values will be released in mid-April 2022 (for Q1 2022) and in mid-July 2022 (for Q2 2022). If this is the case, then a nowcast of the NZ inflation rate would predict Q1 2022 inflation, and a 1Q Ahead Forecast would predict the inflation rate for Q2 2022.

Table 23 – Relative RMSE of Professionals and Households Compared to ARIMA Nowcast Benchmark

Inflation Rate Prediction Relative RMSE	**1Q Ahead Forecast**	**Nowcast**
ANZ CPI Preview	NA	0.383
RBNZ MPS	0.839	0.425
ANZ QEF + QEO	0.733	0.437
NZIER Mean	0.936	0.528
Treasury EFU	1.102	0.530
ASB	1.354	0.684
BERL	1.573	1.093
Westpac RMSE	1.455	1.114
RBNZ Household Mean	NA	2.304

The relative RMSEs are calculated using the formula $Professional\ or\ Household\ Prediction\ RMSE/Benchmark\ RMSE$, where the benchmark model is the ARIMA model. The benchmark RMSEs are calculated three months before the inflation rate values are released using a recursive approach. In other words, they are calculated at Month 1 in the *Recursive Nowcast Results*. The benchmark RMSEs are calculated for the timeframe that each forecast is available. For example, suppose a nowcast was only available between Q1 2010 and Q4 2019. The benchmark RMSE would be calculated using nowcasts from Q1 2010 and Q4 2019.

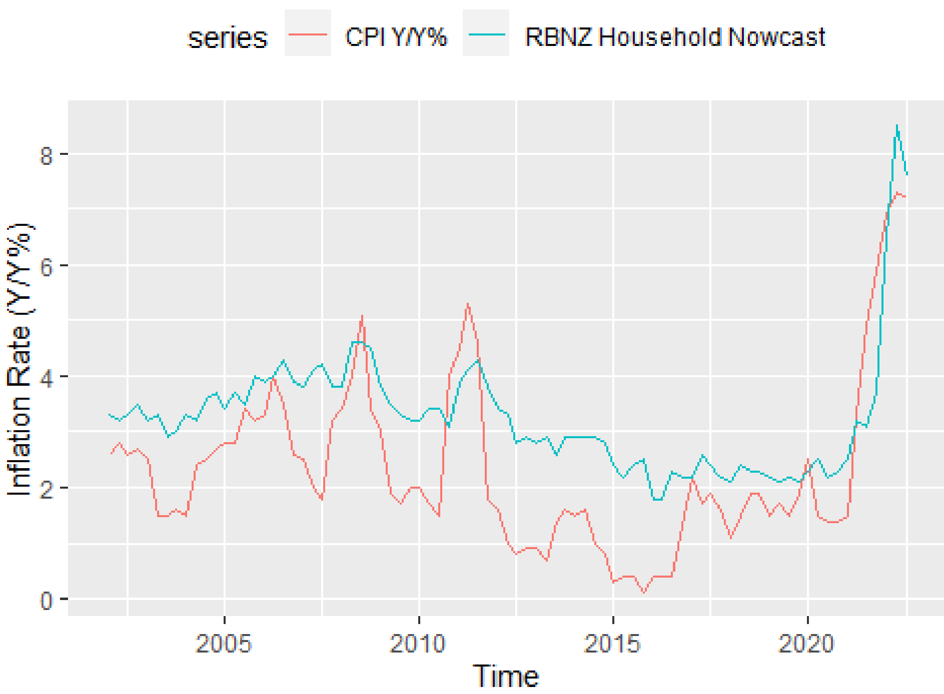
When nowcasting the NZ inflation rate for quarter t, the benchmark models can use all NZ inflation rate data from Q1 1992 until quarter $t-1$. All professionals and households make their nowcasts around one to three months after the ARIMA nowcast is made. However, the one-quarter-ahead forecasts are generally made one to two months before the ARIMA nowcast is made. When making a one-step-ahead forecast, the professionals only have access to inflation rate data until $t - 2$.

Most organisations have lower RMSE values than the ARIMA benchmark when nowcasting inflation. Despite this, four out of seven one-quarter-ahead forecasts had a higher RMSE value than the benchmark. Similar to the findings in the literature review, it is not surprising that the relative RMSE values increase as the projections are made further out from the inflation rate release date.

Note that the relative RMSEs of households and professionals are not comparable to each other. This is because each of their projections are only available for particular periods. Comparing relative RMSEs could give a misleading impression of which models are best. A low relative RMSE might occur because the ARIMA model did not perform well during that timeframe and not because the household/professional predictions were high-quality.

The RBNZ Household Mean nowcast of the NZ inflation rate has, by far, the highest relative RMSE value. This finding is not surprising as research shows that households (including New Zealand households) consistently overestimate real-time inflation levels (Hayo & Neumeier, 2022; Leung, 2009). Between 2002 and 2021, there were only three periods where the actual inflation rate was higher than the RBNZ Household Mean predictions. These occurred during the Global Financial Crisis, when GST increased from 12.5% to 15%, and during the Covid-19 pandemic recovery.

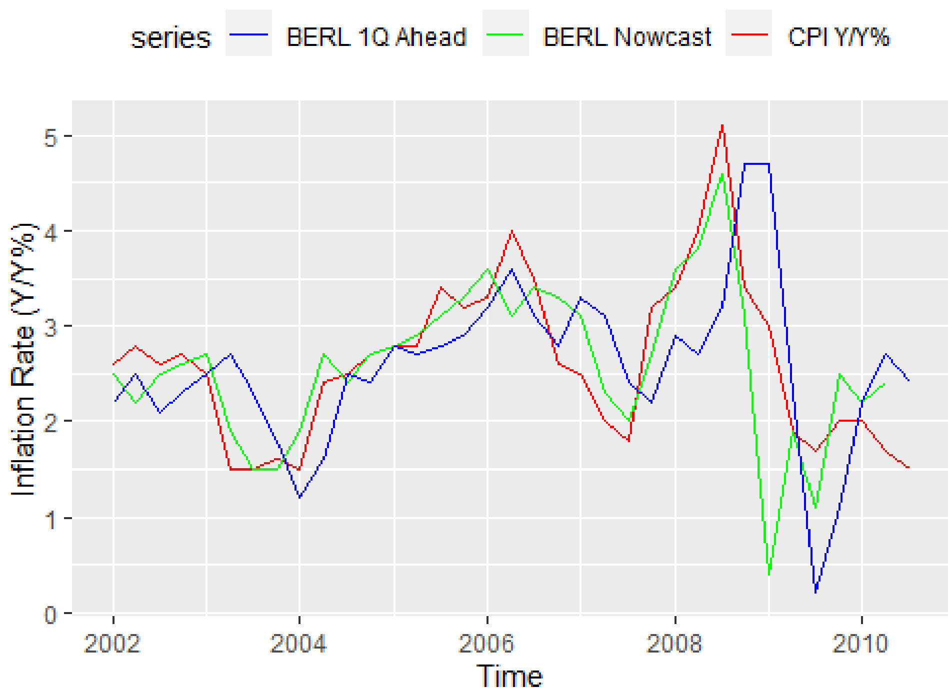
Figure 5 – RBNZ Household Mean Nowcasts Graph



The Westpac and BERL nowcasts had a higher RMSE than the ARIMA models, despite these predictions being made after the ARIMA models. By looking at the graphs showing their predictions, we can potentially see why this is the case. In the case of BERL, their nowcasts were mostly made during the third month of the quarter.

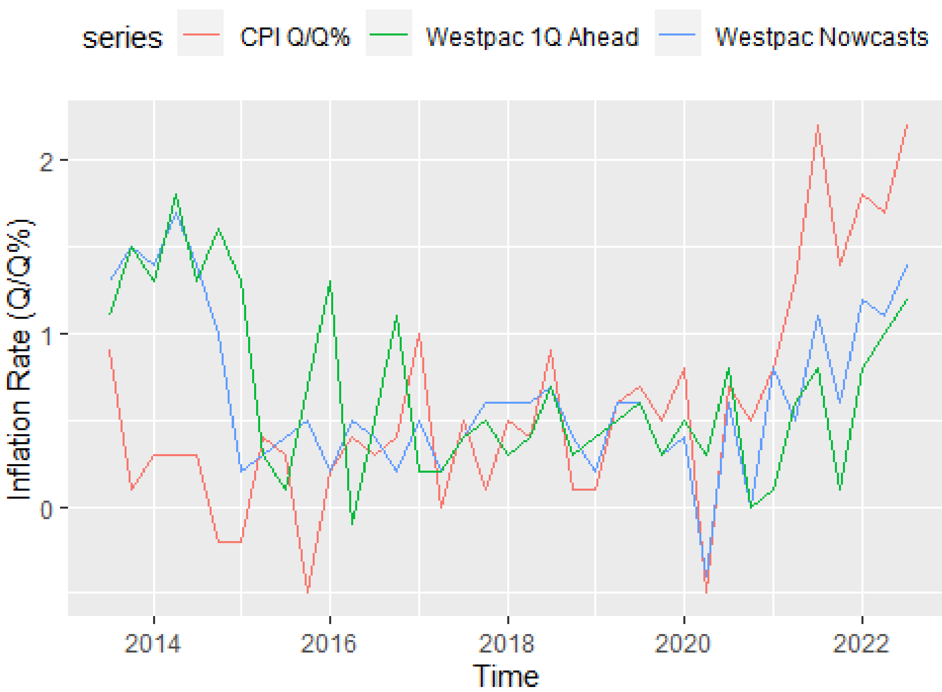
One main reason the BERL predictions have a higher RMSE than the ARIMA model was because of BERL's 2009 Q1 prediction for inflation. This inflation nowcast was 2.6% lower than the actual value of Y/Y% inflation. This nowcast may be a typo published by BERL. I have double-checked that the value for 2009 Q1 is correct. If just this 2009 Q1 value is removed, the relative RMSE of the BERL nowcasts decreases from 1.093 to 0.702.

