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How Do Macroeconomic Variables Affect Which Issues Voters Care About?

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Business cycles are often assumed to affect political cycles (which issues voters care about). This paper quantifies the impact of macroeconomic conditions (unemployment and inflation) on households' policy priorities via political polling. Voter anxiety about unemployment is highly sensitive to national unemployment rates, while cost-of-living anxiety is more sensitive to underlying than headline inflation, and to accelerating inflation than disinflation. Elevated price levels and underlying inflation could explain "sticky" cost-of-living anxiety amid headline disinflation, suggesting alleviation of cost-of-living anxiety may require prolonged low inflation. Falling unemployment and rising inflation collapsed voter anxiety about unemployment in 2021-22 (a "political crowding out effect"). Unemployment anxiety is positively correlated with anxiety about the economy and negatively correlated with cost-of-living anxiety, the latter resembling a "Political Phillips Curve". Regression models are used to predict voter responses under official forecasts. Unemployment anxiety rises to 12 per cent by June 2025 under Treasury's 4.5 per cent unemployment rate forecast, and to 11 per cent under the Reserve Bank of Australia's 4.4 per cent unemployment rate forecast. I find evidence of greater household sensitivity to the as-yet-unannounced unemployment rate (of the reference month in which they are surveyed) than to the latest announced unemployment rate (of two months prior), suggesting a) households are responding more to their own observations of labour market conditions than to media "announcement effects"; and b) polling data could be used to nowcast the unemployment rate.

Keywords

inflation, unemployment, voter sentiment, polling, politics of inflation, politics of unemployment, Phillips Curve, nowcasting

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How do macroeconomic variables affect which issues voters care about?

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Introduction

The state of the economy—particularly inflation and unemployment rates—is widely assumed to influence voter sentiment. However, this relationship has not been quantified recently in the Australian context. This paper is primarily concerned with how voters' policy priorities adjust in response to changes in macroeconomic conditions. In other words, this paper seeks to determine the political transmission of macroeconomic shocks: the impact of macroeconomic variables (business cycles) on which issues voters care about (political cycles), particularly the unemployment issue and the cost-of-living issue.

The motivation for this research is twofold: firstly, to investigate—and quantify—how the low unemployment rates and high inflation of the 2021 to 2024 period have impacted the politics of full employment and political momentum for full employment policies; and secondly, to predict whether (and by how much) unemployment will become a hot-button political issue again if unemployment rates continue to rise and inflation continues to fall.

This paper is therefore concerned with two research questions (RQs):

1. How do macroeconomic variables affect which issues voters care about?

    a) Is there a causal relationship between between business cycles and voters' policy priorities, and can we quantify the impact of a one percentage point rise in unemployment rates on public sentiment?

    b) Can we predict how voters' policy priorities will adjust in response to rising unemployment rates and falling inflation, using official macroeconomic forecasts from the Australian Treasury and the Reserve Bank of Australia?

2. Can we use polling data on voter anxiety about unemployment to reliably nowcast the unemployment rate?

The purpose of this paper is therefore to quantify the relationship between business cycles and political cycles, help policymakers understand which issues voters are most sensitive to, and provide policymakers with advance warning about labour market conditions.

The paper is structured as follows: section one (Introduction) summarises the main contributions from the research and includes a brief literature review; section two sets out the research design (including the model, data, and methodology); section three outlines my findings and model results, and checks for robustness; and section four concludes.

Summary of findings

Household anxiety about unemployment (voters' policy priorities) is positively correlated with anxiety about the economy in general and negatively correlated with anxiety about cost of living, the latter resembling a "Political Phillips Curve" trade-off between voters' prioritisation of unemployment as a national issue and voters' prioritisation of cost of living as a national issue (although this does not necessarily mean voters believe there is a binding trade-off between low unemployment outcomes and low inflation outcomes).

I find evidence that household anxiety about unemployment (voters' policy priorities) is highly sensitive to changes in the trend and seasonally adjusted unemployment rates. In a polynomial regression of trend unemployment rates on voters' unemployment anxiety, the coefficient is -23.1 while the coefficient of the trend unemployment rate raised to the power of 2 is 3.19, with an adjusted R-squared of 0.85 (0.8547) and a p-value of $< 2.2e - 16$. In a polynomial regression of seasonally adjusted unemployment rates on voters' unemployment anxiety, the coefficient is -13.65 while the coefficient of the seasonally adjusted unemployment rate raised to the power of 2 is 2.19, with an adjusted R-squared of 0.83 (0.8257) and a p-value of $< 2.2e - 16$.

