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Meltem Chadwick, Rennae Cherry & Jaqueson K. Galimbert

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Reserve Bank of New Zealand
PO Box 2498
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www.rbnz.govt.nz

Non-response Bias in Household Inflation Expectations Surveys

Meltem Chadwick[1], Rennae Cherry[2], Jaqueson K. Galimberti[3,4,5]

Author Rennae Cherry is affiliated with the Reserve Bank of New Zealand, while co-authors Meltem Chadwick and Jaqueson Galimberti are affiliated with other agencies, as detailed below.

[1]South East Asian Central Banks Research and Training Centre

[2]Economics Department, Reserve Bank of New Zealand

[3]Asian Development Bank

[4]Centre for Applied Macroeconomic Analysis, Australian National University

[5]KOF Swiss Economic Institute, ETH Zurich.

Contact: Rennae.Cherry@rbnz.govt.nz

Abstract

This paper uses micro-data from the Reserve Bank of New Zealand's Household Inflation Expectations survey to obtain an accurate read of households' true inflation expectations by studying how different demographic groups respond (or do not respond) to the inflation expectations question in the survey. We found that non-responses lead to substantial under-representation of some demographic groups in the survey: young, female, low-income, and minority ethnic groups have lower response rates. How the survey is conducted also affects item response rates. The survey response rates increase when the survey is conducted online and when inflation rates deviate from the central bank's target range. Using a sample selection model, we assess whether the survey has item non-response bias by comparing the demographic characteristics of responders and non-responders. After accounting for selection, we found that observed differences in inflation expectations by gender, ethnicity, and income decrease substantially, while differences by age increase. We quantify and demonstrate how to adjust average aggregate and subgroup inflation expectations for bias caused by item non-response. We show that there is a positive bias, with the aggregate and subgroup inflation expectation series shifting down after the adjustment. We also show that inflation expectations disagreement, both across and within subgroups, tends to decrease with the correction for non-response bias. These findings have important implications for survey design and monetary policy communication.

Keywords: inflation expectations, household surveys, item non-response, demographic heterogeneity.
JEL classifications: C83, D84, E31, E71.

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1 Introduction

Measures of inflation expectations are of paramount importance for monetary policy. Inflation expectations are key determinants of prices through the forward-looking behaviour of households and firms while also underpinning whether beliefs are anchored to the central bank's inflation target. Surveys are the most common instrument used to measure inflation expectations. Whereas the focus is on aggregate measures, such as averages and medians, it is crucial to understand the accuracy of survey data in tracking the population's beliefs about inflation. Moreover, the relevance of inflation disagreement for inflation dynamics and the transmission of monetary policy has raised interest in the characterisation of subgroup inflation expectations. In this paper, we use micro-data from the Reserve Bank of New Zealand's (RBNZ) Household Inflation Expectations survey to investigate how non-responses to inflation expectations questions can bias measurements obtained from such surveys.

Our main contribution is quantifying non-response bias in inflation expectations and proposing a method to adjust average expectations for the effects of non-response bias. First, we show that certain demographic groups tend not to respond more frequently than the target population when asked about their inflation expectations. These non-responses amount to about 44% on average throughout our sample period: respondents who are young, female, have low income, or come from minority ethnic groups end up under-represented due to non-responses. Because these non-responses are not random, aggregate and subgroup measures of inflation expectations derived from the sample of respondents can be biased. We propose a sample selection model to adjust for non-response bias in inflation expectations. Figure 1 presents the evolution of mean one-year-ahead inflation expectations throughout our sample period, from 1998Q2 to 2022Q4. We found that non-responses artificially raise average inflation expectations by about 0.3 percentage points.[1]

Another important finding relates to the effect of survey mode on non-responses. Starting in 2018 Q3, the survey changed from being conducted by telephone to online mode. We found that this change significantly affected the incidence of non-response to the inflation expectations question.

[1]Throughout this paper, we focus on so-called item non-responses to the specific survey question on inflation expectations instead of unit non-responses to the whole survey. The use of survey weights corrects the incidence of unit non-response (see Meyer et al., 2015, for further discussion).

The average of non-responses decreased to about 24% since the survey moved to online mode. As evidenced in Figure 1, this change also significantly reduced the effect of non-response bias in estimating average inflation expectations. According to our estimates, the move to online mode generally reduced the gaps in non-responses across the different population groups. In other words, conducting the survey online has made it more inclusive for previously under-represented demographic groups.

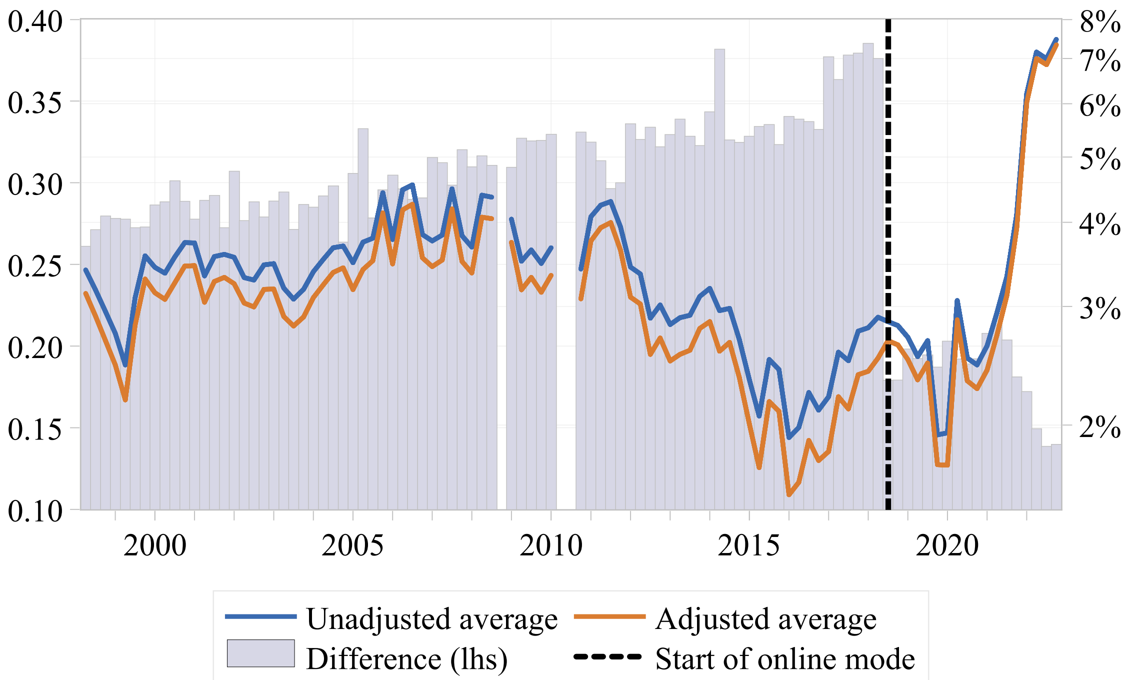
Another important finding is that non-response bias also depends on the level of the inflation rate at the time the survey is conducted. We found that response rates tend to increase non-linearly when the previous quarter's inflation is away from the central bank's target range.[2] For example, an inflation rate increase from 2% to 7% increases the average response probability by 12%, while this probability barely changes over an inflation range between 0% and 4%. This effect is also apparent in Figure 1, where the adjustment for non-response bias decreases in magnitude since the onset of the recent increase in inflation rates.

Our methodological approach is based on sample selection models. We first identify potential determinants of responses to the expectations question by estimating Probit regressions on several demographic variables collected with the survey. Probit regressions model the probability of an event, in our case, a response to the inflation expectations question, using a set of explanatory variables. These estimates help us define a selection equation, which determines when a respondent is likely to answer the inflation expectation question depending on their characteristics.[3] We consider several specifications for the set of explanatory variables depending on their availability across the sample period. We found that the effects of variables included in our baseline specification, namely, gender, age, region, ethnicity, income, and employment, are robust across sample periods and to the inclusion of more information such as occupation, exposure to grocery shopping, whether there are children in the household and types of home ownership.

[2] We used lagged values of the inflation rate because these are the latest available information to respondents at the time the surveys are conducted each quarter.

[3] Our regressions include additional 'macro' variables, such as lagged inflation and lagged inflation squared, an annual linear trend, seasonal dummy variables, and a dummy variable accounting for the change to online mode.

Figure 1: *The RBNZ Survey of Household Inflation Expectations.*



Notes: The lines depict quarterly averages of one-year-ahead inflation expectations from the RBNZ household inflation expectations survey. The unadjusted average is a raw weighted average across respondents, while the adjusted average is calculated using our methodology to adjust for non-response bias. The gaps in 2008Q4 and 2010Q2/Q3 are due to missing observations. The dashed line depicts when the survey switched to online mode in 2018 Q3. Previous to 2018 Q3 the survey was conducted by telephone.

We then study inflation expectations bias accounting for non-responses using a Heckman selection model (Heckman, 1974, 1979). The Heckman correction addresses sample selection as a form of omitted variable bias. Specifically, the method draws on Probit estimates of the selection equation to calculate the inverse Mills ratio, which is then used as an additional explanatory variable in the regression with missing observations.[4] Compared to estimates that do not account for selection, we found that most differences in bias across subgroups turn insignificant after accounting for non-response bias. Namely, observed differences in inflation expectations by gender, ethnicity, and income turn insignificant or decrease substantially in magnitude. The only exception is age, where older individuals tend to over-predict inflation more than the young, which is stronger after accounting for selection. For robustness purposes, we also consider different estimation methodologies and find that our estimates are not sensitive to the choice of estimation method.[5] Finally, we also compare our results to the approach of random imputation of missing data and find that this approach gives a similar distorted picture of inflation expectations biases as obtained without accounting for non-response bias.

Our proposed adjustment to the calculation of average and dispersion of inflation expectations goes along similar lines: average and variance indices can be easily obtained by running a regression of survey inflation expectations and their squared deviations from quarterly means, respectively, on quarter dummy variables. After including our baseline estimates of the Heckman correction term as an additional variable in this regression, we obtain average and dispersion of inflation expectations adjusted for non-response bias – the former are the adjusted average expectations reported in Figure 1. The simplicity of this approach makes it attractive for operational purposes: to obtain updated estimates every quarter, all that is required are new estimates of the inverse Mills ratio, which can be easily computed from the pre-fitted Probit model. Indeed, the fact that the Probit model estimates are relatively stable across sub-samples indicates that the adjustment is unlikely to undergo severe revisions over time. Finally, our estimates use survey weights to account for unit non-response

[4]The Heckman selection model estimates the selection equation and uses the predicted probabilities from the selection equation as a correction term in the outcome equation. This correction term, known as the inverse Mills ratio, accounts for the selection bias by adjusting the coefficients in the outcome equation.

[5]The Heckman sample selection model can be estimated using either a maximum likelihood approach or the original two-step approach (see, e.g., Puhani, 2000, for more details). Here, we extend those methods to account for survey weights and derive weighted estimates.

bias arising from difficulty in obtaining a representative population survey sample. Although these weights cannot account for determinants of non-responses to the inflation expectations question, we also find that they are relevant for the analysis of inflation expectations bias.

1.A Related Literature and Surveys

This paper relates to the broader literature on the heterogeneity of inflation expectations. Looking at a sample from the US Michigan Survey of Consumers, Bruine de Bruin et al. (2010) corroborate findings that demographic variables play a significant role in determining inflation expectations. Pfajfar and Santoro (2010) document pervasive heterogeneity in forming inflation expectations in that same survey. Malmendier and Nagel (2016) shows that consumer inflation expectations also vary with age due to learning from experience. D'Acunto et al. (2023) document that household inflation expectations are upward biased and systematically different across gender, income, education, and race. Our findings based on New Zealand data add to this literature by showing that some demographic differences are a product of non-response bias. Namely, when accounting for selection, we found that differences by gender, ethnicity, and income decrease substantially.

Our findings about the under-representation of some demographic groups are consistent with previous studies in the literature. Exploring UK survey micro-data, an early study by Blanchflower and MacCoille (2009) also found significant non-response bias from young, female, and low-income respondents. Leung (2009) reported similar findings with a shorter sample from the RBNZ household survey. Our finding that online survey mode can attenuate non-response bias is consistent with previous studies. Bruine de Bruin et al. (2017), for example, find that online surveys achieve higher response rates to the inflation expectations question than face-to-face surveys.

None of the papers above provided an adjustment for the non-response bias in inflation expectations surveys. One standard approach to deal with non-responses is to replace the non-responses or missing observations by imputation. The US Michigan Survey of Consumers (MSC), for example, uses distribution-based imputations to replace "Don't Know" responses with random draws from a distribution that matches the properties of observed data (Curtin, 1996). However, this imputation method does not consider the socio-demographic composition of the sample of respondents. It can, therefore, reinforce the effects of selection bias in analysing survey of expectations data.

More broadly, the issue of item non-response has received increased attention in recent related studies. Focusing on a US longitudinal survey of professional forecasters, Bürgi (2023) compares methods for filling in missing observations due to survey attrition – naturally, this is a different problem than what we face with repeated cross-sectional surveys as the one we study here. An alternative approach for that case involves the use of survey design features. McGovern et al. (2018) explore HIV testing data to show that randomised incentives or survey interventions can provide ideal selection variables to correct for non-response bias. Comerford (2023) proposes using a verbal question to deal with non-response bias found in inflation expectations derived from density forecasts. Ex ante, these methods provide vital insights into survey design. However, the required survey features are rarely available for long-running surveys. Our approach offers a potential solution to these cases.

Finally, non-response bias can be important for other household surveys of inflation expectations. For example, in the U.S. MSC, a major survey in this area, non-responses to the inflation expectations question (prior to imputation) amounted to an average of 9% of the monthly samples collected between 1978 and 2022; non-responses also varied substantially over time, ranging from lows of about 3%, mostly observed in 1985 and 2022, to highs of about 25% observed in 1978.[6] Another example is the Bank of England's (BoE) Inflation Attitudes Survey, where non-responses to the inflation expectations question amounted to an average of about 15% of the quarterly samples collected between 2001 and 2022, and ranging from 8% to 25% over the period.[7,8] Needless to say, these are examples of surveys from advanced economies, and we would expect the relevance of item non-response to

[6]The MSC also distinguishes between respondents refusing to answer the inflation question (0.14% of the 1978-2022 sample, on average), those that don't know (DK) a point estimate either the direction of change (0.84%, on average) and those that can answer about the direction but not about a point estimate (7.53% DK UP and 0.54% DK DOWN, on average), discarding the first two and imputing the last for index calculations.