Figure 6 – BERL Nowcasts Graph



In a large portion of the Westpac sample, the Q/Q% inflation rate stays between zero and one percent. ARIMA has a lower RMSE value on average when the actual Q/Q% inflation rate stays within this range. The ARIMA model's overperformance during this timeframe may be why Westpac's nowcasts had a higher RMSE than the ARIMA model's nowcasts. Additionally, in most quarters during 2014 and 2015, the Westpac nowcasts overestimated the Q/Q% level of inflation by around one percent. If 2014 and 2015 were removed from the sample, the relative RMSE of the Westpac nowcasts would reduce from 1.114 to 0.777.

Figure 7 – Westpac Nowcasts Graph



Seven organisations had data available for a one-quarter-ahead forecast of the NZ inflation rate. Four of these seven organisations had a relative RMSE higher than one – The Treasury, ASB, Westpac, and BERL. At first, we may presume that this is because the ARIMA model has access to more recent data on the inflation rate. However, I did some extra testing to investigate this further. I used an ARIMA model which produced its inflation rate projections six months before the release of each inflation rate value. By using this model, the ARIMA model would produce its predictions of inflation before all the professionals would. However, even when such an ARIMA model was used, not all the professionals managed to outperform this model.

There are three economic and fiscal updates (EFUs) during election years, but I omit the election year EFUs in the dataset as they are published irregularly. An intriguing result occurs with the Treasury EFU predictions. These projections are unique in this dataset because they are usually released only twice a year. We can split The Treasury EFU predictions into two portions. The first is the Treasury Half-Year Economic and Fiscal Update (HYEFU), published around Mid-December (quarter 4). The second is The Treasury Budget Economic and Fiscal Update (BEFU), published around mid-to-late May (quarter 2).

Table 24 – Budget Economic and Fiscal Update (BEFU) Absolute RMSE Table

Model/Forecast	1Q Ahead Forecast (for Q3)	Nowcast (for Q2)
BEFU RMSE	0.335	0.363
RW RMSE	0.480	0.506
ARIMA RMSE	0.361	0.478
RBNZ Target RMSE	0.416	0.471

Table 25 – Half-Year Economic and Fiscal Update (HYEFU) Absolute RMSE Table

Model/Forecast	1Q Ahead Forecast (for Q1)	Nowcast (for Q4)
HYEFU RMSE	0.356	0.328
RW RMSE	0.604	0.863
ARIMA RMSE	0.253	0.799
RBNZ Target RMSE	0.289	0.725

The HYEFU's nowcasts predicts the NZ inflation rate for quarter 4, while their one-quarter ahead forecasts predicts the NZ inflation rate values for quarter 1 of the following year. The BEFU's nowcasts predicts the NZ inflation rate values for quarter 2, while their one-quarter ahead forecasts predicts the NZ inflation rate values for quarter 3. The one-quarter ahead forecasts for both the HYEFU and BEFU have somewhat similar RMSEs to the HYEFU and BEFU nowcasts. Despite this, this result is not reflected in the relative RMSE table.

Without further context, Table 23 might make someone think that the one-quarter-ahead inflation forecasts of the Treasury EFUs have a higher RMSE than the nowcasts. However, the tables above help to show otherwise. Quarters one and three are the "one-step-ahead quarters" for The Treasury EFUs. These quarters coincide with the quarters with the lowest RMSE values for ARIMA. Meanwhile, quarters two and four are the "nowcast quarters". They coincide with the quarters that have the highest RMSE values for ARIMA. Due to this, the relative RMSE values for the Treasury EFU's one-step-ahead forecasts may look less accurate than they are. This problem does not generally exist with the other datasets. This is because, for most data sources, the one-quarter ahead forecast data is available for a very similar set of years and quarters as the nowcast data.

Chapter 10: Conclusion

10.1 General Concluding Notes

This thesis aimed to examine how best to nowcast inflation in New Zealand thoroughly. I wanted to answer the following three questions:

1. Which models and data could be best suited to nowcast the New Zealand inflation rate (the percentage change in the NZ CPI)?
2. Are there situations where nowcasting models perform better or worse than usual?
3. Can a model nowcast outperform New Zealand professional forecasters and Kiwi household forecasts?

To do this, I have conducted research in two areas. Firstly, I have created nowcasting models to nowcast inflation in New Zealand. I have thoroughly examined these models using data from 1992 to 2021 (2002 to 2021 as the test set). This analysis included analysing the accuracy of these models depending on the year, quarter, and data used. I analysed how using a rolling window impacted the accuracy of the nowcasts. I also examined the performance of my nowcasts depending on whether the actual NZ inflation rate was between 0% to 1% or not. Secondly, I compared the accuracy of the nowcasts and one-quarter-ahead forecasts from professionals and households in New Zealand. I used nine different data sources and compared their predictions to my best-performing benchmark model: the ARIMA model.

Two areas of my research are novel. Firstly, my research provides a substantive overview of nowcasting inflation in New Zealand. Before this thesis, as far as I am aware, no research had been conducted on nowcasting inflation in New Zealand. Secondly, my thesis incorporated new information and techniques from recent years. For example, my research looks at the effects of the pandemic on nowcast accuracy and uses neural networks.

I have gathered the following answers to my three research questions.

Question 1: The RBNZ Target and ARIMA models may be good benchmark models to use to nowcast percentage changes in New Zealand's inflation rate. Generally speaking, the Neural Network Autoregression (NNAR) model performed similarly to the ARIMA and RBNZ Target models. The MIDAS-R and

MIDAS-U models showed some potential to be good models for nowcasting the NZ inflation rate. However, the accuracy of these models highly depends on the model's specifications. In some months, the RMSE of MIDAS models was around 20% higher than the ARIMA model. A rolling window model specification was not found to improve accuracy for any model.

From a set of 16 independent variables, I also created models using only soft, economic activity, price, financial, or Phillips curve data. I found their RMSE values were, on average, similar to or better than when all 16 independent variables were used. The models with the lowest RMSE generally used only price or soft data. This finding suggests that soft and price data could be most helpful in predicting the NZ inflation rate.

Question 2: There are situations where my nowcasting models perform better or worse than usual. In my sample, models generally had a lower RMSE during quarter 1, followed by quarter 3, quarter 2, and then quarter 4. Models also had much lower RMSE values when the actual inflation rate (the value published by Stats NZ) for the quarter being pseudo-nowcasted was between zero and one percent.

Question 3: The predictions from New Zealand professional forecasters and Kiwi households sometimes produce a lower RMSE value than a benchmark nowcast. Most nowcasts produced a lower RMSE value than the three benchmark models: ARIMA, RBNZ Target, and random walk. Despite this, four of the seven one-step-ahead forecasts had a higher RMSE value than an ARIMA nowcast, the best benchmark model in my testing. The nowcasts with the lowest relative RMSE for the NZ inflation rate came from ANZ Bank and the Reserve Bank of New Zealand. These nowcasts had a relative RMSE value of around 0.4 compared to the ARIMA model. In other words, their nowcasts produced an RMSE around 60% lower than the ARIMA model.

10.2 Limitations

There are limitations to my research that are necessary to note.

Firstly, the literature review mentioned that it is ideal to use a vintage dataset for forecasting and nowcasting research. Unfortunately, when doing my research, I could not find a vintage dataset I could use. As a result, I have chosen to use the latest available values of each variable, but unfortunately, I cannot track revisions in my datasets because of this. While this is not ideal, it is not the end of the world. Many of the values in our dataset are likely not subject to regular revisions, meaning many data used may still be identical if a vintage dataset were available.

However, it is important to acknowledge that vintage datasets for variables do exist, such as for the NZ CPI (Federal Reserve Bank of St. Louis, n.d.). Furthermore, Richardson et al. (2021) used vintage datasets when nowcasting New Zealand GDP. I recommend incorporating a vintage dataset when nowcasting NZ inflation as an area of future research.

Secondly, in some cases, it was impossible to ascertain the release date of variables published several years ago. For example, it is hard to ascertain the GDP release date in 1992. In such cases, I have researched the release timing of a variable over recent years. Then, in my analysis, I assumed that this release timing stayed the same across all years. Despite this, these assumptions may not hold in full.

Thirdly, the lack of sample size for my dependent variables was problematic. When producing my results for my six models, I only had 80 observations for my test set. The lack of observations makes it hard to prove statistical significance. Due to this, tests such as the Diebold-Mariano test were not so practical. Statistical significance tests like these generally need more observations to find statistical significance.

Additionally, most professional forecasters in my sample had fewer than 80 observations available. Some results in the nowcasts from the professionals and households subchapter (Subchapter 9.7) may change if more data were available. Furthermore, there were additional models and data I wanted to use. Unfortunately, I had to leave these out, in part because of the small sample size for some of my data.