Voter sensitivity to national unemployment rates holds for both positive and negative labour market shocks. Indeed, a higher (lower) than average unemployment rate is typically accompanied by higher (lower) than average voter anxiety about unemployment. Voter anxiety about the unemployment issue accordingly spiked during the COVID-19 pandemic and then collapsed in tandem with the seasonally adjusted unemployment rate from October 2021 to July 2022. In the decade before COVID-19, on average 20 per cent of voters nominated unemployment as one of the top issues facing Australia. Post-pandemic, voter anxiety about unemployment has averaged 9.5 per cent.

By contrast, while household (voter) anxiety about cost of living is sensitive to rising inflation, it remains "sticky" in the face of headline disinflation, consistent with Brassil et. al. (2024)'s finding that household inflation expectations seem to be more backward-looking and based on past data than, for example, wages expectations. Moreover, households appear more politically sensitive to underlying inflation—particularly seasonally adjusted weighted median inflation—than headline inflation in original terms. The "stickiness" in household cost of living anxiety potentially reflects the elevated price level, possible misunderstanding among some voters regarding the difference between a fall in inflation and a fall in prices, or sticky underlying inflation—or a combination of all three. In a simple linear regression of annual headline inflation on cost of living anxiety, the coefficient is 5.87 (5.8659) with an adjusted R-squared of 0.61 (0.6076). Polynomial regressions of seasonally adjusted annual weighted median inflation and seasonally adjusted annual trimmed mean inflation each yield coefficients of 3.01 and 0.92 (for weighted median inflation raised to the power of 2) with an adjusted R-squared of 0.7605, and 11.44 and -0.49 (for trimmed mean inflation raised to the power of 2) with an adjusted R-squared of 0.6977.

Finally, I found that voter anxiety about unemployment is better explained by the as-yet-unannounced unemployment rate of the same reference month (with an adjusted R-squared of 0.8257), rather than the latest announced unemployment rate of two months prior (with an adjusted R-squared of 0.7588). This suggests voters may not be responding to news headlines alone (the "announcement" effect), but to their own observations of labour market conditions "on the ground". A polynomial regression model is used to nowcast the unemployment rate based on polling data, with a residual standard error of 0.4033. A basic regression model is therefore not useful for nowcasting very small changes in the unemployment rate, but may be useful for nowcasting larger labour market shocks. A subsequent paper will explore more sophisticated nowcasting techniques (machine learning and MIDAS regressions).

Literature review

Brassil et. al. (2024), exploring household expectations of inflation and wages using data from the Melbourne Institute Consumer Survey, found a divergence in the formation of the two, observing that households regard higher wages growth as a sign of strong macroeconomic conditions, while regarding higher inflation as a sign of worse macroeconomic conditions. Furthermore, they observed a number of stylised facts, including:

- A negative relationship between economic conditions and spending intentions on the one hand and expected inflation on the other, juxtaposed with a positive relationship between conditions/spending intentions and wages.

- A relatively weak contemporaneous relationship between wage and inflation expectations.

- A limited effect of estimated monetary policy (as an example of demand) shocks on expectations.

- A positive effect of oil price (as an example of supply) shocks on inflation expectations, and a negative effect on real wage expectations.

- An apparent overweight placed by households on past movements in some prices in particular—and automotive fuel prices especially—when forming their expectations of inflation.

Gordon (2024) adopts a similar approach as this paper in the context of the United States, running regressions of economic indicators on Presidential approval ratings, the Michigan Consumer Sentiment Index, and Presidential election outcomes from 1956-onwards. Of particular relevance is Gordon's exploration of the predictive relationship of specific macroeconomic variables on sentiment, sentiment on presidential approval, and approval on electoral votes. Interestingly, Gordon also observes non-static relationships between variables over time (see Figure 10 of this paper on the 12-month moving Pearson's correlation coefficient between the 'Unemployment' issue and the 'Cost of Living' issue in Australia), noting periods where presidential approval diverged from its long-run relationship with consumer sentiment and macroeconomic conditions, and where actual electoral vote outcomes diverged from the outcomes predicted by his econometric models. This is particularly pertinent to Part 3 of the Findings section of this paper, where predicting voter sentiment towards the Cost of Living issue based on inflation indicators proves more difficult than predicting voter sentiment towards the Unemployment issue based on labour market indicators.