[7]These statistics on the BoE survey exclude the data from 2020/Q2, when non-responses declined to 0.12% due to a design issue in the switch to online mode during the COVID-19 social distancing guidance. The problem was that the option of "Don't know/No idea" appeared only if the respondent tried to move on to the next question without answering the inflation expectations question. In subsequent surveys, the "Don't know/No idea" option was reintroduced with the other options for the question, and non-responses returned to usual levels.

[8]Intriguingly, the more recently launched European Central Bank (ECB) Consumer Expectations Survey does not allow the respondent to proceed with the survey without answering the inflation expectations question, which is a potential design flaw as discussed in the previous footnote.

be even greater in less developed contexts. Our methodology can be easily applied to analysing and adjusting these surveys using their corresponding socio-demographic information on the surveyed households.

The remainder of this paper is organised as follows. Section 2 provides details about the survey and sample statistics. Section 3 analyses potential determinants of non-responses to the inflation expectation question using Probit models. Section 4 focuses on estimates of inflation expectations bias and outlines our proposed approach to account for non-responses using a sample selection model. Section 5 shows how the correction for non-responses can be used to adjust indices of average and dispersion of inflation expectations, including a description of the empirical properties of the adjusted indices. Finally, section 6 discusses the policy implications and section 7 concludes.

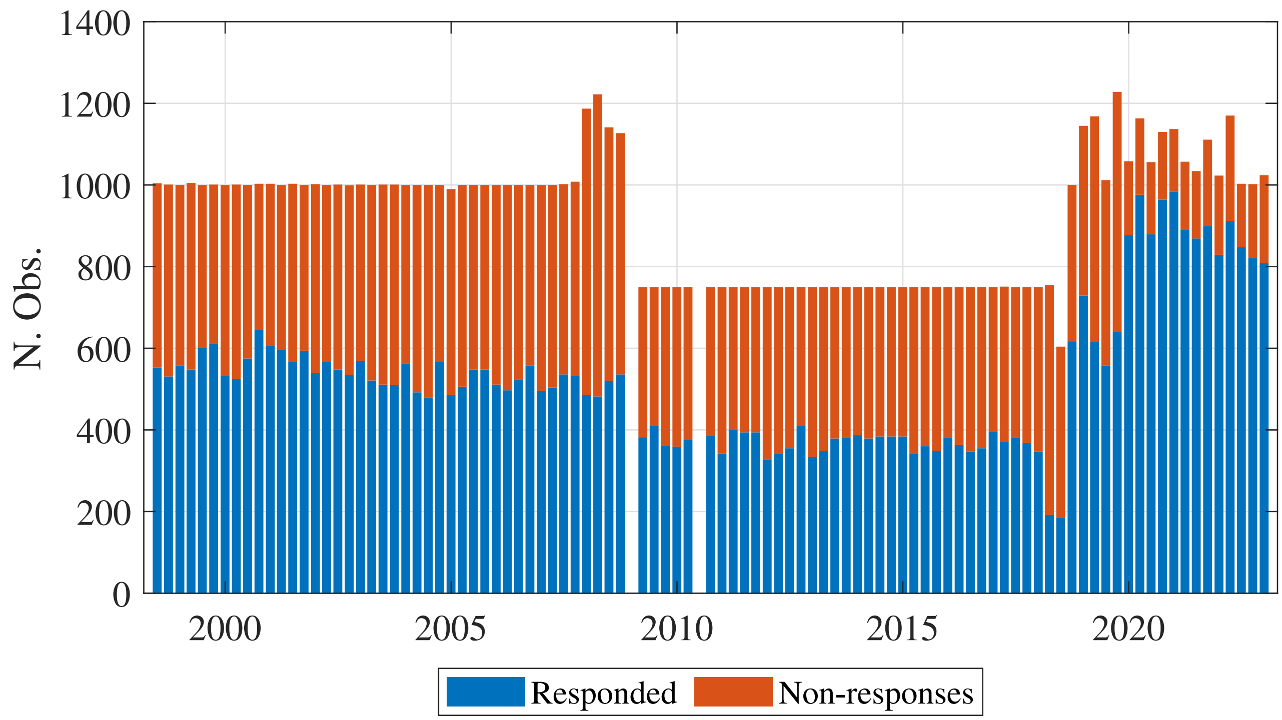
2 Data

2.A Survey Design and Sample

The RBNZ Household Inflation Expectations survey is conducted quarterly and achieves approximately 1,000 household responses per wave. Our sample covers the period from 1998 to 2022 and contains 89,834 individual responses. The individual responses are anonymised every quarter. Hence, survey waves are treated as repeated cross-sectional data. The survey goes into the field after the previous quarter's consumer price index inflation data have been released. The survey asks for households' perceptions of current inflation and expected inflation at varying horizons starting one year ahead. The inflation expectation question we focus on in this paper is formulated as follows: "As a percentage, what do you think will be the annual rate of inflation/deflation in the next 12 months?"

Figure 2 illustrates that approximately half of the respondents chose not to answer the inflation expectations question. While we attempt to understand the determinants of such non-responses by looking at household characteristics and macroeconomic factors, it is not immediately obvious why some survey respondents do not answer the inflation expectations question. Although collected for a limited period, one question in the survey can be informative about this issue. Between 2018 Q3

Figure 2: *Responses and Non-responses to Inflation Expectation Question.*



Notes: The bars depict the number of survey responses collected across the quarters, decomposed by response/non-response to the inflation expectations question.

and 2021 Q4, the survey asked a question about the respondent's understanding of inflation.[9] Non-responses over that sub-period amounted to 26% of the sample, but only 5% of the respondents indicated not understanding inflation (answering "unsure" or "no comment"). Hence, for the majority of non-responses to the inflation expectations question, 81% to be precise, the reason for not providing an estimate of future inflation is not a lack of understanding about inflation.[10] Another potential explanation is that non-responses are driven by uncertainty regarding inflation. Binder (2017) provides evidence supporting this idea, showing that individuals who do not respond typically exhibit greater inflation uncertainty. Moreover, micro-level estimates of inflation uncertainty reveal socio-demographic patterns similar to those identified in our analysis of non-responses to the inflation expectations question.

[9]Options to the question "What is your understanding of inflation?" included: (i) Increased prices and cost of living, (ii) Erosion of wages, (iii) An index/a measure, (iv) Other (specify), (v) Unsure, (vi) No comment.

[10]This finding suggests that cultural norms, such as gender roles, can be the underlying determinant of non-responses (see, e.g., D'Acunto et al., 2021), while financial literacy and IQ, which have been found to explain inflation forecast errors (see, e.g., Bruine de Bruin et al., 2010; D'Acunto et al., 2022), may have a more limited role in non-responses.

Figure 2 also shows that the number of responses collected by the survey changed over time, ranging from a minimum of 604 responses in 2018 Q2 to a maximum of 1,228 in 2019 Q3. Another significant change relates to the way the survey was conducted. Up until 2018, the survey was conducted by telephone. Starting in 2018 Q3, the survey changed to online mode. As evidenced in Figure 2, this change significantly affected the incidence of non-response to the inflation expectations question. The average of non-responses decreased to about 24% since the survey moved to online mode.

The dataset contains various demographic information about survey respondents, including age, gender, ethnicity, income, employment, occupation, region, children in the household, number of adults in the household, marital status, home ownership status, and grocery shopping. While the survey has been redeveloped over time to improve data quality and better align with international best practices for capturing household inflation expectations, the data are limited by changes in collection and measurement. The most common evolution in the measurement of variables over time is the move from granular to less granular levels. In such cases, we merge granular observations into less granular categories to provide consistency.[11] Figure 3 presents the evolution of our sample compositions according to different demographic variables.

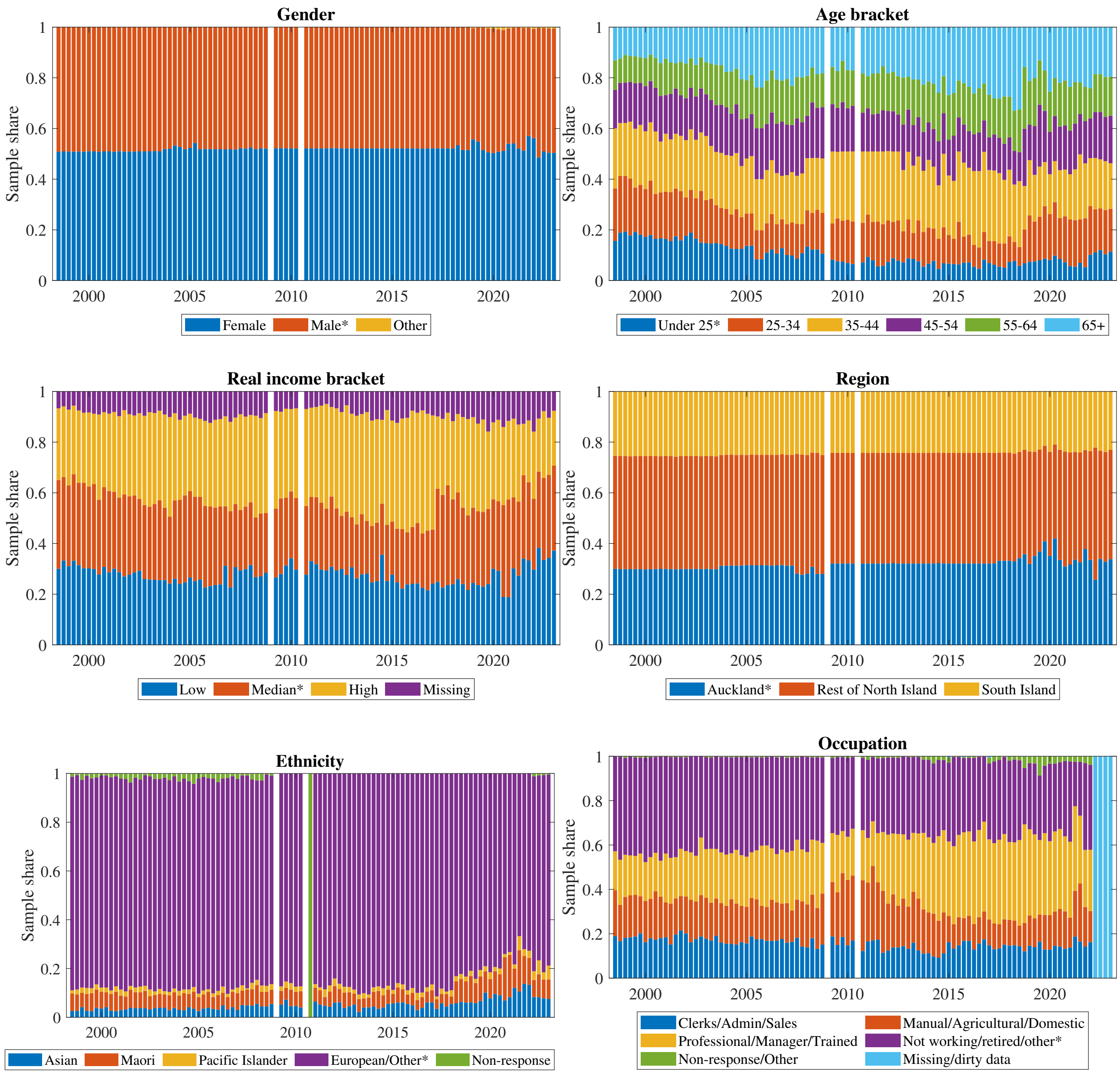
Figure 4 shows how the composition of responses and non-responses to the inflation expectation question compare across some selected population groups. There is a case for sample selection bias by variables such as age, gender and ethnicity. Note how the group compositions change across participants who responded versus those who did not respond to the inflation question. This non-random incidence of item non-responses undermines the accuracy of the survey as a representative depiction of the inflation beliefs of New Zealand's population.