Fourthly, my analysis in Subchapter 9.2 had some drawbacks. One reason is that there are only twenty quarters between 2002 and 2021 where the NZ inflation rate exits the 0% to 1% Q/Q% bracket. Another reason is that we had knowledge that nowcasters would not have when creating a nowcast. When nowcasting in real life, we cannot know whether the next inflation rate value published will be inside or outside this 0% to 1% band.

Lastly, I have not included a dynamic factor model in my analysis. This is one typical model used in the academic literature. Implementing a dynamic factor model to nowcast New Zealand inflation could be done in future research.

10.3 Future Directions

I suggest four additional directions for future research.

Firstly, researchers could look at how the frequency of data given to models affects the accuracy of nowcasts for the NZ inflation rate. Researchers could use dynamic factor models, similar to Matheson (2005), to investigate this. Using these models avoids some of the problems present with using MIDAS models. This research direction is also of interest because my MIDAS model results find that adding more data variables does not automatically improve the NZ inflation rate nowcasts.

A second area of research involves combination nowcasts. Combination nowcasts combine the predictions of multiple models to create an updated inflation projection. Literature has found that combination forecasts can improve the accuracy of predictions (Fan, 2019; Mariano & Ozmucur, 2021). It may be helpful to see how the accuracy of NZ inflation rate nowcasts would change if combination nowcasts were implemented.

The third area of future research could be in using alternative data sources. Many innovative data sources, such as online price data and news sentiment, have been used recently to predict inflation with some success (e.g., Macias & Stelmasiak, 2019; Rambaccussing & Kwiatkowski, 2020). It would be helpful to see whether using these data sources helps improve the nowcasts of my multivariate models and the nowcasts of professional nowcasters.

Lastly, academics could further the analysis in the professional and household nowcasts subchapter (Subchapter 9.7) as more data becomes available. For example, investigating the nowcast accuracy of professionals by year and quarter could be one area of further research. Researchers could also investigate what the nowcasting methods of the most accurate professionals in New Zealand are.

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Appendix

Appendix A1: Modelling Work Tables

Table A1 – Release Timing of Quarterly Data Variables in Modelling Chapters

Variable	Frequency	Data Released at or Before	Comments on Release Timing
CPI (Q/Q%)	Quarterly	Month 1	Generally released 12 working days after the end of the period, except for the Oct-Dec quarter (because of Christmas break) (Stats NZ DataInfo+, 2022)
PF CPI 1Y	Quarterly	Month 2	The RBNZ releases this data "in the first or second week of the second month of the reference quarter." (Reserve Bank of New Zealand, 2022b)
PF UE Rate 1Y	Quarterly	Month 2	Same as PF CPI 1Y
PF GDP 1Y	Quarterly	Month 2	Same as PF CPI 1Y
PMC	Quarterly	Month 2	Same as PF CPI 1Y
UE Rate	Quarterly	Month 2	Around four weeks after the end of the quarter (Statistics New Zealand, 2017)
GDP	Quarterly	Month 3	Generally published 11 weeks after the end of the reference quarter, based on previous recent history

Table A2 – Release Timing of Monthly Data Variables in Modelling Chapters

Variable	Frequency	Comments on Release Timing
YS	Monthly	Released during the first week after the end of the reference month
TWI	Monthly	Released during the first week after the end of the reference month
FPI	Monthly	Stats NZ "generally publish the FPI 10 working days after the reference month." (Statistics New Zealand, 2022e)
MSW	Monthly	Published approximately three to seven days after the month has finished, based on recent history
FP	Monthly	Same as MSW
Aluminium	Monthly	Same as MSW
Gold	Monthly	Data needed to create this statistic is available immediately after the end of the month
Silver	Monthly	Same as Gold
WTI Cushing	Monthly	Same as Gold

Table A3 – Soft Data Absolute RMSE Table

Model RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Soft Data	NA	NA	NA	NA
MIDAS-U Soft Data	0.572	0.486	0.486	0.486

Table A4 – Economic Activity Data Absolute RMSE Table

Model RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Economic Activity Data	NA	NA	NA	NA
MIDAS-U Economic Activity Data	0.537	0.533	0.536	0.536

Table A5 – Financial Data Absolute RMSE Table

Model RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Financial Data	NA	NA	0.558	0.565
MIDAS-U Financial Data	NA	0.546	0.554	0.558

Table A6 – Price Data Absolute RMSE Table

Model RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Price Data	NA	NA	0.552	0.549
MIDAS-U Price Data	NA	0.483	0.510	0.558

Table A7 – Phillips Curve Absolute RMSE Table

Model RMSE	Month 1	Month 2	Month 3	Month 4
MIDAS-R Phillips Curve	NA	NA	0.536	0.571
MIDAS-U Phillips Curve	NA	0.501	0.513	0.518

Appendix A2: Recursive Nowcasts Graphs

Below are the recursive nowcasts graphs for each of the models. Before viewing the MIDAS-R and MIDAS-U models, remember that the accuracy of the Month 3 and Month 4 models may easily be affected by parameter proliferation. As a result, some of the nowcasts may look odd. This is especially in Months 3 and 4 where more parameters are estimated compared to Months 1 and 2.