Turning to the effect of macro-labour market conditions on household political behaviour, Rombi (2016), employing economic voting theory in the context of European Parliament elections from 1999 to 2014, found the "change of unemployment rate is... the most important factor explaining trends" in the decline of European governing parties and the rise of Eurosceptic parties following economic crises.

In the Danish context, Alt et. al (2022) investigated the diffusion of information about unemployment shocks through interpersonal networks and its effects on voting behaviour. Their findings indicated that while "voters' beliefs about national aggregates respond to all shocks similarly", individuals' subjective perceptions primarily responded to job losses in their extended social networks among people in similar vocations, suggesting that "information diffusion through social ties principally affects political preferences via egotropic—rather than sociotropic—motives." Indeed, the share of "second-degree social ties—individuals that voters learn about indirectly—that become unemployed within the last year increases a voter's perception of national unemployment, self-assessed risk of becoming unemployed, support for unemployment insurance, and voting for left-wing parties." Furthermore, using an instrumental variables approach Alt and Lassen (2014) identified a causal effect of voters' subjective forecasts of unemployment and the macroeconomy on voting behaviour.

This contrasts with Veiga (1999), whose empirical study of voting functions from a sample of 13 European economies from 1960 to 1997 found inflation is the most important determinant of electoral results and unemployment is the least important, situating this apparent electoral tolerance for persistent unemployment within the discursive policymaking context of the time (the "emergence of a neoliberal consensus among European policymakers... [and] the spread of these conservative ideas...").

The value-add of my research is it will investigate whether a) similar phenomena and causal relationships are supported by Australian data; b) voters are responding endogenously to changing economic conditions on the ground or exogenously to "announcement" effects (reporting of official statistics); and c) polling results can be used to predict macroeconomic variables, not just the other way around.

Research design

Data

I drew on the Ipsos National Issues Monitor for voter sentiment data, as this provides both a regular time series from 2010-onwards and consistency in its list of 19 policy issues, enabling detection of business cycle interactions. Economic data was drawn from the Australian Bureau of Statistics (ABS) Labour Force Survey and Consumer Price Index (CPI).

My dependent variables are here termed “public anxiety about a given issue”, measured by the Ipsos National Issues Monitor. The Ipsos Issues Monitor is “an ongoing quantitative survey of Australians about the issues facing the nation, Australian states and territories and Australians’ local areas”, conducted monthly via online panel. Each month, a representative sample of approximately 1,000 Australians aged 18 and over is asked the survey question “What would you say are the three most important issues facing Australia today?” The 19 issues that respondents are presented with to select from are, in no particular order:

1. The Economy
2. Immigration
3. Race relations/racism
4. Defence/Foreign affairs/Terrorism
5. Crime/Law and Order/Violence/Anti-Social Behaviour
6. Drug/Alcohol abuse
7. Education
8. Housing/Price of Housing
9. Healthcare/Hospitals
10. Environmental/Pollution/Water concerns
11. Population/Overpopulation

12. Poverty/Inequality
13. Taxation
14. Transport/Public Transport/Infrastructure
15. Unemployment
16. Issues facing Aboriginal and Torres Strait Islanders
17. Petrol prices/Fuel
18. Household Debt/Personal Debt
19. Inflation/cost of living

Public (household, or voter) "anxiety about a given issue" in this paper therefore refers to the percentage of Ipsos survey respondents in a given month who nominate that issue as one of the "three most important issues facing Australia today."

Summary data on the Ipsos National Issues Monitor from November 2010 to September 2024 are contained in Table 1 below.

Table 1: Summary statistics of Ipsos *National Issues Monitor* data

National Issue	N	Mean	St. Dev.	Min	Max
Cost of Living issue	167	35.0	13.3	18.6	67.7
Housing issue	167	23.7	7.9	12.6	44.9
Healthcare issue	167	35.7	5.6	23.9	54.7
The Economy issue	167	31.2	9.2	16.4	56.1
Crime issue	167	23.3	5.3	10.1	37.9
Immigration issue	167	16.9	6.2	4.8	28.9
Poverty issue	167	13.3	2.7	7.2	20.5
Environment issue	167	16.5	6.1	7.5	41.3
Petrol Prices issue	167	10.5	5.9	2.5	28.9
Personal Debt issue	167	9.3	2.5	4.0	16.9
Population issue	167	7.9	2.6	4.2	20.1
Unemployment issue	167	19.1	8.6	6.0	47.6
Taxation issue	167	7.7	1.8	4.3	14.1
Education issue	167	13.7	4.3	4.6	23.5
Drug Abuse issue	167	11.9	4.1	4.3	22.6
Defence issue	167	7.7	4.5	2.0	22.9
Transport issue	167	7.3	2.3	2.5	13.4
Indigenous Issues	167	3.7	1.4	0.9	7.2
Racism issue	167	5.7	1.9	2.2	14.3
Survey sample size (persons)	167	1,025.8	25.1	996	1,182