2.B Adjustment for Response Outliers

Outlier responses are commonplace in survey instruments and can significantly impact estimates derived based on this type of data. In addition, respondents who report extreme inflation expectations may be similar to individuals who would otherwise choose not to respond to the survey question. The method for outlier detection used in constructing aggregate indices from the RBNZ

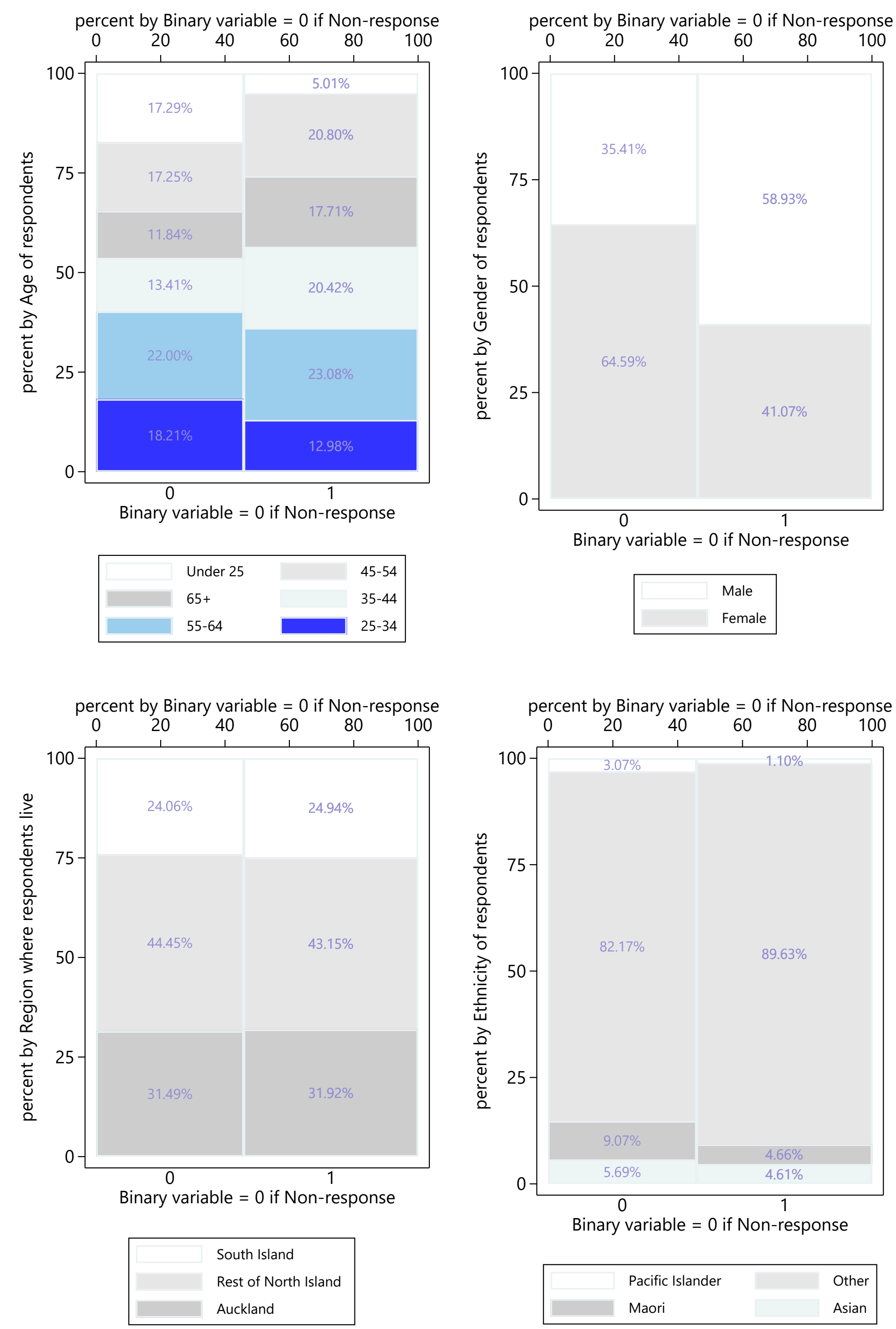
[11] See Appendix A for tabulations of these data and further discussion of adjustments.

Figure 3: *Evolution of Sample Compositions by Selected Variables.*



Notes: The bars depict the survey sample composition by selected variables across the quarters. Categories with a * indicate the base categories used in the regression analysis.

Figure 4: *Responses and Non-responses to Inflation Expectation Question by Group.*



household survey of inflation expectations also changed over time. Starting from 2022, the methodology shifted from a fixed interval rule, which discarded inflation expectations lower than -2% and higher than 15%, to an interquartile range (IQR) method based on a whisker equal to 1.5.[12] Here, we adopt the latter rule, which excludes a total of 4,535 observations from the analysis. In Appendix C, we evaluate the robustness of our baseline estimates to the use of different outlier detection rules, including the fixed interval rule, a hybrid IQR rule, and top/bottom 5% rules. That analysis shows that our Probit model estimates are insensitive to the definition of outliers. Moreover, although the probabilities of giving outlier responses and of non-responses to the inflation expectations question share certain similarities, they differ regarding the magnitude of demographic effects and in how trends and inflation levels influence them.

3 Determinants of Responses to the Inflation Question

3.A Probit Model

As a first step in finding the non-response bias and correcting for it, we study the determinants of each household's non-response behaviour. To do so, we estimate different Probit models that relate the choice of response to the household's demographic characteristics. We evaluate the effects of socio-demographic and personal characteristics from Probit models on the likelihood of response to the quantitative question of inflation expectations for the next 12 months. Equation 1 represents the general structure of Probit models we estimate.

$$Pr(Response_i = 1 | \mathbf{X}_i, \mathbf{Z}_i, Y_i, \mathbf{Q}_i, O_i) = \Phi(\beta_0 + \beta_1 \mathbf{X}_i + \beta_2 \mathbf{Z}_i + \beta_3 Y_i + \beta_4 \mathbf{Q}_i + \beta_5 O_i). \tag{1}$$

Demographic variables are represented by $\mathbf{X}_i$, and macroeconomic variables are represented by $\mathbf{Z}_i$. Note the subscript i indexes for the survey/response observation. Macroeconomic variables do not vary across responses within a survey wave but across survey waves. Y_i is the yearly trend. $\mathbf{Q}_i$ are

[12] The IQR method excludes observations falling outside the following limits:

$$Lower\, limit = Q1 - whisker \times IQR,$$
$$Upper\, limit = Q3 + whisker \times IQR,$$

where $Q1$ refers to the 25th percentile, $Q3$ refers to the 75th percentile, and IQR is the difference between $Q1$ and $Q3$ in the data series.

quarter seasonal dummy variables. O_i is also a dummy variable that indicates whether the response i occurred after 2018 Q2 when the survey switched to online mode. $Response_i$ is a dummy variable equal to 1 if respondent i answered the question related to inflation expectation. Φ is the standard Normal cumulative distribution function.

3.B Model Estimates

We estimate four specifications of such Probit models with different sets of explanatory variables to maximise our sample coverage. Table 1 lists estimates of the average partial effects associated with each of these Probit specifications.[13] Females seem to be less likely to respond to the inflation expectations question, with an average probability of responding about 20% lower than men. Maori and Pacific Islanders are also more likely to be in the non-response category. In contrast, older individuals who are employed and have higher incomes, are more likely to respond. Additionally, conducting the survey in online mode significantly increases the response rates, increasing the probability of response by about 33% – we discuss further the effects of conducting the survey in online mode below.

We also find a significant downward trend in response rates to the inflation question. Despite the recent increase in responses due to the shift to online mode, and after accounting for that, the long-run trend estimates indicate an increase of item non-responses of about 1% per year. This is consistent with more broad evidence of increased rates of both unit and item non-responses in household surveys (see Meyer et al., 2015). These findings are robust across the different specifications.

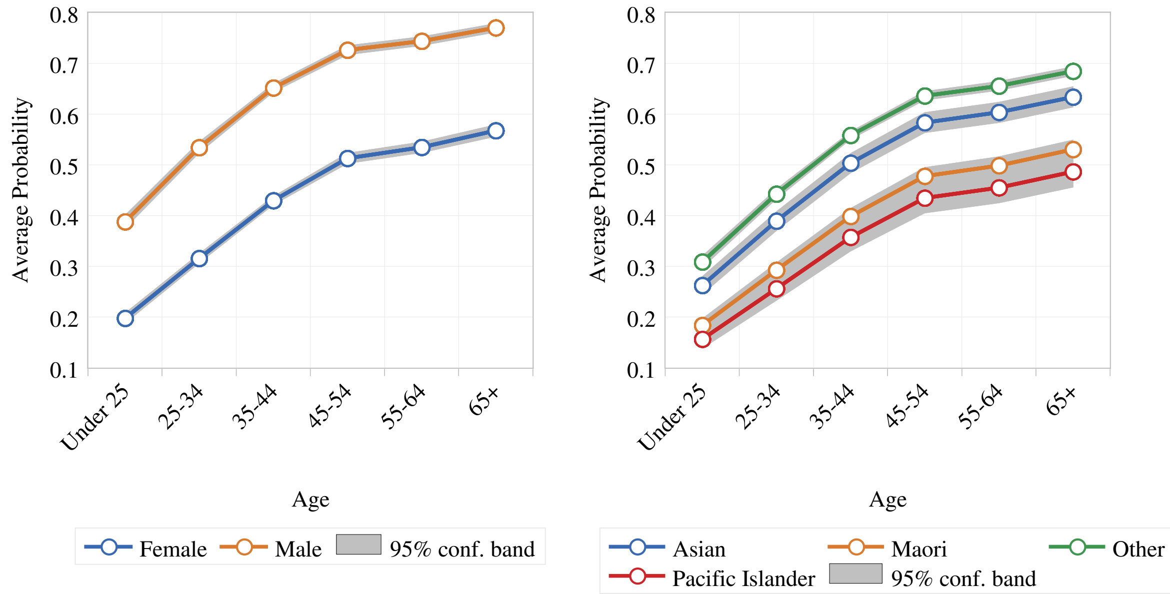
[13] Estimates of the coefficients of equation 1 are presented in Table B.1 in Appendix B.

Table 1: *Average Partial Effects on Responses to the Inflation Expectation Question.*

Variables (base category)	**Categories**	**(1)**	**(2)**	**(3)**	**(4)**
Gender (base=Male)	Female	-0.210*** (0.004)	-0.221*** (0.004)	-0.235*** (0.007)	-0.197*** (0.005)
Age (base=under 25)	25-34	0.131*** (0.008)	0.131*** (0.008)	0.168*** (0.011)	0.058*** (0.013)
	35-44	0.245*** (0.007)	0.254*** (0.008)	0.321*** (0.011)	0.133*** (0.013)
	45-54	0.323*** (0.008)	0.326*** (0.008)	0.393*** (0.011)	0.192*** (0.013)
	55-64	0.343*** (0.008)	0.336*** (0.008)	0.404*** (0.011)	0.184*** (0.013)
	65+	0.372*** (0.007)	0.351*** (0.008)	0.371*** (0.012)	0.205*** (0.013)
Region (base=Auckland)	Rest of North Island	-0.012*** (0.004)	-0.012** (0.005)	-0.020*** (0.006)	-0.010 (0.006)
	South Island	-0.001 (0.005)	0.000 (0.005)	-0.000 (0.007)	-0.008 (0.007)
Ethnicity (base=European/Other)	Asian	-0.052*** (0.009)	-0.054*** (0.010)	-0.035** (0.016)	-0.059*** (0.012)
	Maori	-0.152*** (0.007)	-0.148*** (0.008)	-0.185*** (0.012)	-0.116*** (0.010)
	Pacific Islander	-0.192*** (0.013)	-0.190*** (0.014)	-0.222*** (0.022)	-0.164*** (0.018)
Real Income (base=Median)	High	0.103*** (0.004)	0.095*** (0.005)	0.108*** (0.007)	0.095*** (0.006)
	Low	-0.089*** (0.005)	-0.092*** (0.005)	-0.096*** (0.008)	-0.089*** (0.007)
Employment (base=Unemployed/Other)	Employed	0.027*** (0.005)			0.018** (0.007)
Occupation (base=Unemployed/Other)	Clerks/Admin/Sales		-0.003 (0.006)	-0.041*** (0.008)	
	Manual/Agricultural/Domestic		-0.015*** (0.006)	-0.034*** (0.008)	
	Professional/Manager/Trained		0.055*** (0.006)	0.050*** (0.008)	
Dependent Children (base=No)	Yes		-0.031*** (0.004)	-0.032*** (0.006)	-0.019*** (0.007)
Groceries Shopping (base=No)	Yes - jointly/shared			0.012 (0.009)	
	Yes - main			-0.025*** (0.008)	
Home Ownership (base=Owner)	Living with parents				-0.226*** (0.012)
	Mortgage				-0.078*** (0.007)
	Other				-0.116*** (0.016)
	Renting				-0.129*** (0.008)
Online (base=No)	Yes	0.334*** (0.001)	0.337*** (0.001)		0.333*** (0.001)
Year Trend		-0.009*** (0.000)	-0.010*** (0.000)	-0.014*** (0.000)	-0.004*** (0.000)
Lagged Inflation		0.002 (0.001)	0.001 (0.002)	0.008*** (0.003)	0.007** (0.003)
N.Obs.		75,180	71,799	36,011	35,993
Sample		98Q2-22Q4	98Q2-21Q4	98Q2-08Q3	09Q1-21Q4
McFadden R^2		0.170	0.169	0.185	0.170

Notes: Average partial effects are calculated using the delta method and averaging over the sample observations, holding other variables constant at their sample values. Numbers in parenthesis are robust standard errors. ***,**,* stand for 1%, 5%, 10% statistical significance, respectively.

Figure 5: *Predicted Probabilities of Response by Age, Gender, and Ethnicity.*



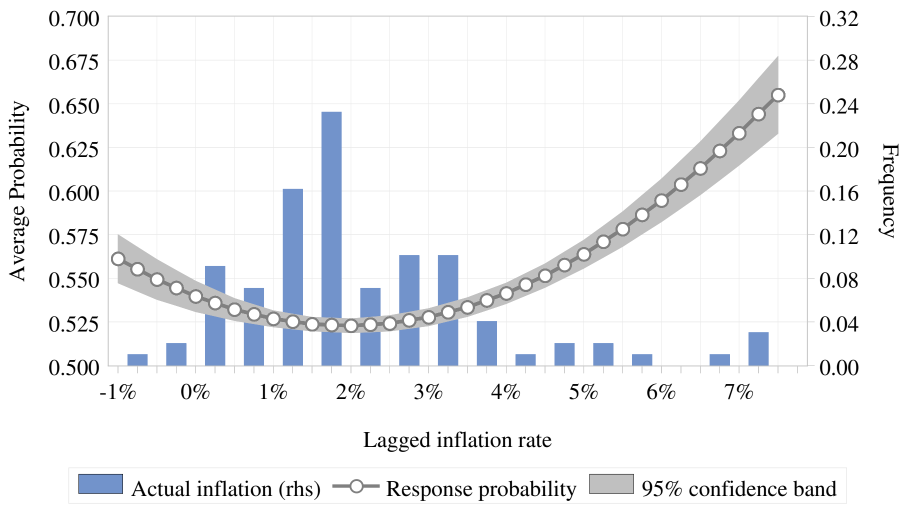
Notes: Response probabilities are based on the baseline Probit model estimates, column (1) from Table B.1. They are obtained as the average of predicted probabilities holding other variables constant at their sample values.

Figure 5 summarises some of the results illustrated in the first column of Table 1. Accordingly, gender is an essential determinant of the response probability: males are more likely to respond, and this probability increases with age. Ethnicity is also an important determinant of response probability: a significantly lower response rate is attached to being a Maori or a Pacific Islander.