Figure A1 – RBNZ Target Recursive Nowcasts

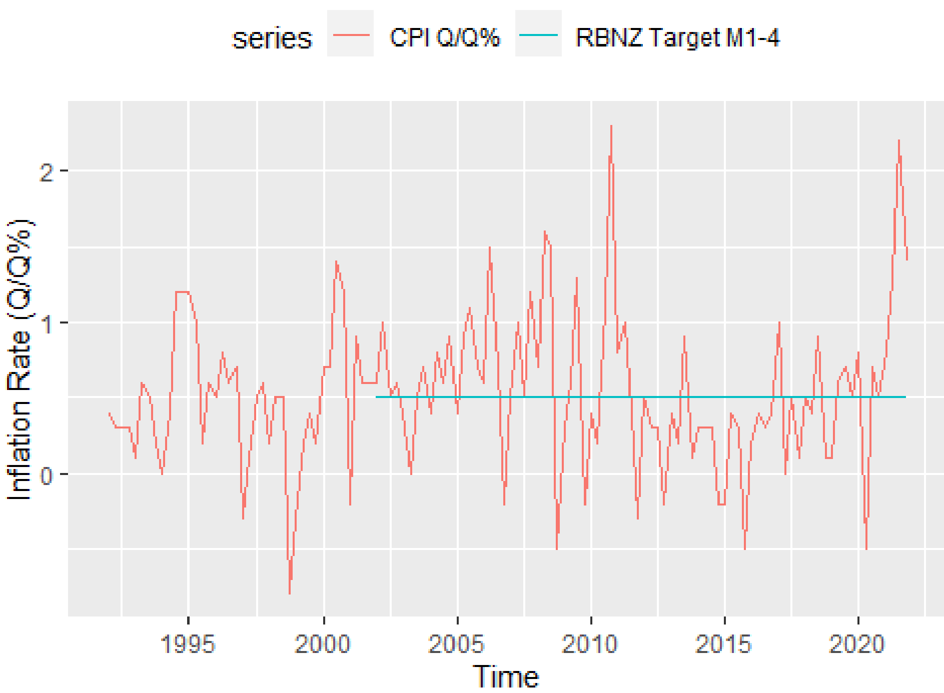


Figure A2 – ARIMA Model Recursive Nowcasts

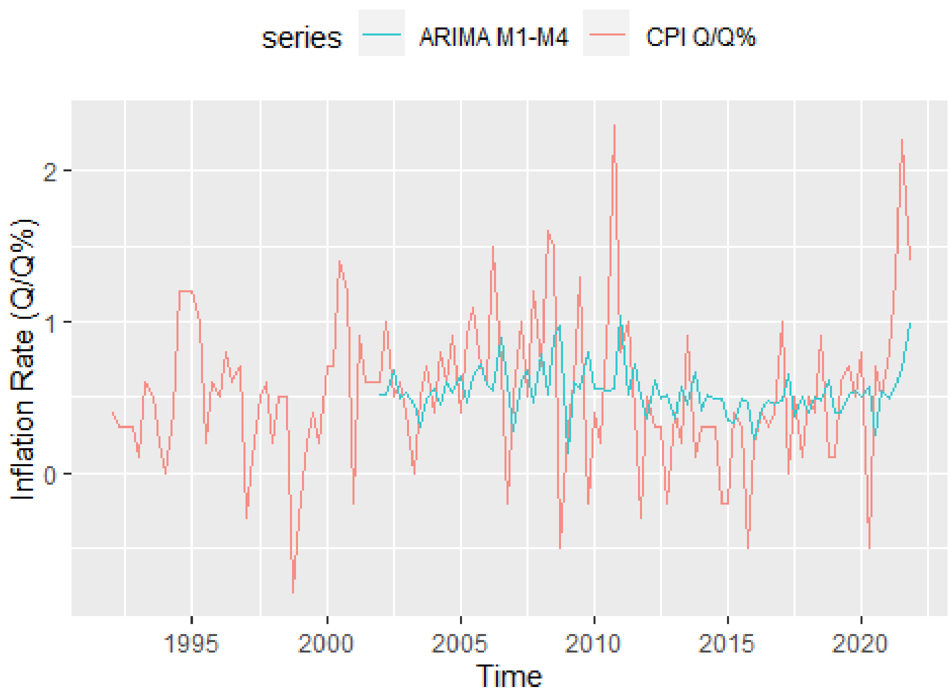


Figure A3 – Neural Network Autoregression (NNAR) Recursive Nowcasts

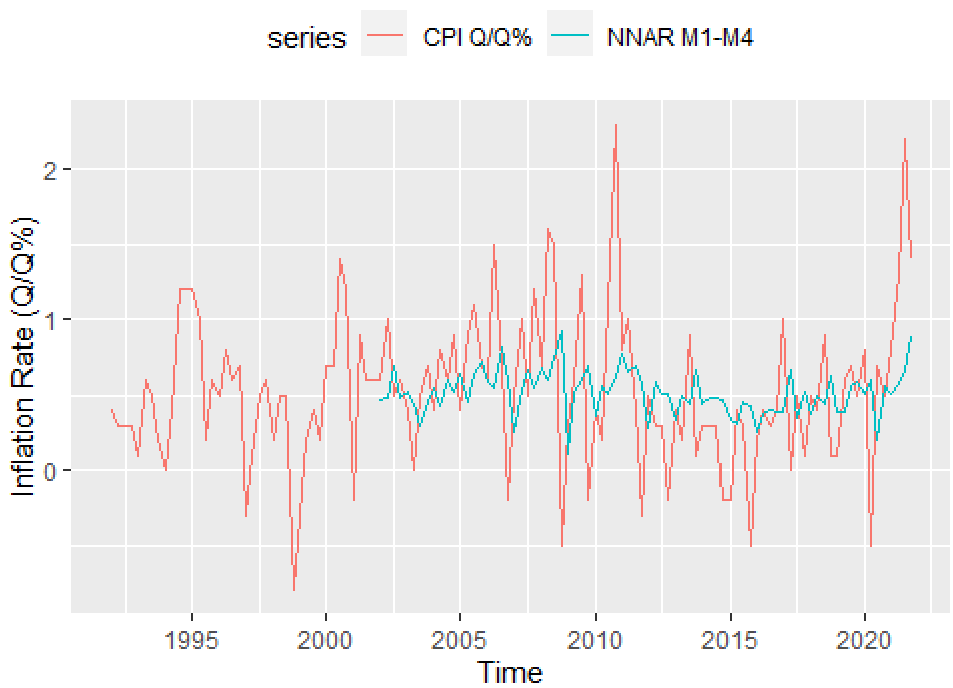


Figure A4 – Random Walk Recursive Nowcasts

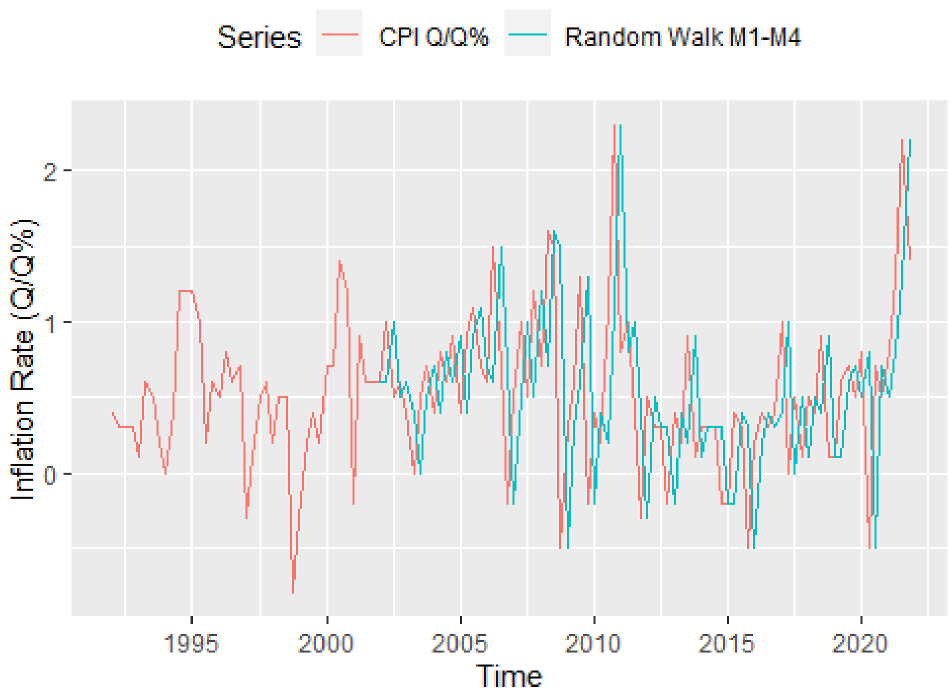


Figure A5 – MIDAS-R Month 3 Recursive Nowcasts

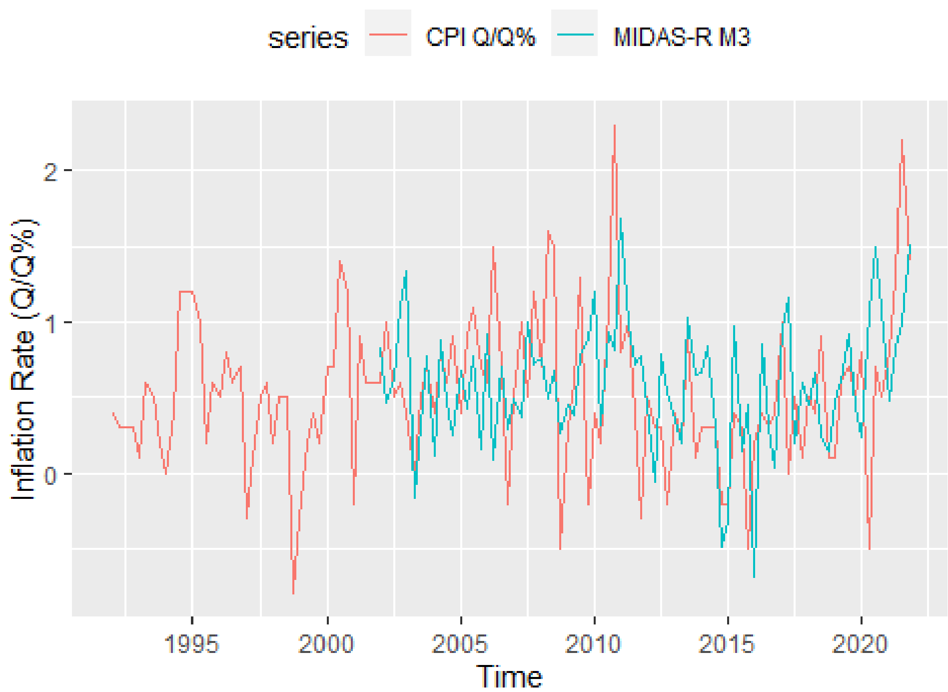


Figure A6 – MIDAS-R Month 4 Recursive Nowcasts

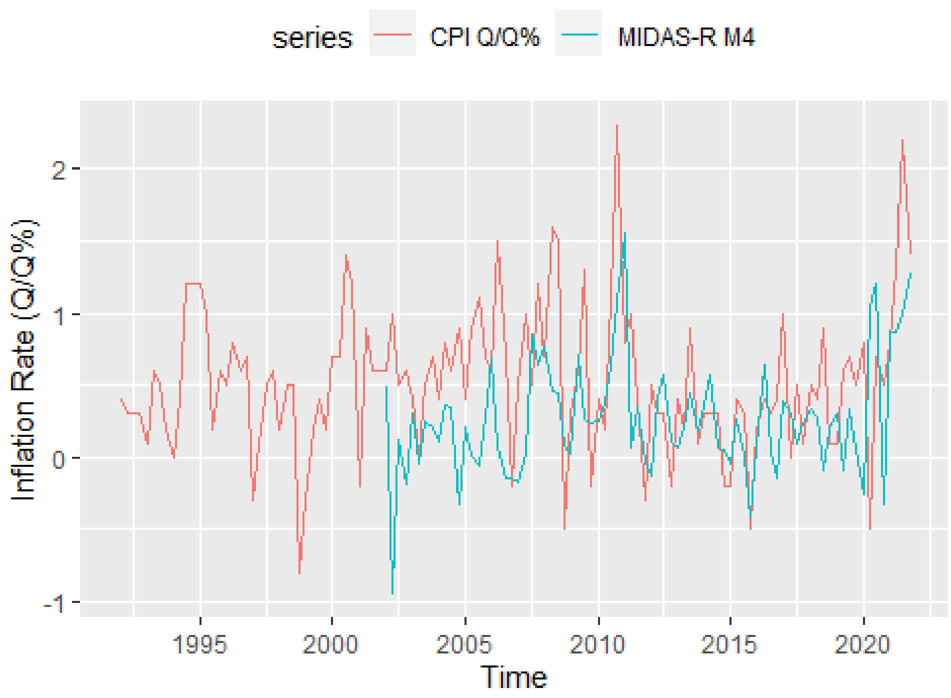


Figure A7 – MIDAS-U Month 1 Recursive Nowcasts

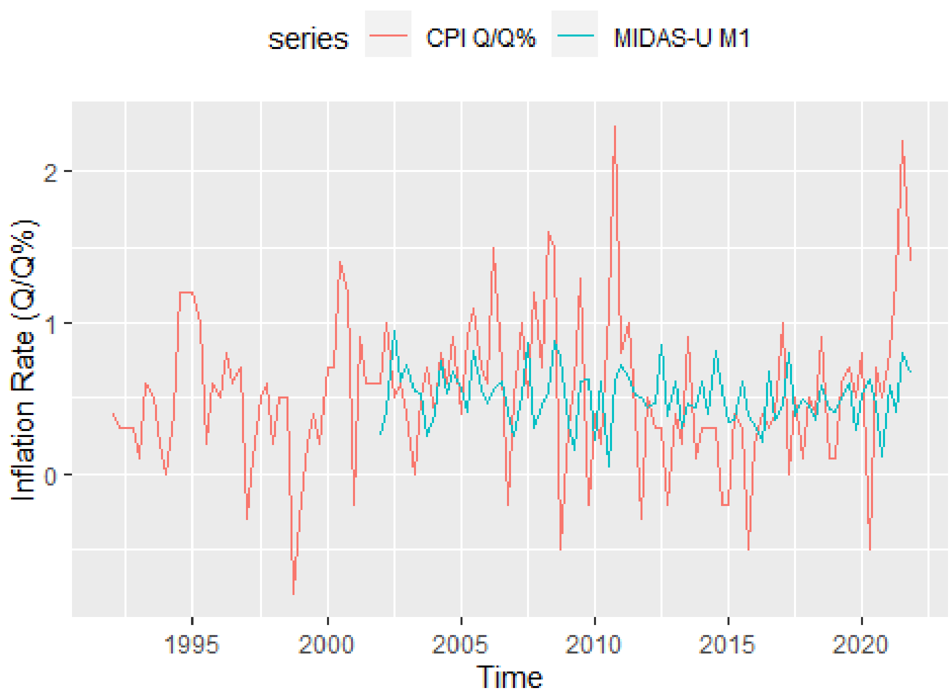


Figure A8 – MIDAS-U Month 2 Recursive Nowcasts

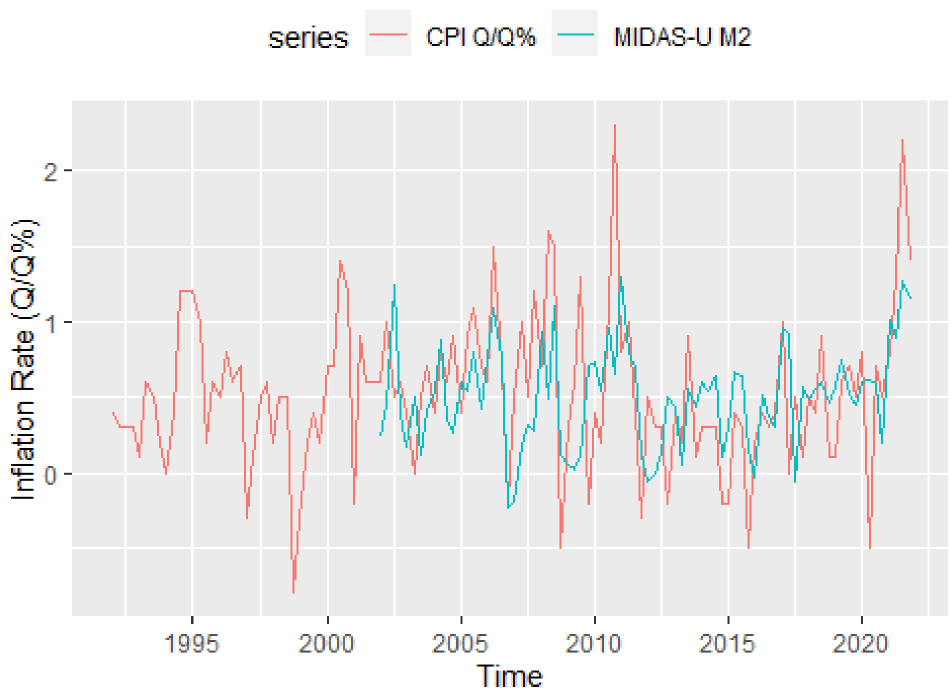


Figure A9 – MIDAS-U Month 3 Recursive Nowcasts

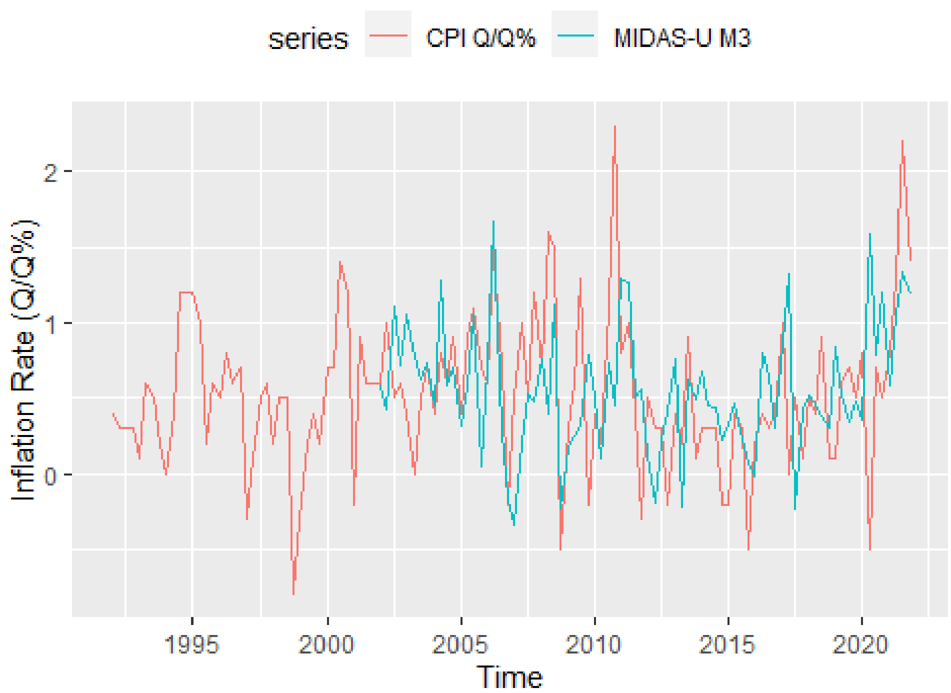
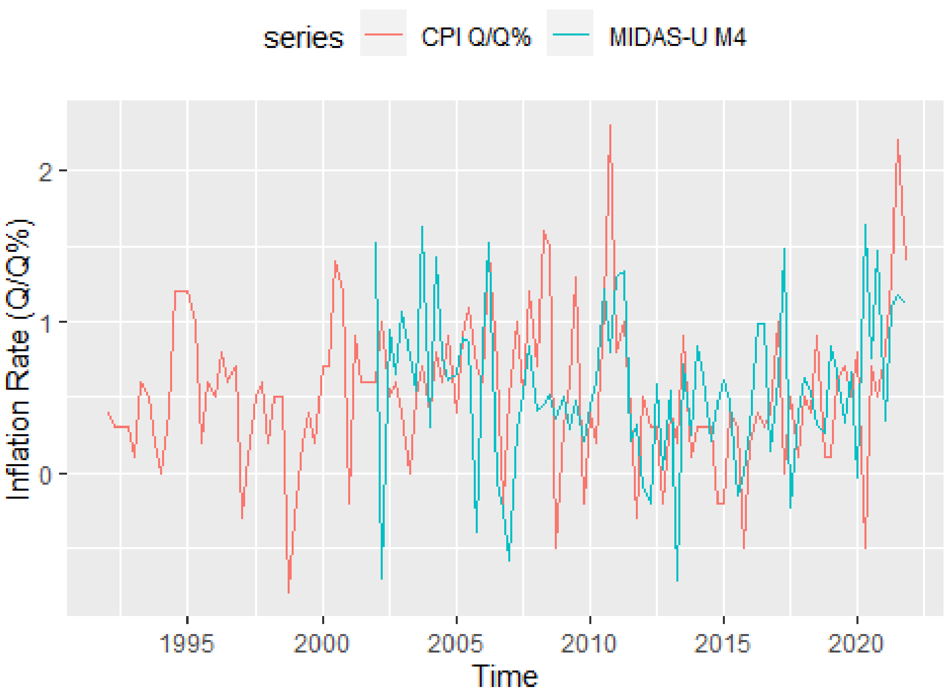


Figure A10 – MIDAS-U Month 4 Recursive Nowcasts



Appendix B1: Professional and Household Inflation Predictions Tables

Table B1 – Publication Dates, Frequency, and Release Times of Professionals and Household Data