Methodology and models

As the Ipsos Issues Monitor asks respondents to select the most important current issues, rather than asking respondents whether-or-not they are concerned overall about particular issues, the Ipsos polling data is a measure of relative, rather than absolute, levels of concern about various issues. An unanticipated shock to other, unrelated variables could induce voters to (perhaps temporarily) change their policy priorities, affecting the polling results for another (suddenly relatively less important) issue. For instance, an oil price shock, inflation shock and monetary policy shock could conceivably result in some respondents changing their selection of the top three national issues from, for example, “Unemployment”, “Cost of Living” and “Education” in one reference month to “Petrol Prices”, “Cost of Living” and “Household/Personal Debt” in the next reference month. Even though they may be just as concerned in absolute terms about unemployment and education as they were in the previous reference month, an exacerbation in other issues may displace those issues as top priorities, knocking them out of a respondent’s top three issues in a “political crowding out” effect. A rise or fall in the share of voters selecting the “Unemployment” issue in the Ipsos survey may therefore be conceivably unrelated to labour market conditions.

This potential “crowding out” effect means we must first identify any significant relationships between survey responses on the “Unemployment” issue and survey responses on any of the other 18 national issues.

To do this, I ran a Lasso regression of all the other 18 national issues on the “Unemployment” issue to determine which issues affect—or “crowd out”—the “Unemployment” issue. I then ran simple linear and polynomial regressions of each of the other 18 issues individually on the “Unemployment” issue, to identify and illustrate individual relationships. The Findings Part 1 section of this paper summarises the key results. This leads to the first hypothesis test: did rising voter anxiety about cost of living contribute to the fall in voter anxiety about (and political urgency regarding) the unemployment issue (the “political crowding out” effect)?

These models are given, in simple linear form, as:

$$y = \alpha + \beta_1 x + \epsilon$$

And in polynomial form, as:

$$y = \alpha \ + \beta_1 \ x \ + \beta_2 \ x^2 \ + \epsilon$$

where y denotes the share of voters selecting "Unemployment" as a top-three issue, x denotes the share of voters selecting "Cost of Living" as a top-three issue, and β denotes the coefficients.

This leads to Part 2 of the Findings section, identifying the macroeconomic drivers of household cost of living anxiety. I ran simple linear and polynomial regressions of 13 key Australian Bureau of Statistics indicators of inflation on household "Cost of Living" issue anxiety. The ABS Monthly CPI Indicator (year-on-year change and in original terms) is used as one predictor variable, with the other twelve predictors sourced from the quarterly ABS CPI release:

- Headline inflation (year-on-year and quarter-on-quarter change in the Consumer Price Index) in original terms

- Headline inflation (year-on-year and quarter-on-quarter change in the CPI), seasonally adjusted

- Underlying inflation as measured by Trimmed Mean inflation (year-on-year and quarter-on-quarter), seasonally adjusted

- Underlying inflation as measured by Weighted Median inflation (year-on-year and quarter-on-quarter), seasonally adjusted

- Non-discretionary inflation (year-on-year and quarter-on-quarter), original

- Discretionary inflation (year-on-year and quarter-on-quarter), original

The quarterly nature of the predictor (inflation) variables' time series presents a methodological challenge, as the target variable (the Ipsos National Issues Monitor polling data on cost of living anxiety) is a monthly timeseries, resulting in monthly gaps in the predictor variable data (with the exception of the ABS Monthly CPI annualised inflation data, which is only available from September 2018 onwards).

Given this challenge, I therefore considered three options:

1. Extract the monthly Ipsos data for only March, June, September, and December, and use this as quarterly target variable data.

2. Average the monthly Ipsos data for the three months of each quarter and use this as quarterly target variable data.

3. Replicate the quarterly inflation (predictor) data in the three months of each quarter to ensure both the target and the predictor variables were monthly timeseries.