Figure 6 illustrates the link between lagged inflation rates and the predicted response probabilities. In our Probit estimations, we have found evidence of a quadratic relationship between responses and lagged inflation rates. Intriguingly, the averaged nonlinear effects of lagged inflation over our sample are mostly insignificant, as reported in Table 1. However, this is a misleading artefact of averaging. As we can see from Figure 6, lagged inflation has an interesting profile of regime-dependent effects on responses. Particularly, when the lagged inflation hits the range of 5–7%, the slope of the response probability turns steeply positive. This may imply that when inflation moves out of the "rational inattention" zone, where economic agents hardly notice inflation, price changes snap into sharp focus and increase agents' ability/willingness to respond to the inflation expectations question.[14] This state-dependence of responses is also consistent with the inflation uncertainty ex-

[14] For related research on this see, e.g., Borio et al. (2023); Weber et al. (2023).

Figure 6: *Predicted Probabilities of Response by Lagged Inflation Rate.*



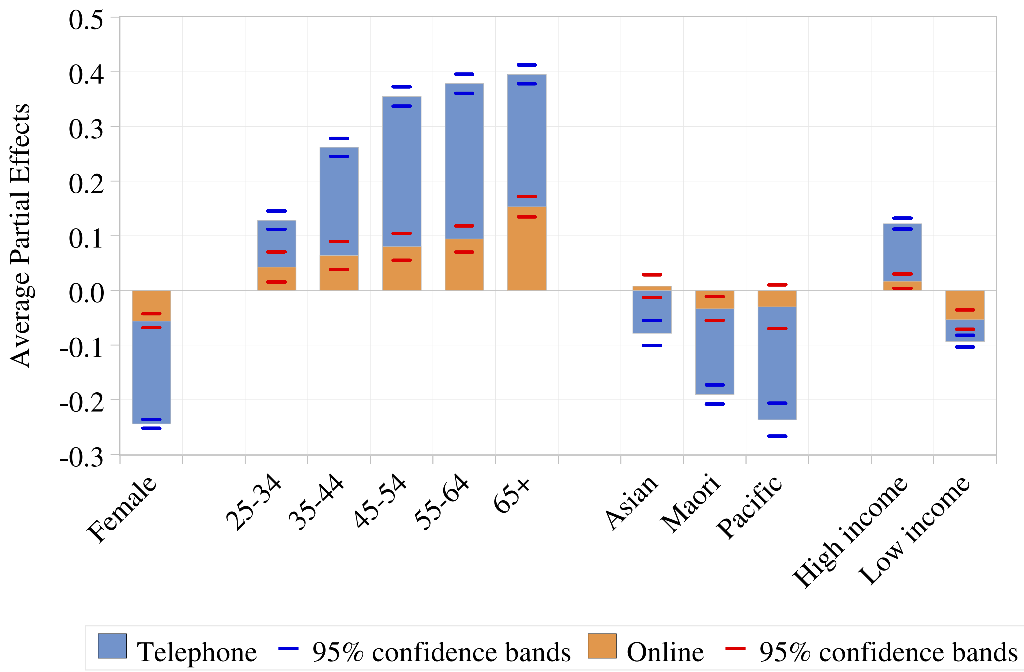
Notes: The blue bars depict the distribution of actual inflation rates over the sample period. Response probabilities are based on the baseline Probit model estimates, column (1) from Table B.1. They are obtained as the average of predicted probabilities holding other variables constant at their sample values.

planation as this has been found to co-move with the inflation level (Binder, 2017). Nevertheless, it is important to note that there have been fewer instances of inflation rates outside the normal range around the inflation target, while other uncontrolled factors may have driven response rates in those occasions (e.g., the Covid pandemic, recessions, etc.). Hence, until further evidence is accumulated, the finding that response rates are non-linearly related to the level of inflation should be interpreted with caution.

The estimates using the extended specifications (columns 2-4 in Table 1) provide additional insights into the determinants of (non-)responses to the inflation expectations question. First, only the more skilled occupations, covering professionals, managers and trained service workers, show a probability of response greater than the base group of unemployed/retired/others. As depicted in Figure 3, that occupation also shows the greatest increase in the survey sample composition, which explains why the employment variable (roughly averaging over occupations) shows a positive effect in columns (1) and (4) of Table 1.

Households with dependent children and those not owning a freehold house tend to respond less to the inflation question. At the same time, the effect of grocery shopping is only significant and negative when the respondent was the main responsible for that chore. The latter effect can be a

Figure 7: *Average Partial Effects of Online Mode for Selected Variables.*



Notes: Average partial effects are obtained holding other variables constant at their sample values. The estimates presented here are based on a re-estimation of the baseline Probit specification, column (1) from Table B.1, splitting the effects by survey mode. See Table B.2 in Appendix B for the corresponding numerical estimates and other specifications.

critical determinant of the relevance of the beliefs elicited by the survey. Previous research suggests exposure to grocery prices as an essential determinant of consumers' belief formation (D'Acunto et al., 2021; D'Acunto et al., 2023). Although being the main responsible for grocery shopping in the household is found to decrease the probability of responding to the inflation expectations question, the magnitude of that effect is small relative to other determinants.

Finally, we also look at how conducting the survey in online mode can change the effects of demographic characteristics on response probabilities. To do that, we re-estimate our Probit model specifications with additional terms interacting the online dummy variable with the demographic variables. These estimates are summarised in Figure 7, focusing on the case extending our baseline specification.

Overall, conducting the survey in online mode reduces the effects of demographic characteristics on the probabilities of response. For example, before switching to online mode, women were 24.4%

less likely to respond to the inflation question than men; this difference decreased to only 5.5% since the survey moved to online mode. Similarly, most of the differences by ethnicity turned insignificant after the survey moved online. This evidence indicates that conducting the survey online made it more inclusive for previously underrepresented demographic groups.

4 Inflation Expectations Bias

4.A Econometric Framework

In this section, we are interested in evaluating how biased household inflation expectations are. Bias is defined as the average of inflation expectations errors, taking into account the timing of the forecasts and their target realization. More formally,

$$Bias \equiv E\left[\pi_i^e\left(\underbrace{t}_{base},\overbrace{t+h}^{target}\right)-\pi_{t+h}\right], \tag{2}$$

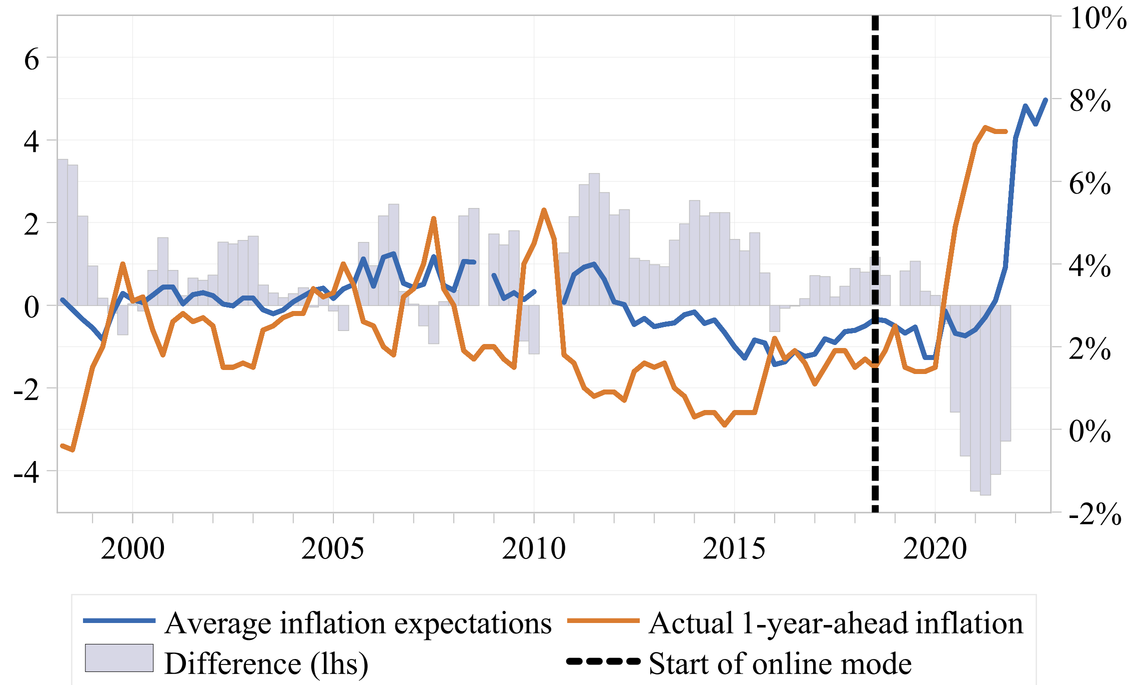
where $\pi_i^e\left(t,t+h\right)$ is respondent i period t forecast of inflation between t and $t+h$, and π_{t+h} is the actual inflation rate over that same period. In our case, h is 4 quarters. Figure 8 illustrates how the average bias evolved over our sample.

The richness of information available in the micro-data from the survey of households' expectations allows us to go one step further and attempt to understand how inflation expectations bias depends on household characteristics. For that purpose, we run regressions of the following form:

$$\pi_i^e-\pi_{t+1}=\alpha_0+\alpha_1\mathbf{X}_i^{'}+\alpha_2\mathbf{Z}_i^{'}+\alpha_3\mathbf{Q}_i+\alpha_4 O_i+u_i, \tag{3}$$

where, as in our previous notation, $\mathbf{X}_i^{'}$ contains household characteristics, $\mathbf{Z}_i^{'}$ contains macroeconomic variables at the time the respondent answered the survey, $\mathbf{Q}_i$ are quarter dummy variables, and O_i is a dummy variable for the survey mode. Note the household characteristics and the macroeconomic variables included in Equation 3 need not be the same as those included in the Probit model of Equation 1. As discussed below, identification in the sample selection model posits the exclusion of variables that are not relevant to the outcome equation.

Figure 8: *Average Inflation Expectations and Actual Inflation Rates.*



Notes: The lines depict quarterly averages of one-year-ahead inflation expectations from the RBNZ household inflation expectations survey and the corresponding one-year-ahead actual inflation rate. The gaps in 2008Q4 and 2010Q2/Q3 are due to missing observations in the micro dataset. The dashed line depicts the period at which the survey switched to online mode in 2018 Q3.

If the survey data were not affected by sample selection, Equation 3 could be estimated by Ordinary Least Squares (OLS), or Weighted Least Squares (WLS) to account for survey weights. However, as our results from the previous section indicated, the missing responses to the inflation expectation question are not random. In order to account for such selection bias, we estimate inflation bias using the Heckman selection model (Heckman, 1974, 1979). The Heckman selection model is a statistical model that addresses the issue of selection bias in econometric analyses. Selection bias arises when a subset of observations is systematically different from the rest of the sample, leading to biased estimates of model parameters. The Heckman selection model consists of two equations: the selection equation and the outcome equation.

The selection equation models the probability of selection into the sample, while the outcome equation models the relationship between the outcome variable and the explanatory variables. The selection equation is typically a Probit model that relates the probability of being included in the sample to a set of variables that are correlated with the selection process. The selection equation for our case is defined by the extended baseline specification of Equation 1, including the variables in column 1 of Table 1, plus the interaction terms with the online dummy variable. We chose this specification as a selection equation because most of the other variables we used for robustness usually restrict our sample size. In contrast, the inclusion of the online interaction terms provides a more accurate identification of the heterogeneity of response rates.

The outcome equation can include the same set of explanatory variables as the selection equation, as well as an additional error term that captures the unobserved factors that affect the outcome variable. For identification purposes, it is often recommended that the selection equation includes additional variables, also known as exclusion restrictions, that are correlated with selection but not with the outcome (see Puhani, 2000, for further discussion). In our estimations, we drop four variables from the outcome equation for identification purposes: region, employment status, year trend, and lagged inflation squared. Although these variables can arguably be excluded *a priori* for not being expected to be related to bias, in our experimental estimations, these variables were indeed found to be either statistically insignificant (region and employment) or leading to estimation variance inflation due to high collinearity (year trend and lagged inflation squared).[15]

4.B Estimation Results

Table 2 presents a comparison of estimates of inflation expectations bias for different groups of the population and across different estimation methods. There are several interesting findings. First, in contrast to the Probit regressions, using survey weights seems relevant for estimates of expectations bias. Comparing the estimates without selection, in columns (1) and (2), we note important differences on the effects of age and ethnicity; namely, accounting for the survey weights increases the magnitudes and significance of these variables' effects. Respondents older than 25 years old are found to have an average bias of more than 0.23 percentage points (p.p.) higher than respondents from the younger (<25 years) base age bracket. Pacific Islanders have an average bias of 0.34 p.p. higher than the base ethnic group (Others/NZ Europeans), while Maori people and Asians have an average bias of 0.15 and 0.12 p.p. higher than the base group, respectively. Of course, these estimates reflect only the sample of respondents who responded to the inflation expectations question.

[15]The full-information maximum likelihood estimator of the Heckman model is particularly known to be sensitive to collinearity problems (see Puhani, 2000).