Variable	Start Date of Publication Data Sample	Finish Date of Publication Data Sample	Frequency	Data Released At or Before	Comments on Publishing Schedule
ANZ Preview	Q1 2016	Q3 2022	Quarterly	Month 4	Published around one week before the CPI/inflation rate comes out – early-to-mid Month 4
ANZ QEF + QEO	Q1 2007	Q2 2015	Quarterly	Month 2 to Month 4	Published at irregular intervals. Published between the second month and the fourth month of the quarter
ASB	Q1 2016	Q3 2022	Quarterly	Month 2 to Month 3	As time passed, the predictions started to be published after Month 2 passed
BERL	Q1 2002	Q2 2010	Quarterly	Month 3 to Month 4	As time passed, the predictions started to be published after Month 3 passed
NZIER Mean	Q4 2008	Q3 2022	Quarterly	Month 3	Published beginning of the third month of the quarter
RBNZ Household	Q1 2002	Q3 2022	Quarterly	Month 2	Published in the middle of the second month of the quarter
RBNZ MPS	Q1 2003	Q4 2015	Quarterly	Month 3	Published middle of the third month of the quarter
Treasury EFU	Q2 2003	Q2 2019	Twice A Year	Month 3	Published mid-to-late May and mid-December
Westpac	Q3 2013	Q3 2022	Quarterly	Month 2	Published beginning of the second month of the quarter