Given the goal of this paper is to explain and predict monthly measures of public anxiety about different issues (and determine whether monthly polling data on public anxiety about unemployment can be used to nowcast the monthly unemployment rate), I chose option three, even though this renders fitting a best-fit regression line more difficult and risks introducing noise into the model. The other two options also have the disadvantage of losing valuable monthly data from a fast-moving inflation episode.

Part 2 of the Findings section outlines the key results. From here, I built a multiple linear and polynomial regression model to explain relative public anxiety about cost of living using the four inflation indicators with the highest Adjusted R-squared values.

This model takes the form

$$y = \alpha \ + \beta_{CPI}x_{CPI} \ + \beta_{WM}x_{WM} \ + \beta_{WM^2}x_{WM}^2 \ + \beta_{TM}x_{TM} \ + \beta_{TM^2}x_{TM}^2 \\ + \beta_{MCPI}x_{MCPI} \ + \beta_{MCPI^2}x_{MCPI}^2 \ + \epsilon \quad (1)$$

where y denotes the share of voters (households) nominating the 'Cost of Living' issue as a top-three national issue, x denotes the year-on-year inflation rate of a given measure of inflation, subscript $_{CPI}$ denotes headline annual CPI inflation (in original terms), subscript $_{WM}$ denotes seasonally adjusted annual Weighted Median inflation, subscript $_{TM}$ denotes seasonally adjusted Annual Trimmed Mean inflation, and subscript $_{MCPI}$ denotes annualised Monthly CPI inflation (in original terms). β denotes the coefficients, noting that the coefficients of the polynomial (squared) forms of the predictor variables are different from those of the linear forms, and therefore are denoted as subscript-superscript ^{2}. Hence β_{TM} denotes the coefficient of Annual Trimmed Mean Inflation (x_{TM}) while β_{TM^2} denotes the separate coefficient of "Annual Trimmed Mean inflation squared" (x_{TM}^2).

In Part 3 of the Findings section, I ran 18 individual regressions (one simple linear, one polynomial) on each of nine possible labour market predictor variables on voter anxiety about the "Unemployment" issue: the unemployment rate, the underutilisation rate, and the employment-to-population ratio, each in trend, seasonally adjusted, and original terms.

An example model is the polynomial regression of the seasonally adjusted unemployment rate on voters' unemployment anxiety

$$y = \alpha \ + \beta_{URSA} x_{URSA} \ + \beta_{URSA^2} x^2_{URSA} \ + \epsilon \tag{2}$$

where y denotes the share of voters (households) nominating the 'Unemployment' issue as a top-three national issue, x^2_{URSA} denotes the seasonally adjusted unemployment rate, x^2_{URSA} denotes the seasonally adjusted unemployment rate squared, and β with respective subscripts denotes their respective coefficients.

In Part 4 of the Findings section, I used the simple linear and polynomial regression models of 'Unemployment' issue anxiety and the seasonally adjusted unemployment rate and switched the predictor variable and the target variable in order to nowcast the seasonally adjusted unemployment rate. While up to this point I have primarily used macroeconomic data to one decimal place, here I also estimated the nowcast models using seasonally adjusted unemployment rate data to seven decimal places, to test whether nowcast models trained on more granular data perform better in predictions.

Nowcast Model 1 (Simple Linear Regression) takes the form

$$y_{URSA} = \alpha \ + \beta_{UA} x_{UA} \ + \epsilon$$

where y_{URSA} denotes the seasonally adjusted unemployment rate, α denotes the intercept, β_{UA} denotes the coefficient of public anxiety about unemployment, and

x_{UA} denotes the share of voters nominating 'Unemployment' as a top-three national issue (in other words, public anxiety about unemployment).

Nowcast Model 2 (Polynomial Regression) similarly takes the form

$$y_{URSA} = \alpha \ + \beta_{UA} x_{UA} \ + \beta_{UA^2} x_{UA}^2 \ + \epsilon$$

Part 4 of the Findings section concludes by addressing whether voter anxiety about the "Unemployment" issue in a given reference month is more sensitive to the most recent announced unemployment rate (of two months' prior), or more sensitive to the as-yet-unannounced unemployment rate of the Ipsos polling reference month. In other words, are voters (households) reacting to the latest official labour market statistics reported by the media, or are they reacting endogenously to changing labour market conditions on the ground in real-time, such as their own experiences and broader observations of macroeconomic conditions (job losses and gains among their extended social networks, job advertisements in local shop windows, etc).