Table 2: *Estimates of Inflation Expectations Bias With and Without Selection.*

Variables (base category)	**Categories**	**(1) No Selection OLS**	**(2) No Selection WLS**	**(3) Heckit Two Step**	**(4) Heckit ML**	**(5) Imputed WLS**
Gender (base=Male)	Female	0.240*** (0.023)	0.275*** (0.024)	-0.011 (0.041)	0.115** (0.055)	0.152*** (0.017)
Age (base=Under 25)	25-34	0.106* (0.063)	0.239*** (0.066)	0.463*** (0.071)	0.377*** (0.080)	0.110*** (0.036)
	35-44	0.067 (0.058)	0.244*** (0.061)	0.612*** (0.073)	0.467*** (0.093)	0.098*** (0.033)
	45-54	0.104* (0.059)	0.233*** (0.062)	0.694*** (0.081)	0.506*** (0.106)	0.094*** (0.035)
	55-64	0.165*** (0.059)	0.317*** (0.062)	0.789*** (0.082)	0.600*** (0.109)	0.182*** (0.036)
	65+	0.131** (0.060)	0.287*** (0.062)	0.780*** (0.083)	0.586*** (0.113)	0.127*** (0.035)
Ethnicity (base=European/Other)	Asian	-0.093 (0.065)	0.121* (0.066)	0.036 (0.067)	0.076 (0.068)	0.031 (0.045)
	Maori	0.007 (0.063)	0.155** (0.066)	-0.060 (0.071)	0.032 (0.077)	0.019 (0.038)
	Pacific Isl.	0.053 (0.141)	0.337** (0.158)	0.052 (0.157)	0.161 (0.167)	0.142** (0.072)
Real Income (base=Median)	High	-0.044* (0.025)	-0.086*** (0.026)	0.040 (0.030)	-0.014 (0.035)	-0.047** (0.021)
	Low	0.121*** (0.033)	0.148*** (0.034)	0.017 (0.037)	0.068 (0.042)	0.068*** (0.024)
Online (base=No)	Yes	-2.766*** (0.032)	-2.575*** (0.035)	-2.278*** (0.046)	-2.477*** (0.043)	-2.562*** (0.028)
Lagged Inflation		0.155*** (0.009)	0.194*** (0.009)	0.206*** (0.010)	0.192*** (0.010)	0.205*** (0.007)
Heckman	λ (lambda)			0.774*** (0.092)		
	ρ (rho)				0.264*** (0.094)	
N.Obs.		39,312	39,312	39,312	39,312	68,906
R^2 **(unweighted)**		0.238	0.233	0.236		0.185
Root MSE		2.136	2.143	2.139	2.147	2.097

Notes: Regressions (2) to (4) are weighted using survey weights. All regressions include quarter dummies. Estimates for the selection equation under the Heckman selection models are not presented for succinctness – these are based on the Probit baseline specification from Section 3 extended with interaction terms for online mode, i.e., the estimates underlying Figure 7. The R^2 statistics refer to the outcome equation. Numbers in parenthesis are robust standard errors. ***,**,* stand for 1%, 5%, 10% statistical significance, respectively.

To account for selection, we estimate Heckman selection models using the baseline Probit estimates from the previous section for the selection equation. We also explore two alternative estimation approaches: the two-step estimator and the maximum likelihood (ML) estimator, presented in columns (3) and (4) of Table 2, respectively. The Heckman model estimates are mostly consistent across the two estimation methods; the only prominent difference relates to the statistical significance of gender, which is insignificant under the two-step estimator. Estimates of the significance of correction for selection, as captured by the lambda and rho (correlation between error terms) parameters, indicate the appropriateness of the selection model.

Perhaps more importantly, the estimates accounting for selection are in stark contrast to those obtained without the correction. First, after accounting for selection bias, the difference in inflation expectations between women and men decreases by more than half. In fact, under the two-step estimator (column 3), gender does not seem to have a statistically significant effect on inflation expectations bias. Second, the differences in expectations bias by ethnicity and income bracket also turn insignificant after accounting for selection.

These are interesting findings in relation to the previous literature. Systematic differences in inflation expectations by gender have long been reported (e.g., Jonung, 1981) and corroborated by many studies across countries. For example, D'Acunto et al. (2021) find that women have persistently higher inflation expectations than men and associate this difference with gender roles in household grocery shores. There is also evidence about differences by race (admittedly, not exactly the same as ethnicity, but a reasonable proxy) and income. Using cross-sectional information from the New York Fed Survey of Consumer Expectations, D'Acunto et al. (2023) document that average inflation expectations of Blacks tend to be above those of Whites and Asian Americans, while lower-income households also tend to report higher expectations. Although their findings are based on different surveys and populations, our results indicate that part of those differences by gender, race, and income may be explained by non-response bias. In other words, the sources associated with observed heterogeneity in surveys of inflation expectations across these characteristics are, in fact, determining participation and responses to the inflation expectations question rather than the subgroup's average expectations.

Third, the effects of age increase in magnitude after accounting for selection, particularly steepening the profile of higher over-predictions for older respondents. According to the two-step estimates (column 3), inflation expectations of respondents older than 35 are more than two times higher than what is estimated without accounting for selection (column 2). This finding can have important implications for the literature on learning from experience. Malmendier and Nagel (2016) showed that the dispersion of household inflation expectations by age can be associated with their lifetime experiences of inflation. Our results suggest that these effects could be even stronger when accounting for non-response bias. Besides, an upward-sloping profile of inflation expectations by age is more clearly identified when accounting for selection. Hence, the age effects may also be associated with exposure to prices of age-specific baskets of products that would not be apparent from purely observed data.

Fourth, some macro effects seem robust to selection bias and weighting: the higher the previous quarter's inflation, the higher respondents' over-prediction of inflation, and the switch to online mode decreased inflation predictions by more than 2.27 p.p., after controlling for the effects of the other variables.[16]

Finally, the findings obtained with the Heckman correction are compared with the approach of random imputation of missing data. Column (5) of Table 2 presents the bias estimates obtained on a sample that imputes missing responses using each quarterly survey sample of responses to the inflation expectations question.[17] Overall, the estimates using imputation go in similar directions as those obtained without accounting for selection. First, gender effects are stronger than those obtained under the Heckman correction. Second, age differences are smaller and similar to those obtained without accounting for selection. Third, the expectations of Pacific Islanders appear to be significantly more biased than other ethnicities. Lastly, the effects of real income are also similar to what is obtained without accounting for selection.

[16] The large magnitude of the estimate on the online mode dummy variable should be interpreted with caution, as it is also capturing the large negative biases that emerged from 2020Q3 onwards due to the sluggish adjustment of expectations to the increase of actual inflation rates 4 quarters ahead starting from 2021Q3 (see Figure 8).

[17] More details about the imputation method are provided in Appendix D, where we show how it is affected by assumptions about survey weighting and random seeds.

Our estimates indicate that inflation biases calculated directly from the sample of observations or randomly imputed, i.e., without accounting for selection, give a distorted picture of the socio-demographic differences in the population's inflation expectations. Many differences across groups, such as gender, income and ethnicity, turn statistically insignificant after accounting for selection bias.

5 Adjusted Indices

5.A Method

In this section, we show how the correction for non-responses developed in the previous section can be used to adjust indices of average inflation expectations. The adjustment is again based on the Heckman correction for regressions, except that here, the regression is designed to provide estimates of average inflation expectations.

A simple approach to obtain average indices of inflation expectations is to run a linear regression of the micro survey of inflation expectations data on quarter dummy variables, i.e.,

$$\pi_i^e = \hat{\delta}_1 I\left(t = 1998q2\right) + \ldots + \hat{\delta}_{99} I\left(t = 2022q4\right) + \hat{\varepsilon}_i, \tag{4}$$

where $I\left(\bullet\right) = 1$ when the condition between brackets is true, and $\left\{\hat{\delta}_t\right\}$ are estimates of average inflation expectations for each quarter. This regression can be estimated using WLS to account for survey weights in constructing the expectations index.

The Heckman correction for non-response bias can be applied to equation 4 by including the inverse Mills Ratio, $\tilde{\lambda}_i$, obtained from the baseline Probit model, as an additional explanatory variable,

$$\pi_i^e = \hat{\theta}\tilde{\lambda}_i + \hat{\delta}_1' I\left(t = 1998q2\right) + \ldots + \hat{\delta}_{99}' I\left(t = 2022q4\right) + \hat{\varepsilon}_i'. \tag{5}$$

The regression-based approach to adjust indices of average expectations for non-responses can be easily extended to calculate subgroup indices, e.g., with average expectations by gender or other socio-demographic characteristics, by interacting dummy variables on the subgroups with the time dummy variables, $I(\bullet)$, in equation 5. Moreover, the framework can also be extended to calculate an adjusted measure of inflation disagreement based on the variance of individual expectations; to accomplish that, one only needs to replace the left-hand side variable by the squared deviation of inflation expectations from the quarterly survey average, $(\pi_t^e - \overline{\pi}_t^e)^2$.

5.B Empirical Properties

Estimates of equations 4 and 5 are presented in Figure 1 as the unadjusted and adjusted averages of inflation expectations, respectively. The average adjustment for selection bias amounts to -0.288 over the full sample and ranges from a minimum of -0.385 (2018 Q1) to a maximum of -0.138 (2022 Q3).[18]

One common observation about household inflation expectations is that these tend to be systematically higher than actual inflation rates and forecasts of professionals (D'Acunto et al., 2023). This divergence may be partly due to non-response bias. Table 3 reports estimates of the relationship between household and professional forecasters' inflation expectations. The negative and statistically significant intercept coefficient estimate in column (1) confirms the finding from previous literature. Correcting for non-response bias makes that average expectation difference statistically insignificant (column 2). Nevertheless, the slope coefficient in both regressions still indicates that household inflation expectations do not scale one-to-one to professional forecasters' expectations, a result consistent with Carroll (2003)'s estimates using US data.

The adjustment for non-response bias also has implications for assessments of inflation expectations disagreement, both across and within subgroups. Mankiw et al. (2003) document that such disagreement is significant and tends to move together with macroeconomic conditions. Disagreement about inflation expectations also has been found to interact with the transmission of monetary policy (Falck et al., 2021) and to be an important determinant of inflation dynamics (Brandão-Marques et al., 2023; Meeks and Monti, 2023), while certain subgroup inflation expectations can play

[18] Annual averages of these estimates are also presented in Table B.3 in Appendix B, where we also compare our estimates to published average inflation expectations – those can differ due to the method used to detect and exclude outliers from computations.

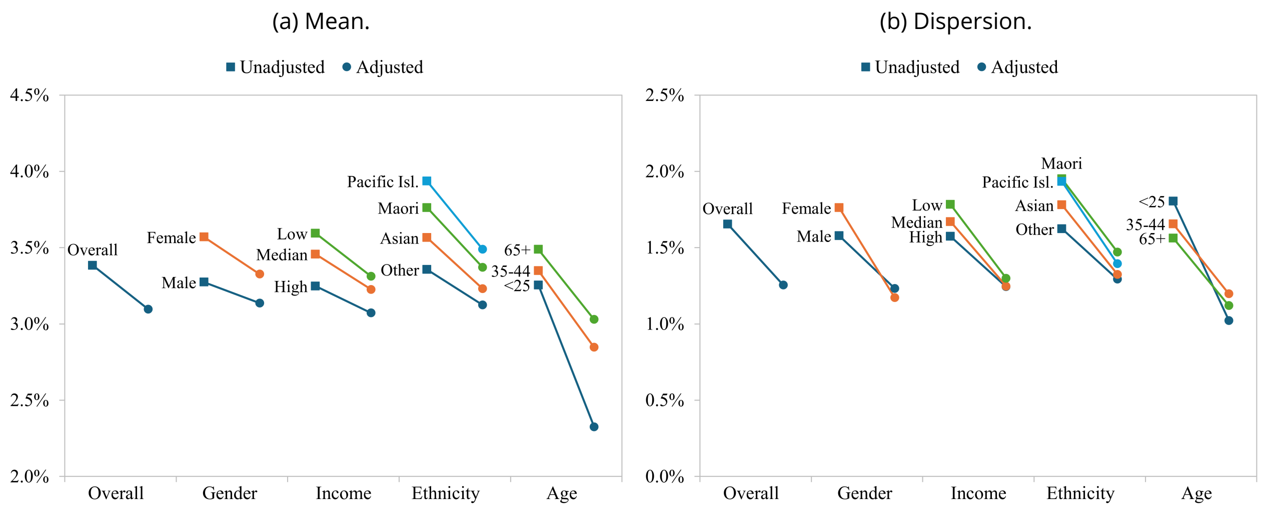
Table 3: *Relationship Between Household and Professional Forecasters' Inflation Expectations.*

Regressor	**(1) SPF**	**(2) SPF**
Intercept	-0.294**	-0.019
	(0.129)	(0.123)
Household inflation expectations:		
Unadjusted average	0.759***	
	(0.036)	
Adjusted average		0.740***
		(0.038)
N.Obs.	96	96
R^2	0.809	0.806

Notes: One-year-ahead inflation expectations from the Survey of Professional Forecasters (series M14 from RBNZ) regressed on the average one-year-ahead household inflation expectations. Unadjusted average does not correct for item non-response bias, while Adjusted average is the average obtained after the correction proposed in this paper. Standard errors are HAC robust. ***,** stand for 1%, 5% statistical significance, respectively.

a larger role in inflation dynamics than aggregate expectations (Binder, 2015). Hence, it is important to evaluate how non-response bias can affect the measurement of expectations disagreement.

Figure 9: *Effects of Non-response Bias Adjustment on Mean and Dispersion of Inflation Expectations.*



Notes: The statistics presented are the sample averages of the quarterly means and dispersions of inflation expectations, which are calculated using the approach described in Section 5.A. Dispersion is the standard deviation of the respondents' inflation expectations.

Figure 9 presents the effects of non-response bias on the disagreement of inflation expectations between (mean) and within (dispersion) subgroups. Although accounting for the non-responses generally decreases mean inflation expectations for all subgroups, the differential effect on subgroups with more non-responders leads to a decrease in disagreement about the mean of inflation expectations across gender, income, and ethnicity, and an increase across age (panel a). The effect on mean disagreement across age brackets is particularly driven by younger respondents, who tend to have lower inflation expectations possibly due to low experienced inflation rates during their lifetimes (Malmendier and Nagel, 2016).

Disagreement of inflation expectations within subgroups generally decreases with the adjustment for non-response bias (Figure 9, panel b). Moreover, the difference in the dispersion of inflation expectations among respondents of different gender, income, ethnicity, and age, also shrinks after accounting for non-responses. In fact, there is even less disagreement among females and younger respondents than among males and older respondents, respectively. In the context of the literature cited above, these results suggest that accounting for non-response bias can have important implications for the understanding of how the distribution of inflation expectations affects inflation dynamics and the transmission of monetary policy.[19]

6 Policy Implications

Item non-response bias in household inflation expectations surveys carries important implications for monetary authorities.