Table B2 – Count and Missing Observations for Professionals and Household Data

Variable	Count Nowcast	Count 1 Ahead Forecast	Quarters With Missing Observations in Sample
ANZ Preview	27	NA	
ANZ QEF + QEO	29	29	No nowcast for 2007 Q3, 2009 Q4, 2011 Q3, 2012 Q4, and 2013 Q4. No one-step-ahead forecasts for 2007 Q4, 2010 Q1, 2011 Q4, 2013 Q1, and 2014 Q1.
ASB	27	26	No nowcast for 2016 Q2. No one-step-ahead forecast for 2016 Q3.
BERL	34	34	
NZIER Mean	55	36	One-step-ahead forecasts were only published from Q2 2013. No nowcast for 2021 Q2 and no one-step-ahead forecast for 2021 Q3.
RBNZ Household	83	NA	
RBNZ MPS	52	51	No 2003 Q1 one-step ahead forecast.
Treasury EFU	33	33	2011 Dec EFU did not have appropriate nowcasts or forecasts on inflation that could be used.
Westpac	38	37	One-step ahead forecast for 2022 Q4 was not used, hence the omission.

Table B3 – Relative RMSE of Professionals and Households Compared to Random Walk Nowcast Benchmark

Inflation Rate Prediction Source Relative RMSE	1Q Ahead Forecast	Nowcast
RBNZ MPS	0.695	0.356
ANZ QEF + QEO	0.610	0.369
ANZ CPI Preview	NA	0.384
NZIER Mean	0.868	0.464
Treasury EFU	0.636	0.494
ASB	1.355	0.696
BERL	1.227	0.862
Westpac	1.453	1.117
RBNZ Household Mean	NA	2.040

Table B4 – Relative RMSE of Professionals and Households Compared to RBNZ Target Nowcast Benchmark

Inflation Rate Prediction Source Relative RMSE	1Q Ahead Forecast	Nowcast
ANZ CPI Preview	NA	0.323
RBNZ MPS	0.856	0.435
ANZ QEF + QEO	0.758	0.438
NZIER Mean	0.806	0.501
Treasury EFU	0.959	0.570
ASB	1.141	0.582
Westpac	1.260	0.968
BERL	1.650	1.152
RBNZ Household Mean	NA	2.180

Appendix B2: Professional and Household Inflation Predictions Graphs

The nowcasts and one-quarter ahead forecasts for organisations that predict year-on-year changes in inflation as opposed to quarter-on-quarter changes may look “more accurate” by looking at the graph. However, this is not necessarily the case because the scales of each of the graphs are different. In other words, the scales of each graph can make a forecast or nowcast seem more accurate than it is.

There are no values for some organisations in some quarters. The reason could either be that the organisation did not produce these projections for that particular quarter, or that I was unable to find data for that particular quarter.

The Treasury’s one-step-ahead forecasts and nowcasts have been combined into one line. This is so the graphs look consistent and do not have lots of gaps. Q1 and Q3 values for The Treasury EFU are one-step-ahead forecasts. Q2 and Q4 values for The Treasury EFU are nowcasts.

Figure B1 - ANZ CPI Preview Graph

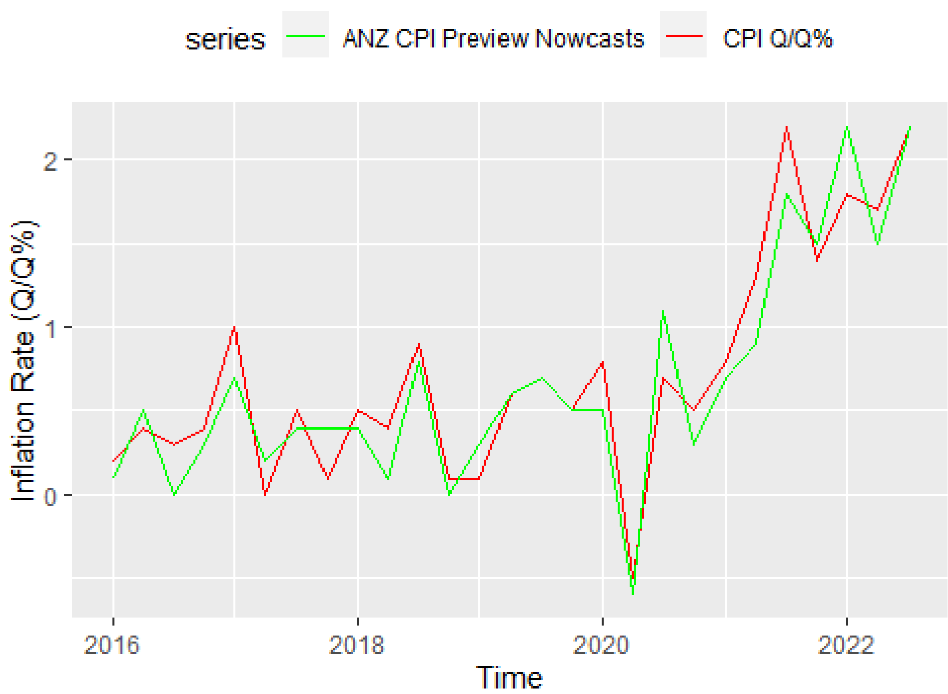


Figure B2 - ANZ Quarterly Economic Forecast + Quarterly Economic Outlook Graph

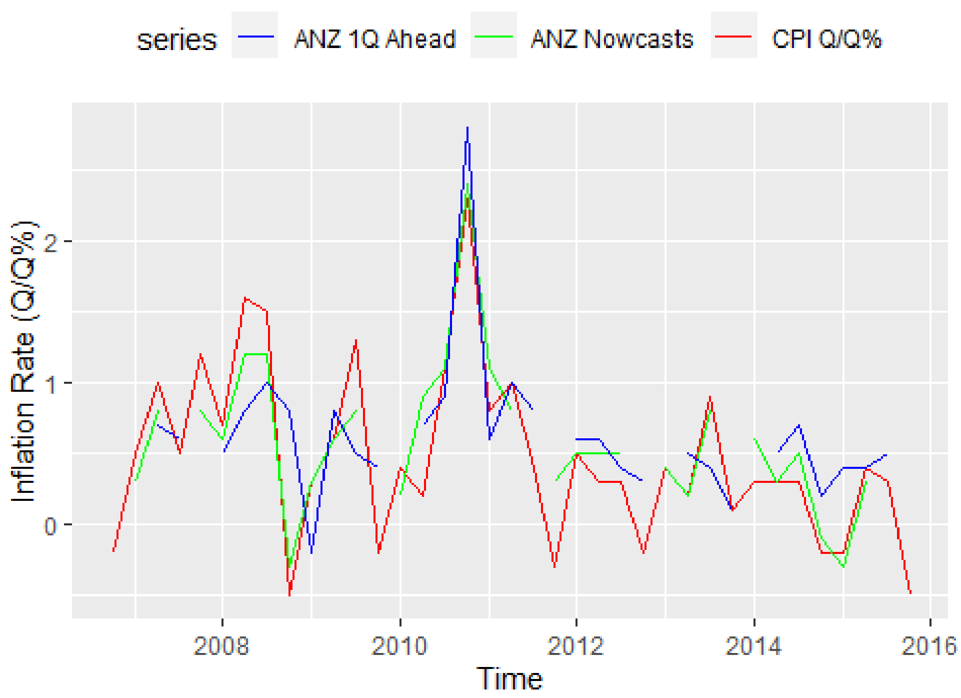


Figure B3 – ASB Graph

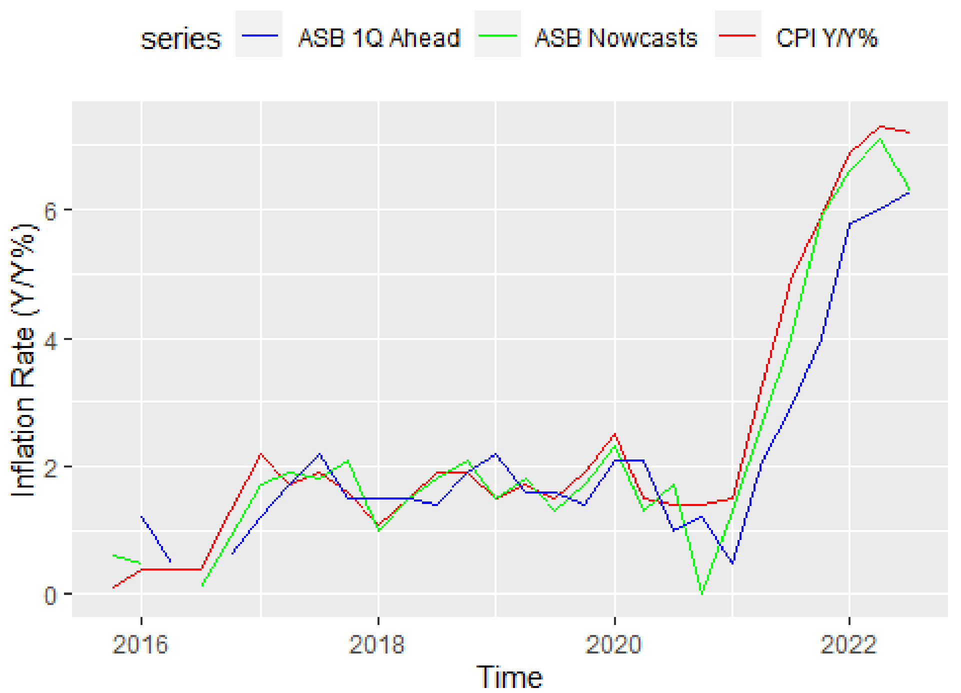


Figure B4 – BERL Forecasts Graph

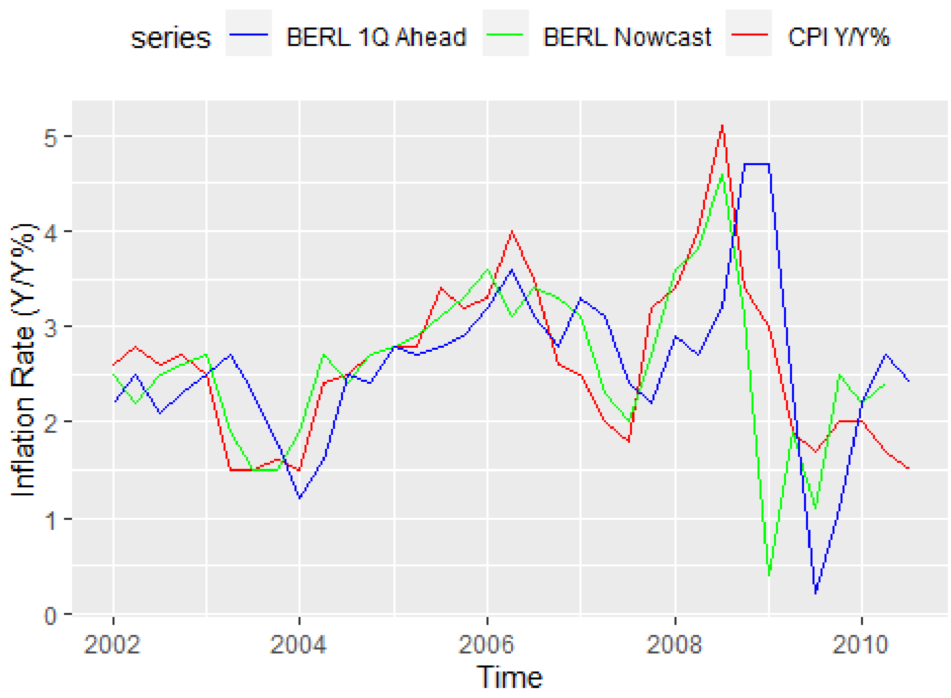


Figure B5 – NZIER Mean Graph

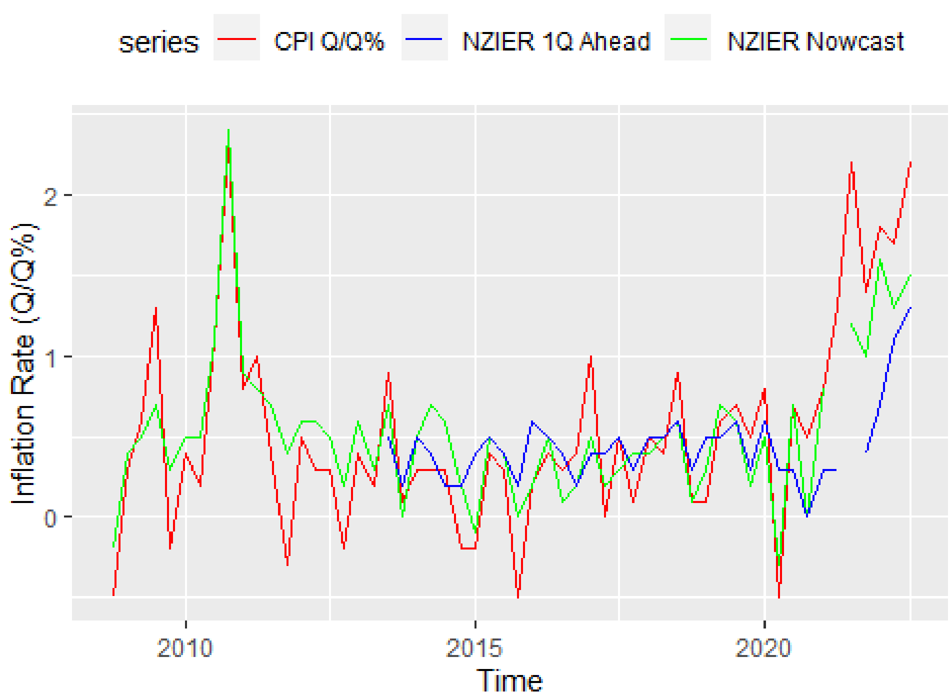


Figure B6 – RBNZ Household Mean Graph

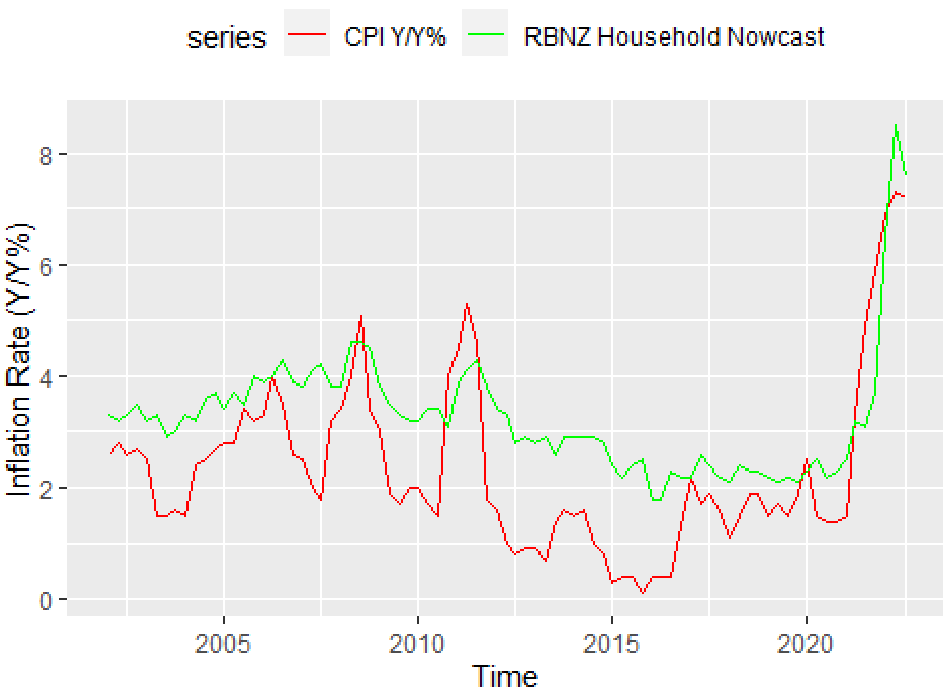


Figure B7 – RBNZ MPS Graph

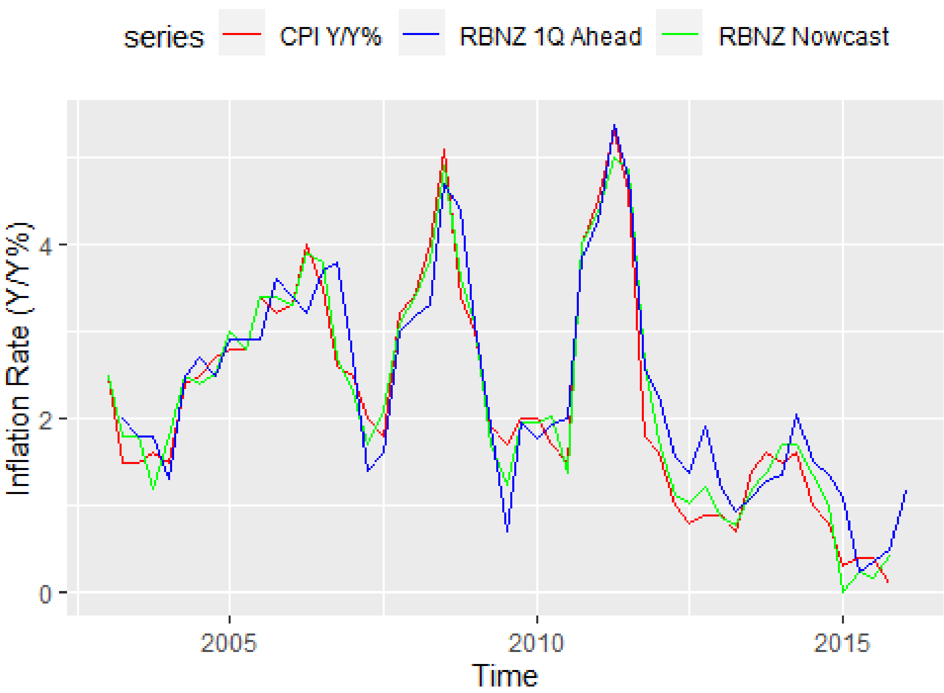


Figure B8 – Treasury EFU Graph[2]