Our findings indicate that younger, female, lower-income, and minority respondents exhibit higher rates of item non-response, which distorts the sample distribution and leads to biased aggregate estimates of inflation expectations. This suggests that survey-based measures may not accurately capture the full dispersion of inflation expectations across the population. Such measurement error can compromise the reliability of these estimates as critical inputs for monetary policy decision-making, potentially leading to suboptimal policy responses. Previous research suggests that individuals are more likely to engage with monetary policy communication when they perceive alignment with policymakers, which has been shown to enhance trust and responsiveness (D'Acunto et al., 2021). This underscores the necessity for monetary authorities to adopt communication strategies that are both

[19] In Appendix E we also present an exercise where we test for the inclusion of adjusted versus unadjusted subgroup inflation expectations in a forward-looking Phillips curve, similar to Binder (2015). These estimates suggest the adjusted indices are always preferred over the unadjusted series.

inclusive and representative, ensuring that policy messages effectively reach and resonate with underrepresented groups.

Second, our analysis reveals that responsiveness to inflation expectation questions increases when actual inflation deviates from the central bank's target, indicating that heightened inflation dynamics trigger greater survey engagement. Given that public attention to central banks rises during periods of elevated inflation volatility, central banks could strategically leverage these periods to enhance public understanding of monetary policy (Blinder et al., 2022). This requires a shift from a historical focus on financial market participants toward broader outreach targeting audiences with lower levels of economic literacy (Haldane and McMahon, 2018). Monetary authorities can achieve this by implementing layered messaging strategies that tailor content complexity to diverse audiences (Gardt et al., 2021; Mochhoury, 2023).

Third, the mode of survey administration plays a crucial role in shaping response rates and sample composition. Our findings demonstrate that transitioning from telephone to online surveys substantially reduces item non-response bias, particularly by increasing participation among groups previously underrepresented in inflation expectations data. This finding underscores the importance of survey design in obtaining high-quality, representative data and suggests that digital platforms can serve as effective tools for improving survey coverage. This aligns with evidence that online survey modes can yield higher response rates compared to traditional methods, especially among younger and digitally engaged respondents (Bruine de Bruin et al., 2017). Nonetheless, it is critical to ensure digital accessibility for respondents with limited internet use or technological proficiency to avoid introducing new forms of selection bias.

Collectively, these insights highlight that mitigating non-response bias requires not only methodological adjustments but also a comprehensive communication strategy. Enhancing the inclusion, accessibility, and adaptability of monetary policy communication can reduce measurement error and improve the representativeness of survey data. By adopting targeted outreach strategies, refining the timing and framing of messages, and employing layered communication approaches, central banks can enhance public engagement and data quality. Such concerted efforts will support the collection of more representative inflation expectations data, thereby reinforcing its role as an instrumental tool for effective monetary policy formulation.

7 Concluding Remarks

In this paper, we explore the demographic determinants of non-responses to inflation expectations questions in the RBNZ's Household Inflation Expectations survey. To address that issue, we use a Probit modelling approach. We find significant item non-response in this survey. Non-respondents to the one-year ahead inflation question are especially likely to be aged under 25, female, from a minority ethnic group (Māori, Pacific, Asian), unemployed, and from low-income households. A switch in the conduct of the survey to online mode is found to substantially decrease non-responses to the inflation question, as well as decrease the effects of socio-demographic characteristics on response rates.

We also identify consistent differences in inflation expectations according to the age of the respondent but find that observed differences in expectations by gender, ethnicity and income are primarily due to sample selection bias. Namely, after accounting for sample selection, most of the differences in inflation expectations by socio-demographic characteristics turn insignificant or decrease substantially. The only exception is age, where we found that older individuals tend to over-predict one-year-ahead inflation more than the young.

These findings have important implications for how central banks use household inflation expectations measures. Even though the survey assigns weights based on the population distribution and thus attempts to correct for unit non-response bias, it does not correct for item non-response bias. Because both inflation perceptions and non-responses can differ across demographic groups, the weights allocated to the individual responses are likely to misrepresent the population. To address this issue, we propose an adjustment to the calculation of mean inflation expectations estimates using a sample selection correction model. We found that the unadjusted aggregate measure commonly used to gauge households' expectations is, on average, about 0.3 percentage points higher than a measure that accounts for item non-response bias. [20]

Our findings also allow us to draw important recommendations for how policymakers communicate with the population. Most households are likely to rely on the guidance provided by policymakers when forming their expectations about future inflation. The socio-demographic differences we identify in this paper suggest that some groups of the population may be less confident in responding to the inflation expectations question. A potential way to address these gaps would be to improve the outreach of policy with more targeted communications. We hope our research will help inform the development of such policies and lead to more accurate measures of inflation expectations.

A Data Appendix

This Appendix provides additional details about the survey data. A key issue in the compilation of our data relates to the consistency of information across the survey waves. Over time, the survey went through several changes in the formulation of the survey questions. Particularly, the options to some survey questions changed over time.

For example, from 1998 Q1 to 2008 Q3, Pacific Island respondents could identify as one of six Pacific Island ethnic groups: Cook Island, Niuean, Fijian, Tongan, Samoan, or other Pacific Islands. In 2008 Q4, the six Pacific Island ethnic groups were aggregated into a single ethnic umbrella group, leaving Pacific Island respondents with one response option: Pacific Islanders. To maintain consistency, respondents who identified with one of the six Pacific Island ethnic groups from 1998 Q1 to 2008 Q3 were grouped and categorised following the umbrella Pacific Islander ethnic group.

As another example, we construct a real household income variable based on the availability of different nominal income variables across the sample. Subject to availability, we calculate household income using the median values of the more granular household income bracket intervals. We then adjust the nominal household incomes to real household incomes using the 2022 Consumer Price Index as the base level. Following this, we classify real household incomes into one of 3 cate-

[20] RBNZ own the survey and can change the methodology if considered desirable, for example, application of these findings may be considered for changes to the Household expectations survey in future.

gories: under \$50,000 (low), \$50,000 - \$100,000 (median), and over \$100,000 (high). In the absence of nominal household income, real personal income is used to fill in the missing values (which are calculated similarly). This method assumes that if nominal household income was missing, but real personal income was low/median/high, real household income would have been low/median/high, respectively.[21]

Table A.1 presents the data tabulations for some of the variables in the survey.

Moreover, the mode of data collection of the survey also changed over time, switching from telephone interviews to online survey from 2018 Q3. Over the period that the survey was conducted by telephone, 1998 Q2 to 2018 Q2, 51.75% of respondents were female, 5.8% were Māori, 4.07% Asian, 1.87% Pacific Islander, and 88.26% identified with 'other' ethnic groups. Among the survey respondents, 14.8% were aged 25-34, 23.54% were 35-44, 16.95% were 45-54, 14.68% were 55-64, 18.62% were 65+, and 11.41% were under 25.

Following the move to online mode in quarter 3 of 2018, we observe a redistribution of demographics among respondents. Respondents who identified with Asian ethnicity increased by 117.19%, Māori respondents by 70.17%, Pacific Islanders by 33.69%, and respondents who identified with other ethnicity groups decreased by 10.73%. Survey respondents aged 25-34, 45-54, 55-64, and 65+ increased by 18.04%, 7.14%, 10.76%, and 13.64%, respectively. Contrary to this, respondents under 25 decreased by 31.55%, while those aged 35-44 reduced by 18.69%. Furthermore, female respondents increased marginally by 0.89%.

[21] Upon further inspection of the observations with available data on both household and personal income, we found that these two are highly correlated: the Phi coefficient of correlation based on the contingency table between these two variables equals 0.702, and the hypothesis of independence is strongly rejected (p-value=0).

Table A.1: *Data tabulations.*

(a) Age of Respondents

	Freq.	Percent	Cum.
15-17	2,283	2.74	2.74
18-24	6,564	7.89	10.63
25-34	12,796	15.38	26.01
35-44	18,792	22.59	48.6
45-54	14,320	17.21	65.81
55-64	12,498	15.02	80.83
65+	15,952	19.17	100
Total	83,205	100	

(b) Gender of Respondents

	Freq.	Percent	Cum.
Female	43,140	51.85	51.85
Male	40,065	48.15	100
Total	83,205	100	

(c) Ethnicity of Respondents

	Freq.	Percent	Cum.
Asian	4,246	5.1	5.1
Maori	5,557	6.68	11.78
Other	71,734	86.21	98
Pacific Islander	1,668	2	100
Total		83,205	100

(d) Regions where Respondents Live

	Freq.	Percent	Cum.
Auckland	26,392	31.72	31.72
Rest of North Island	36,398	43.74	75.46
South Island	20,415	24.54	100
Total	83,205	100	

(e) Real Income of Respondents

	Freq.	Percent	Cum.
High	28,759	38.14	38.14
Low	22,694	30.1	68.24
Median	23,947	31.76	100
Total	75,400	100	

(f) Employment Status of Respondents

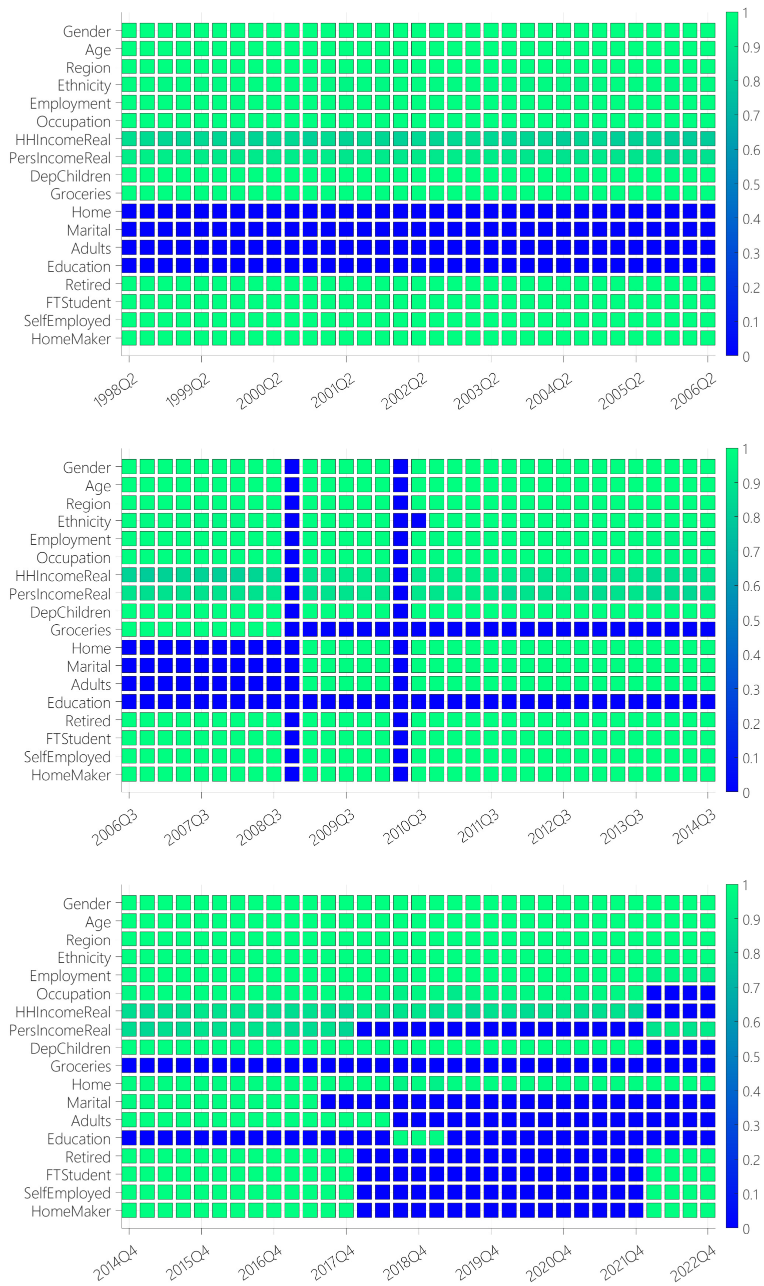
	Freq.	Percent	Cum.
Employed	56,908	68.39	68.39
Unemployed/Other	26,297	31.61	100
Total	83,205	100	

Over the whole sample, from 1998 Q2 to 2022 Q4, the median age range of survey respondents was 45 to 54. In total, 51.85% of respondents were female, 6.68% were Māori, 5.1% Asian, 2% Pacific Islander, and 86.21% identified with 'other' ethnic groups. Over $100,000 was the most frequently reported real household income range, followed by $50,000 to $100,000, with 34.37% and 27.68% of respondents reporting real household incomes within those ranges, respectively. Regarding the real personal income of survey respondents, 37.99% reported incomes under $40,000, 31.99% reported incomes between $40,000 to $80,000, and 19.75% reported incomes over $80,000.

The (measured) average one-year ahead inflation expectation of female respondents has historically been higher than that of male respondents. However, since 2021, the average one-year-ahead inflation expectation of males has marginally surpassed that of females. Similarly, respondents aged 35 and under have traditionally had higher average one-year-ahead inflation expectations than those aged 35 and over. However, this trend has inverted in recent years, resulting in lower inflation expectations among respondents under 35 than those over 35. Likewise, the average one-year-ahead inflation expectation for Pacific Islander respondents is higher than for Māori, Asian and other ethnic groups.

Figure A.1 illustrates changes to survey data collected over time, with the green shaded areas reflecting available observations by variable. The most notable omission is the data for the fourth quarter of 2008 and the second quarter of 2010, which is missing from the data provider database. Some variables are only available for portions of our sample. This is important for our regression analysis in the following sections, as data availability will determine the number of observations available for each specification. For example, grocery shopping was only available up to 2008, while home ownership entered the survey after that point. Hence, we can only evaluate their effects separately according to the corresponding sub-samples.

Figure A.1: *Available Sample Observations by Variable.*



Notes: Each square represents the fraction of observations relative to the total for the corresponding quarter's survey, for which the variable is available.