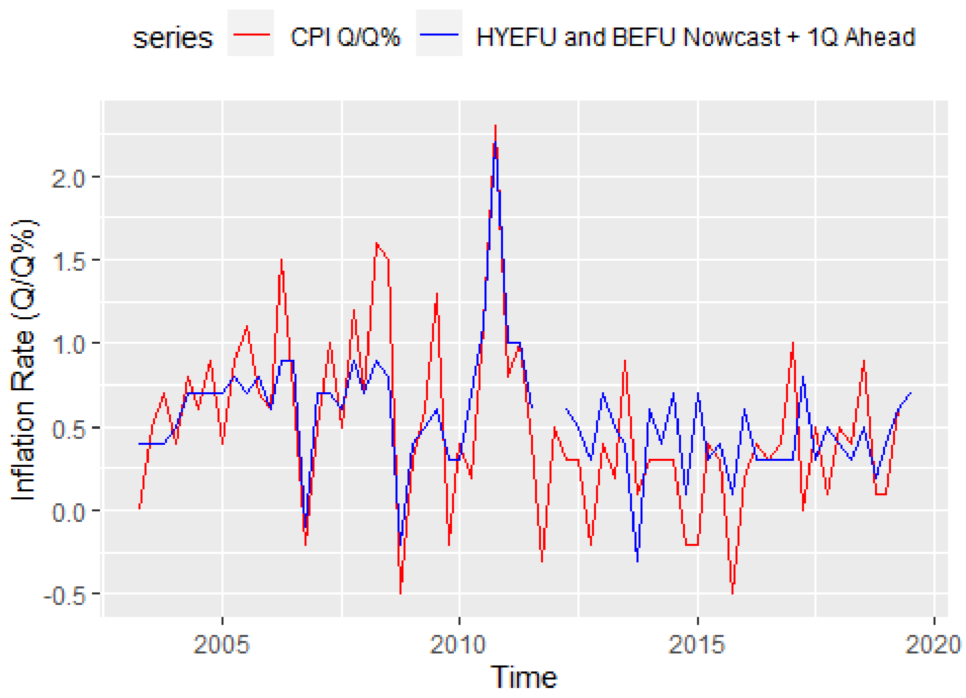
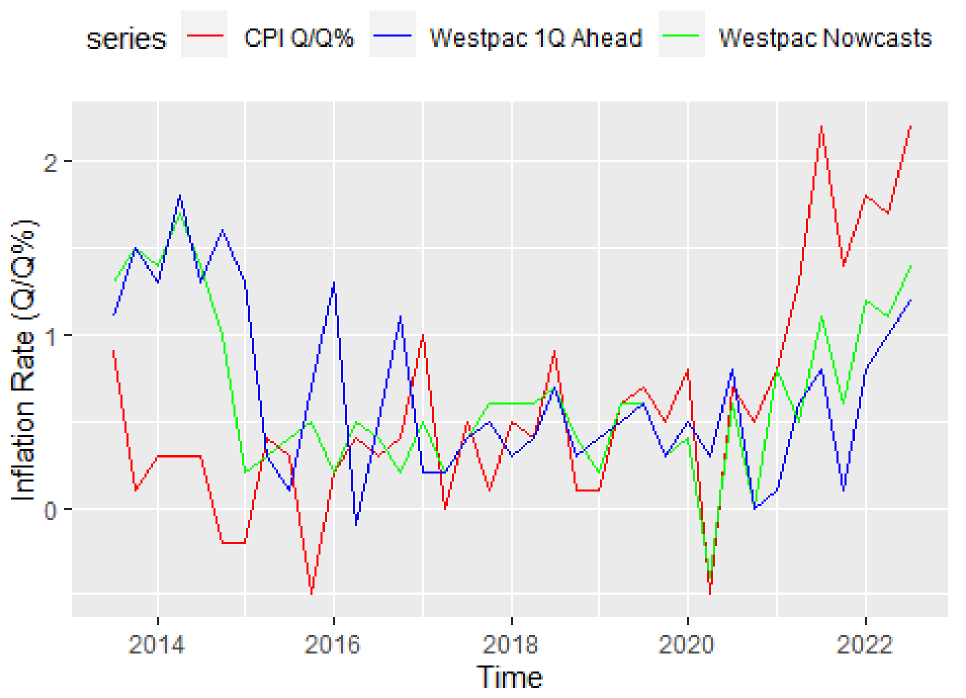


Figure B9 – Westpac Graph



[2] Note that the nowcasts and forecasts from the Treasury HYEFU and BEFU information have been combined all into one line. Graphing the Treasury EFU nowcasts and forecasts separately caused big problems because of the irregular publishing schedule of The Treasury EFUs.

Appendix C: Comparing Quarter-on-Quarter to Year-on-Year Inflation Rate Predictions

To illustrate why we should not use the RMSE to compare a Y/Y% prediction with a Q/Q% prediction without making some adjustments, I show the example below. Say that we are trying to nowcast the year-on-year percentage change (π_t^Y) of the NZ CPI. Variable y is the NZ CPI index, a quarterly variable released four times per year. Let us also note a quarter-on-quarter percentage change for the NZ CPI as π_t^Q. For the year-on-year percentage change we are trying to nowcast, we know the value of π_{t-3}^Q, π_{t-2}^Q, π_{t-1}^Q, y_{t-3}, y_{t-2}, and y_{t-1} already. With that in mind,

$$\pi_t^Y = \frac{y_t}{y_{t-4}} - 1$$

$$\pi_t^Q = \frac{y_t}{y_{t-1}} - 1$$

$$\pi_{t-1}^Q = \frac{y_{t-1}}{y_{t-2}} - 1$$

$$\pi_{t-2}^Q = \frac{y_{t-2}}{y_{t-3}} - 1$$

$$\pi_{t-3}^Q = \frac{y_{t-3}}{y_{t-4}} - 1$$

$$\pi_t^Y = \left[\left(\frac{y_{t-3}}{y_{t-4}}\right) \times \left(\frac{y_{t-2}}{y_{t-3}}\right) \times \left(\frac{y_{t-1}}{y_{t-2}}\right) \times \left(\frac{y_t}{y_{t-1}}\right)\right] - 1$$

$$\pi_t^Y = \left[\left(\frac{y_{t-3}}{y_{t-4}}\right) \times \left(\frac{y_{t-2}}{y_{t-3}}\right) \times \left(\frac{y_{t-1}}{y_{t-2}}\right) \times \left(\pi_t^Q + 1\right)\right] - 1$$

$$\pi_t^Y = \left[\frac{y_{t-1}}{y_{t-4}} \times \left(\pi_t^Q + 1\right)\right] - 1$$

If the official values for the first three quarters are already released, then y_{t-1} and y_{t-4} are known quantities. We can refer to y_{t-1}/y_{t-4} as x. Therefore,

$$\pi_t^Y = \left[x \times \left(\pi_t^Q + 1\right)\right] - 1$$

$$When\ \pi_t^Q = \frac{y_t}{y_{t-1}} - 1$$

$$\pi_t^Y = \left[x \times \left(\frac{y_t}{y_{t-1}}\right)\right] - 1$$

Calculating the error of both a Y/Y% and Q/Q% prediction, we would get,

$$\varepsilon_t^Y = \pi_t^Y - \hat{\pi}_t^Y$$

$$\varepsilon_t^Y = \left(\left[x \times \left(\pi_t^Q + 1\right)\right] - 1\right) - \left(\left[x \times \left(\hat{\pi}_t^Q + 1\right)\right] - 1\right)$$

$$\varepsilon_t^Y = \left[x \times \left(\pi_t^Q + 1\right)\right] - 1 - \left[x \times \left(\hat{\pi}_t^Q + 1\right)\right] + 1$$

$$\varepsilon_t^Y = x\left(\left[\pi_t^Q + 1\right] - \left[\hat{\pi}_t^Q + 1\right]\right)$$

$$\varepsilon_t^Y = x\left(\pi_t^Q - \hat{\pi}_t^Q\right)$$

$$but\ \varepsilon_t^Q = \pi_t^Q - \hat{\pi}_t^Q$$

$\varepsilon_t^Y \neq \varepsilon_t^Q$, provided that $x = y_{t-1}/y_{t-4} \neq 1$. As a result, the RMSE of ε_t^Y would be different to ε_t^Q provided that $x = y_{t-1}/y_{t-4} \neq 1$. This is because $RMSE = \sqrt{mean(\varepsilon_t{}^2)}$. However, the value of x is not considerable. My analysis suggests that inflation in NZ has averaged around 2% per year for the past 30 years. As a result, in an average year, $x \cong 1 + \frac{3}{4}(0.02) = 1.015$.

So, to calculate the relative RMSEs for the Y/Y% predictions of professionals and households, I turn my benchmark nowcasts into Y/Y% nowcasts. Provided that y_{t-1} and y_{t-4} is known at the time the nowcast is made (which is the case when I make my nowcasts), we can do this using the formula below. π_t^Q represents the benchmark Q/Q% nowcast.

$$\pi_t^Y = \left[\frac{y_{t-1}}{y_{t-4}} \times \left(\pi_t^Q + 1\right)\right] - 1$$

After using this formula, the professional/household projections and the benchmarks will be in the same units. Then, we can then calculate the relative RMSEs as normal. If we are in a situation where do not know the values of y_{t-1} and y_{t-4} at the time the nowcast is made, a different approach must be used.