B Supplementary Estimates

Table B.1: *Probit Model Estimates on Responses to the Inflation Expectation Question.*

Variables	Categories	(1)	(2)	(3)	(4)
Gender	Female	-0.622*** (0.011)	-0.652*** (0.012)	-0.702*** (0.020)	-0.587*** (0.016)
Age	25-34	0.407*** (0.023)	0.411*** (0.024)	0.534*** (0.034)	0.174*** (0.039)
	35-44	0.740*** (0.022)	0.766*** (0.023)	0.975*** (0.032)	0.396*** (0.038)
	45-54	0.970*** (0.023)	0.976*** (0.024)	1.190*** (0.034)	0.573*** (0.039)
	55-64	1.030*** (0.024)	1.006*** (0.025)	1.226*** (0.036)	0.551*** (0.039)
	65+	1.121*** (0.024)	1.053*** (0.025)	1.124*** (0.038)	0.613*** (0.041)
Region	Rest of North Island	-0.036*** (0.013)	-0.035** (0.014)	-0.063*** (0.020)	-0.030 (0.018)
	South Island	-0.002 (0.015)	0.000 (0.016)	-0.002 (0.023)	-0.023 (0.021)
Ethnicity	Asian	-0.158*** (0.028)	-0.163*** (0.029)	-0.108** (0.050)	-0.178*** (0.036)
	Maori	-0.462*** (0.023)	-0.447*** (0.024)	-0.575*** (0.039)	-0.352*** (0.031)
	Pacific Islander	-0.587*** (0.042)	-0.582*** (0.044)	-0.698*** (0.075)	-0.503*** (0.056)
Real Income	High	0.313*** (0.013)	0.287*** (0.014)	0.328*** (0.020)	0.289*** (0.019)
	Low	-0.265*** (0.015)	-0.274*** (0.016)	-0.290*** (0.023)	-0.266*** (0.021)
Employment	Employed	0.082*** (0.015)			0.054** (0.021)
Occupation	Clerks/Admin/Sales		-0.009 (0.019)	-0.127*** (0.026)	
	Manual/Agricultural/Domestic		-0.047*** (0.018)	-0.105*** (0.026)	
	Professional/Manager/Trained		0.168*** (0.017)	0.156*** (0.025)	
Dependent Children	Yes		-0.093*** (0.014)	-0.099*** (0.020)	-0.057*** (0.020)
Groceries Shopping	Yes - jointly/shared			0.039 (0.030)	
	Yes - main shopper			-0.079*** (0.024)	
Home Ownership	Living with parents				-0.682*** (0.039)
	Mortgage				-0.237*** (0.022)
	Other				-0.349*** (0.047)

Probit Model Estimates on Responses to the Inflation Expectation Question. (continued)

Variables	Categories	(1)	(2)	(3)	(4)
	Renting				-0.388*** (0.025)
Online Mode	Yes	1.096*** (0.018)	1.119*** (0.019)		1.036*** (0.026)
Year Trend		-0.026*** (0.001)	-0.029*** (0.001)	-0.044*** (0.000)	-0.012*** (0.002)
Lagged Inflation	Linear	-0.052*** (0.010)	-0.076*** (0.014)	-0.060*** (0.021)	-0.020 (0.024)
	Squared	0.013*** (0.002)	0.020*** (0.003)	0.019*** (0.005)	0.012*** (0.004)

Notes: All regressions are weighted using survey weights. All regressions include year trend and quarter dummies. Numbers in parenthesis are robust standard errors. ***,**,* stand for 1%, 5%, 10% statistical significance, respectively.

Table B.2: *Average Partial Effects Split by Survey Mode.*

		(1)		(2)		(4)	
Variables	**Categories**	**Online=0**	**Online=1**	**Online=0**	**Online=1**	**Online=0**	**Online=1**
Gender	Female	-0.244***	-0.055***	-0.252***	-0.043***	-0.250***	-0.048***
		(0.004)	(0.007)	(0.004)	(0.007)	(0.006)	(0.008)
Age	25-34	0.128***	0.043***	0.127***	0.042***	0.083***	0.060***
		(0.008)	(0.014)	(0.009)	(0.016)	(0.017)	(0.018)
	35-44	0.262***	0.064***	0.267***	0.060***	0.197***	0.082***
		(0.008)	(0.013)	(0.008)	(0.015)	(0.019)	(0.017)
	45-54	0.355***	0.080***	0.351***	0.062***	0.283***	0.079***
		(0.009)	(0.012)	(0.009)	(0.015)	(0.020)	(0.017)
	55-64	0.378***	0.094***	0.363***	0.081***	0.277***	0.094***
		(0.009)	(0.012)	(0.009)	(0.014)	(0.020)	(0.017)
	65+	0.395***	0.153***	0.367***	0.137***	0.301***	0.135***
		(0.009)	(0.009)	(0.009)	(0.011)	(0.020)	(0.016)
Region	Rest of North Island	-0.017***	0.010	-0.015***	0.009	-0.016**	0.011
		(0.005)	(0.007)	(0.005)	(0.008)	(0.007)	(0.009)
	South Island	-0.007	0.020**	-0.003	0.018*	-0.015*	0.016
		(0.005)	(0.008)	(0.005)	(0.009)	(0.008)	(0.010)
Ethnicity	Asian	-0.078***	0.008	-0.080***	0.007	-0.105***	0.004
		(0.012)	(0.011)	(0.012)	(0.013)	(0.016)	(0.014)
	Maori	-0.190***	-0.033***	-0.184***	-0.019*	-0.181***	-0.029**
		(0.009)	(0.011)	(0.009)	(0.012)	(0.014)	(0.013)
	Pacific Islander	-0.236***	-0.030	-0.227***	-0.024	-0.223***	-0.042
		(0.015)	(0.020)	(0.016)	(0.023)	(0.023)	(0.026)
Real Income	High	0.122***	0.017**	0.111***	0.001	0.122***	0.022***
		(0.005)	(0.007)	(0.005)	(0.008)	(0.008)	(0.008)
	Low	-0.093***	-0.053***	-0.095***	-0.049***	-0.087***	-0.082***
		(0.006)	(0.009)	(0.006)	(0.010)	(0.008)	(0.011)
Employment	Employed	0.017***	0.047***			0.004	0.061***
		(0.006)	(0.008)			(0.009)	(0.010)
Occupation	Clerks/Admin/Sales			-0.022***	0.088***		
				(0.007)	(0.010)		
	Manual/Agricultural/Domestic			-0.039***	0.069***		
				(0.006)	(0.011)		
	Professional/Manager/Trained			0.050***	0.087***		
				(0.006)	(0.009)		
Dependent Children	Yes			-0.032***	-0.003	-0.027***	0.005
				(0.005)	(0.008)	(0.008)	(0.009)
Home Ownership	Living with parents					-0.101***	-0.265***
						(0.020)	(0.019)
	Mortgage					-0.042***	-0.102***
						(0.009)	(0.012)
	Other					-0.070***	-0.134***
						(0.021)	(0.022)
	Renting					-0.122***	-0.077***
						(0.010)	(0.012)
N.Obs.		75,180		71,799		35,993	
Sample		98Q2-22Q4		98Q2-21Q4		09Q1-21Q4	
McFadden R2		0.181		0.182		0.188	

Notes: Average partial effects are calculated using the delta method and averaging over the sample observations, holding other variables constant at their sample values. Note that the column headers correspond to Table 1 specifications numbering and that every two columns correspond to a separate regression. Numbers in parenthesis are robust standard errors. ***,**,* stand for 1%, 5%, 10% statistical significance, respectively.

Table B.3: *Average Inflation Expectations by Year.*

	1998	Δ	1999	Δ	2000	Δ	2001	Δ	2002	Δ
Published series (H1)	3.83		3.48		4.05		4.05		3.85	
Excl. outliers w/ hybrid IQR	3.18	-0.65	2.97	-0.51	3.53	-0.52	3.57	-0.48	3.42	-0.43
Baseline sample - unadjusted	3.17	-0.01	2.96	-0.01	3.52	-0.01	3.55	-0.02	3.40	-0.02
Baseline sample - adjusted	2.90	-0.27	2.69	-0.27	3.23	-0.29	3.27	-0.28	3.11	-0.29
	2003		2004		2005		2006		2007	
Published series (H1)	3.63		4.10		4.22		4.68		4.53	
Excl. outliers w/ hybrid IQR	3.22	-0.41	3.58	-0.52	3.86	-0.36	4.15	-0.53	3.96	-0.57
Baseline sample - unadjusted	3.23	0.01	3.56	-0.02	3.86	0.00	4.16	0.01	3.97	0.01
Baseline sample - adjusted	2.95	-0.28	3.28	-0.28	3.56	-0.30	3.86	-0.30	3.66	-0.31
	2008*		2009		2010*		2011		2012	
Published series (H1)	4.65		3.98		3.95		4.50		3.53	
Excl. outliers w/ hybrid IQR	4.14	-0.51	3.66	-0.32	3.62	-0.33	4.13	-0.37	3.17	-0.36
Baseline sample - unadjusted	4.14	0.00	3.67	0.01	3.54	-0.08	4.14	0.01	3.17	0.00
Baseline sample - adjusted	3.83	-0.31	3.34	-0.33	3.21	-0.33	3.83	-0.31	2.84	-0.33
	2013		2014		2015		2016		2017	
Published series (H1)	3.23		3.40		2.65		2.43		2.98	
Excl. outliers w/ hybrid IQR	2.95	-0.28	2.96	-0.44	2.35	-0.30	2.07	-0.36	2.50	-0.48
Baseline sample - unadjusted	2.93	-0.02	2.95	-0.01	2.33	-0.02	2.06	-0.01	2.51	0.01
Baseline sample - adjusted	2.60	-0.33	2.61	-0.34	2.00	-0.33	1.72	-0.34	2.13	-0.38
	2018		2019		2020		2021		2022	
Published series (H1)	3.18		2.75		2.85		3.65		6.98	
Excl. outliers w/ hybrid IQR	2.85	-0.33	2.46	-0.29	2.51	-0.34	3.24	-0.41	6.98	0.00
Baseline sample - unadjusted	2.83	-0.02	2.46	0.00	2.50	-0.01	3.24	0.00	6.96	-0.02
Baseline sample - adjusted	2.56	-0.27	2.26	-0.20	2.30	-0.20	3.04	-0.20	6.81	-0.15

Notes: The table presents annual averages of the quarterly cross-section averages of one-year-ahead inflation expectations. The published series is the historical data published at the RBNZ website and using different outlier detection rules across time – see the main text for details. The second series is based on our calculations using the IQR outlier detection rule. The third series uses the same outlier detection rule as the previous but restricts the sample to observations with available demographic information to estimate our baseline Probit specification. The fourth series is adjusted for sample selection bias according to our methodology. (*) Due to missing micro observations, the averages for 2008 are based on quarters Q1 to Q3, and the averages for 2010 are based on quarters Q1 and Q4.

C Outliers Robustness Checks

In this Appendix, we evaluate the robustness of our results to the use of different outlier detection rules. This is important because extreme inflation expectations responses may also correspond to would-be non-respondents in the survey. For robustness purposes we consider six different outlier detection rules:

a. (-2,15) Rule: Fixed interval rule that discards inflation expectations lower than -2% and higher than 15%. This was the rule historically used in the RBNZ household survey of inflation expectations for the calculation of mean and median responses until 2021/Q4.

b. $\pm\mathbf{1.5}\times$IQR Rule: Interquartile range (IQR) method using a whisker value equal to 1.5, which excludes observations falling outside the following limits:

$$\begin{aligned} Lower\,limit &= Q1 - whisker \times IQR, \\ Upper\,limit &= Q3 + whisker \times IQR, \end{aligned} \tag{6}$$

where $Q1$ refers to the 25th percentile, $Q3$ refers to the 75th percentile, and IQR is the difference between $Q1$ and $Q3$ in the data series. This rule started being employed in the RBNZ household survey of inflation expectations since 2022/Q1.

c. $\pm\mathbf{3}\times$IQR Rule: A modification of the previous rule with a whisker value equal to 3 in Equation 6.

d. Hybrid IQR Rule: A hybrid version of rules b and c, where the whisker value equals 1.5 for the pre-2022 period, and is adjusted to 3 from 2022. This was the rule used in a previous version of this paper (Chadwick et al., 2023).

e. Top/Bottom 5% by Quarter: Discards the top and bottom 5% observations of each quarter.

f. Top/Bottom 5% Overall: Discards the top and bottom 5% observations over the full sample.

Table C.1 presents the number of outliers detected by these different rules. Rule $\pm\mathbf{1.5}\times$IQR is the most stringent rule, while the **(-2,15)** rule identifies fewer outliers. Given the potential impact that outliers can have on average expectations, we chose the $\pm\mathbf{1.5}\times$IQR for our estimates in the paper.

One advantage of this rule is that it adjusts the definition of outliers according to the dispersion of responses in each survey wave. Hence, in periods of higher uncertainty, the range of responses included in the estimates will be wider as the IQR is likely to increase, and vice versa.

Table C.1: *Frequency of Outliers by Detection Rule.*

Rule	N. Outliers	% Full Sample	% Responded
a. (-2,15)	2,357	2.62%	4.64%
b. $\pm 1.5\times$IQR	4,787	5.33%	9.43%
c. $\pm 3\times$IQR	2,549	2.84%	5.02%
d. Hybrid IQR	4,535	5.05%	8.93%
e. Top/Bottom 5% Quarter	4,161	4.63%	8.20%
f. Top/Bottom 5% All	4,383	4.88%	8.64%

Table C.2 presents estimates of the baseline Probit model on responses to the inflation expectations question across the different samples defined by these outlier detection methods. Column (2) of Table C.2 corresponds to column (1) of Table B.1, which has the baseline model estimates discussed in the paper. There is little variation in coefficient estimates across the outlier detection rules. The main takeaway is that the Probit model estimates are quite robust to the definition of outliers.

Finally, we evaluate how outlier responses can be associated with the respondents' socio-economic characteristics. Table C.3 presents estimates of Probit models on the outlier responses according to their different definitions. Although there is more variation in the coefficient estimates' magnitudes, the estimates' directions and statistical significance are mostly consistent across the different outlier detection rules. Similar to the results for responses to the inflation expectations question, low-income young females from a minority ethnic group tend to report more outlier responses. The switch to online survey mode also decreased the frequency of outlier responses, although the magnitude of this effect is small relative to the effect of online mode on response rates to the inflation expectations question. Also, there is no clear time trend in outlier responses. Finally, the impact of lagged inflation on outlier responses is mixed across the detection rules. These results indicate that although there are parallels between outlier responses and non-responses to the inflation expectations question, their determinants differ in terms of effect magnitude and the impact of trends and the inflation level.

Table C.2: *Robustness of Baseline Probit Model Estimates to Outlier Detection Rules.*

Variables	Categories	(1) (-2,15)	(2) $1.5\times$IQR	(3) $3\times$IQR	(4) Hyb.IQR	(5) Top/Bot.5Q	(6) Top/Bot.5A
Gender	Female	-0.608***	-0.622***	-0.614***	-0.622***	-0.611***	-0.609***
		(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Age	25-34	0.393***	0.407***	0.404***	0.407***	0.413***	0.408***
		(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
	35-44	0.716***	0.740***	0.729***	0.739***	0.740***	0.730***
		(0.021)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)
	45-54	0.943***	0.970***	0.955***	0.969***	0.968***	0.957***
		(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
	55-64	1.001***	1.030***	1.014***	1.028***	1.031***	1.023***
		(0.023)	(0.024)	(0.023)	(0.024)	(0.024)	(0.024)
	65+	1.078***	1.121***	1.093***	1.118***	1.114***	1.110***
		(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Region	Rest of North Island	-0.040***	-0.036***	-0.041***	-0.036***	-0.045***	-0.045***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
	South Island	-0.007	-0.002	-0.006	-0.002	-0.008	-0.010
		(0.015)	(0.015)	(0.014)	(0.016)	(0.013)	(0.015)
Ethnicity	Asian	-0.144***	-0.158***	-0.154***	-0.159***	-0.151***	-0.150***
		(0.027)	(0.028)	(0.027)	(0.028)	(0.027)	(0.027)
	Maori	-0.414***	-0.462***	-0.423***	-0.458***	-0.425***	-0.421***
		(0.023)	(0.023)	(0.022)	(0.023)	(0.023)	(0.023)
	Pacific Islander	-0.538***	-0.587***	-0.543***	-0.584***	-0.526***	-0.534***
		(0.041)	(0.042)	(0.041)	(0.042)	(0.041)	(0.042)
Real Income	High	0.291***	0.313***	0.297***	0.313***	0.293***	0.295***
		(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
	Low	-0.247***	-0.265***	-0.251***	-0.265***	-0.262***	-0.258***
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Employment	Employed	0.080***	0.082***	0.080***	0.081***	0.078***	0.086***
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Online Mode	Yes	1.060***	1.096***	1.091***	1.100***	1.089***	1.074***
		(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Year Trend		-0.026***	-0.026***	-0.027***	-0.026***	-0.027***	-0.027***
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged Inflation	Linear	-0.042***	-0.052***	-0.054***	-0.060***	-0.057***	-0.023**
		(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
	Squared	0.011***	0.013***	0.014***	0.015***	0.016***	0.008***
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
N.Obs		77,363	75,180	77,171	75,400	75,721	75,522
Sample		98Q2-22Q4	98Q2-22Q4	98Q2-22Q4	98Q2-22Q4	98Q2-22Q4	98Q2-22Q4
McFadden R2		0.158	0.170	0.163	0.170	0.165	0.162

Notes: All regressions are weighted using survey weights. All regressions include year trend and quarter dummies. Numbers in parenthesis are robust standard errors. ***,**,* stand for 1%, 5%, 10% statistical significance, respectively.

Table C.3: *Probit Model Estimates on Outlier Responses.*

Variables	Categories	(1) (-2,15)	(2) $1.5\times$IQR	(3) $3\times$IQR	(4) Hyb.IQR	(5) Top/Bot.5Q	(6) Top/Bot.5A
Gender	Female	0.284*** (0.027)	0.267*** (0.020)	0.320*** (0.025)	0.273*** (0.020)	0.160*** (0.020)	0.169*** (0.021)
Age	25-34	-0.388*** (0.052)	-0.301*** (0.043)	-0.398*** (0.050)	-0.302*** (0.044)	-0.343*** (0.043)	-0.372*** (0.045)
	35-44	-0.510*** (0.049)	-0.441*** (0.041)	-0.541*** (0.047)	-0.445*** (0.041)	-0.449*** (0.041)	-0.439*** (0.042)
	45-54	-0.628*** (0.052)	-0.543*** (0.043)	-0.631*** (0.050)	-0.542*** (0.043)	-0.517*** (0.043)	-0.507*** (0.044)
	55-64	-0.724*** (0.056)	-0.616*** (0.044)	-0.725*** (0.052)	-0.616*** (0.044)	-0.599*** (0.044)	-0.610*** (0.046)
	65+	-0.915*** (0.057)	-0.797*** (0.045)	-0.917*** (0.054)	-0.801*** (0.045)	-0.794*** (0.047)	-0.808*** (0.047)
Region	Rest of North Island	0.034 (0.031)	-0.023 (0.023)	0.014 (0.029)	-0.025 (0.024)	0.057** (0.024)	0.056** (0.025)
	South Island	-0.047 (0.039)	-0.057** (0.028)	-0.058 (0.036)	-0.056** (0.028)	-0.012 (0.027)	-0.004 (0.029)
Ethnicity	Asian	0.372*** (0.063)	0.290*** (0.048)	0.382*** (0.059)	0.295*** (0.048)	0.235*** (0.050)	0.247*** (0.050)
	Maori	0.703*** (0.044)	0.648*** (0.037)	0.679*** (0.043)	0.643*** (0.037)	0.510*** (0.038)	0.481*** (0.038)
	Pacific Islander	0.825*** (0.072)	0.755*** (0.066)	0.809*** (0.073)	0.768*** (0.067)	0.543*** (0.068)	0.555*** (0.065)
Real Income	High	-0.255*** (0.035)	-0.306*** (0.025)	-0.284*** (0.032)	-0.303*** (0.025)	-0.125*** (0.025)	-0.157*** (0.025)
	Low	0.156*** (0.035)	0.195*** (0.027)	0.179*** (0.033)	0.200*** (0.027)	0.193*** (0.028)	0.156*** (0.028)
Employment	Employed	-0.157*** (0.034)	-0.109*** (0.027)	-0.153*** (0.032)	-0.109*** (0.027)	-0.079*** (0.028)	-0.119*** (0.028)
Online Mode	Yes	-0.127 (0.085)	-0.335*** (0.027)	-0.542*** (0.051)	-0.366*** (0.026)	-0.330*** (0.037)	-0.191*** (0.040)
Year Trend		-0.009 (0.006)	0.000 (0.001)	0.003 (0.003)	0.000 (0.000)	0.003 (0.002)	0.007*** (0.002)
Lagged Inflation	Linear	-0.054** (0.022)	-0.004 (0.011)	-0.018 (0.020)	0.042*** (0.014)	-0.004 (0.012)	-0.223*** (0.017)
	Squared	0.032*** (0.003)	0.011*** (0.002)	0.016*** (0.003)	-0.001 (0.002)	0.002 (0.002)	0.043*** (0.002)
N.Obs		45,952	45,952	45,952	45,952	45,952	45,952
Sample		98Q2-22Q4	98Q2-22Q4	98Q2-22Q4	98Q2-22Q4	98Q2-22Q4	98Q2-22Q4
McFadden R2		0.156	0.087	0.116	0.085	0.052	0.075

Notes: All regressions are weighted using survey weights. All regressions include year trend and quarter dummies. The sample includes only observations where there was a response to the inflation expectations questions. Numbers in parenthesis are robust standard errors. ***,**,* stand for 1%, 5%, 10% statistical significance, respectively.

D Imputation Method

A common approach to deal with item non-responses in surveys of inflation expectations is imputation. In this Appendix, we describe the method used for imputation of inflation expectations non-responses that is used as a comparison to the Heckman correction approach. This draws on the approach proposed by Curtin (1996) for the U.S. Michigan Survey of Consumers.

We explore two variations of the imputation method. First, for each quarterly survey wave, we impute the missing responses by randomly sampling from the inflation expectations responses obtained in the corresponding quarter. Because this approach treats every response as equal we denote it as the "unweighted draws" imputation method. A second approach is to use the survey weights for the random sampling, which we denote as the "weighted draws" imputation method. Also, note that the sampling in both methods is based on the full sample of responses, which includes outliers. Hence, the outlier detection rule is re-computed on the full imputed samples.

Table D.1 compares the estimates of inflation expectations bias across the two imputation methods. Additionally, the table provides a comparison across different random seeds as the imputation method can be sensitive to that assumption. As expected, the estimates present some numerical variation across method and random seed. However, qualitatively, the estimates tend to go in similar directions. A few exceptions refer to the statistical significance of bias by age (brackets 25-34 and 45-54), ethnicity (for Asian respondents), and real income (high-income respondents). In the main text, we adopted the imputation corresponding to column (4) in Table D.1.

Table D.1: *Estimates of Inflation Expectations Bias Across Imputed Samples.*

Variables	**Categories**	**Unweighted Draws** **(1)** Seed 1	**(2)** Seed 2	**(3)** Seed 3	**Weighted Draws** **(4)** Seed 1	**(5)** Seed 2	**(6)** Seed 3
Gender	Female	0.137***	0.126***	0.143***	0.152***	0.131***	0.127***
		(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Age	25-34	0.065*	0.091**	0.035	0.110***	0.117***	0.080**
		(0.035)	(0.035)	(0.035)	(0.036)	(0.036)	(0.035)
	35-44	0.092***	0.123***	0.083***	0.098***	0.137***	0.081**
		(0.032)	(0.032)	(0.032)	(0.033)	(0.033)	(0.032)
	45-54	0.082**	0.098***	0.049	0.094***	0.099***	0.047
		(0.034)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)
	55-64	0.165***	0.188***	0.130***	0.182***	0.204***	0.137***
		(0.035)	(0.035)	(0.035)	(0.036)	(0.035)	(0.035)
	65+	0.123***	0.111***	0.061*	0.127***	0.137***	0.080**
		(0.034)	(0.034)	(0.034)	(0.035)	(0.035)	(0.034)
Ethnicity	Asian	0.028	0.073*	0.074*	0.031	0.032	0.008
		(0.044)	(0.044)	(0.044)	(0.045)	(0.043)	(0.044)
	Maori	0.032	0.037	-0.001	0.019	0.025	0.057
		(0.038)	(0.038)	(0.037)	(0.038)	(0.038)	(0.037)
	Pacific Isl.	0.208***	0.153**	0.177***	0.142**	0.182**	0.225***
		(0.070)	(0.068)	(0.068)	(0.072)	(0.071)	(0.070)
Real Income	High	-0.042**	-0.03	-0.037*	-0.047**	-0.035*	-0.039*
		(0.020)	(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
	Low	0.072***	0.093***	0.085***	0.068***	0.098***	0.085***
		(0.024)	(0.024)	(0.023)	(0.024)	(0.024)	(0.023)
Online	Yes	-2.540***	-2.526***	-2.547***	-2.562***	-2.532***	-2.546***
		(0.029)	(0.029)	(0.028)	(0.028)	(0.029)	(0.029)
Lagged Inflation		0.199***	0.186***	0.207***	0.205***	0.191***	0.202***
		(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
N.Obs.		68,889	68,945	68,843	68,906	68,846	68,757
Root MSE		2.068	2.067	2.068	2.097	2.080	2.068

Notes: All regressions are weighted using survey weights. All regressions include quarter dummies. All imputations are drawn on a quarterly basis from the corresponding respondents in the survey wave. "Unweighted draws" gives the same weight to every respondent in the survey wave, while "weighted draws" uses the survey weights in the random sampling. Numbers in parenthesis are robust standard errors. ***,**,* stand for 1%, 5%, 10% statistical significance, respectively.

E Phillips Curve with Subgroup Expectations

One potential implication of non-response bias relates to the relevance of subgroup inflation expectations in the Phillips curve framework (Binder, 2015). Specifically, the forward-looking Phillips curve is extended as

$$\pi_t = \sum_{g \in G} \gamma_g \pi^e_{t,g} + \lambda U_t + \epsilon_t, \tag{7}$$

where π_t denotes quarter t inflation rate (annualized), $\pi^e_{t,g}$ is the one-year-ahead mean inflation expectation of subgroup g, and U_t is the unemployment rate. Specifically, we consider whether the non-response bias-adjusted expectations are preferred over the unadjusted expectations. To that end, we estimate equation 7 with both adjusted and unadjusted subgroup mean expectations, which are calculated using the methodology described in Section 5 to obtain the expectation indices.

Table E.1 presents the estimates, focusing on the overall expectation index and subgroups by gender and real income for succinctness – estimates for the other subgroups by ethnicity and age lead to similar conclusions and are available upon request. Consistent with Binder (2015) estimates for the US, we found that inflation expectations from male and high income respondents are preferred in augmenting the Phillips curve. More importantly for our purposes, the indices adjusted for non-response are always selected over the unadjusted series.[22]

[22] In additional estimates by ethnicity and age (not reported here), only the adjusted expectations for respondents in the European/Other ethnicity group and those aged 35-44 years show statistically significant results.

Table E.1: Estimates of Phillipcs Curve with Subgroup Expectations.

Variables	(1)		(2)		(3)	
Intercept	2.119		1.860		1.690	
	(1.430)		(1.476)		(1.439)	
Unemployment	-0.562**		-0.547**		-0.524**	
	(0.221)		(0.223)		(0.220)	
EXPECTATIONS	Unadjusted	Adjusted	Unadjusted	Adjusted	Unadjusted	Adjusted
Overall	<0.001	1.013***				
	(<0.001)	(0.143)				
Female			<0.001	<0.001		
			(<0.001)	(<0.001)		
Male			<0.001	1.058***		
			(<0.001)	(0.144)		
High income					<0.001	1.098***
					(<0.001)	(0.155)
Median income					<0.001	<0.001
					(<0.001)	(<0.001)
Low income					<0.001	<0.001
					(<0.001)	(<0.001)
N.Obs.	96		96		96	
R-squared	0.343		0.358		0.355	
Durbin-Watson	1.712		1.738		1.756	

Notes: Unadjusted inflation expectations are raw weighted averages across respondents of the corresponding subgroups. Adjusted inflation expectations are calculated using our methodology to adjust for non-response bias. Coefficients on inflation expectations are restricted to be positive. Numbers in parenthesis are HAC robust standard errors. ***,** stand for 1%, 5% statistical significance, respectively.

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