To address this, I applied a two-month lag to the "Unemployment" issue–seasonally adjusted unemployment rate model, and then compared the Adjusted R-squared of the lagged regression model with that of the unlagged regression model. A two-month lag is chosen because the Ipsos survey is conducted over 4-6 days in the first half of each month, while the ABS Labour Force survey for a given month is usually released on the third Thursday of the following month. So, for example, when voters are surveyed for the September Issues Monitor, the latest official unemployment data they have available is the July unemployment rate.

Findings

Part 1: Identifying "political crowding out" effects

Non-labour market factors in voter prioritisation of unemployment

A simple correlation matrix reveals voter prioritisation of the 'Unemployment' issue is positively correlated with prioritisation of 'The Economy' issue to a coefficient of 0.63, and negatively correlated with prioritisation of 'Cost of Living' and 'Petrol Prices' to coefficients of -0.75 and -0.73 respectively.

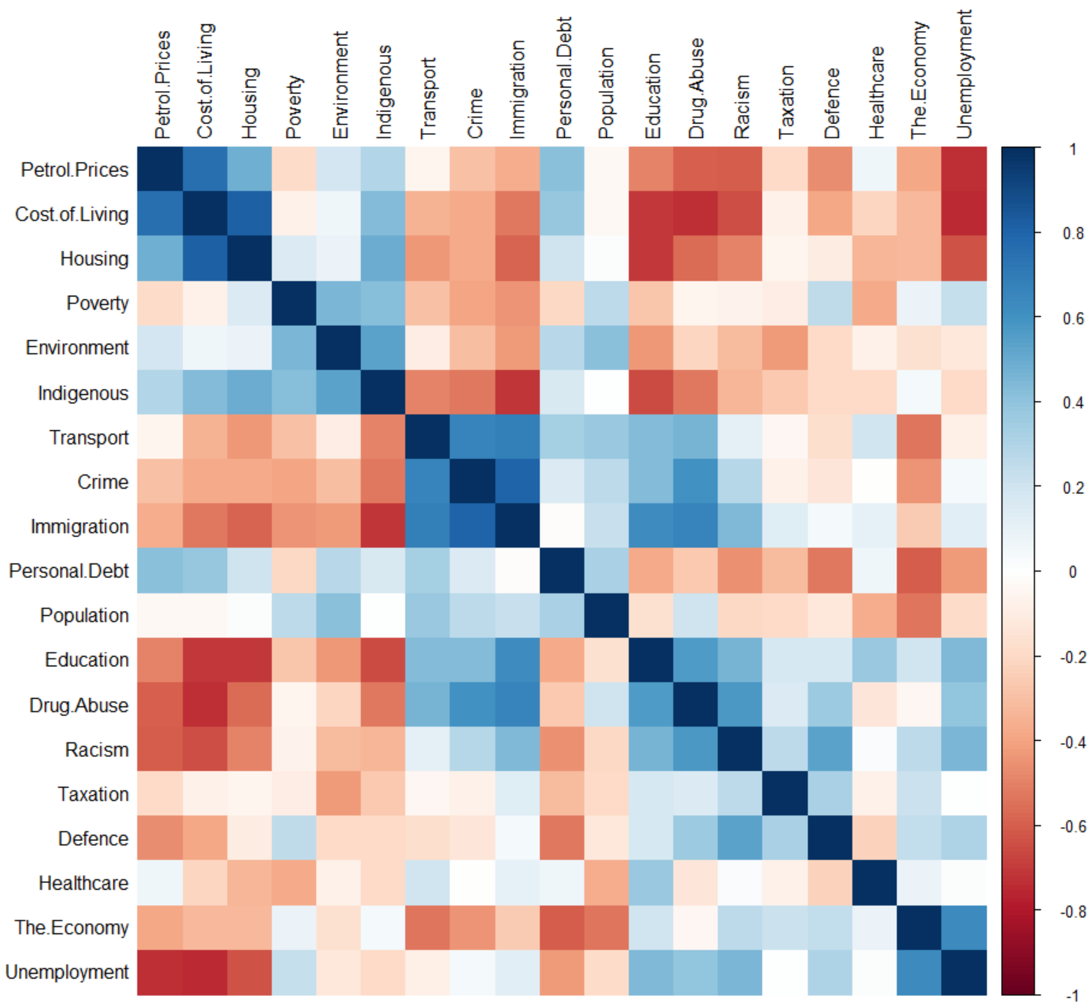

Figure 1: Pearson's correlation matrix

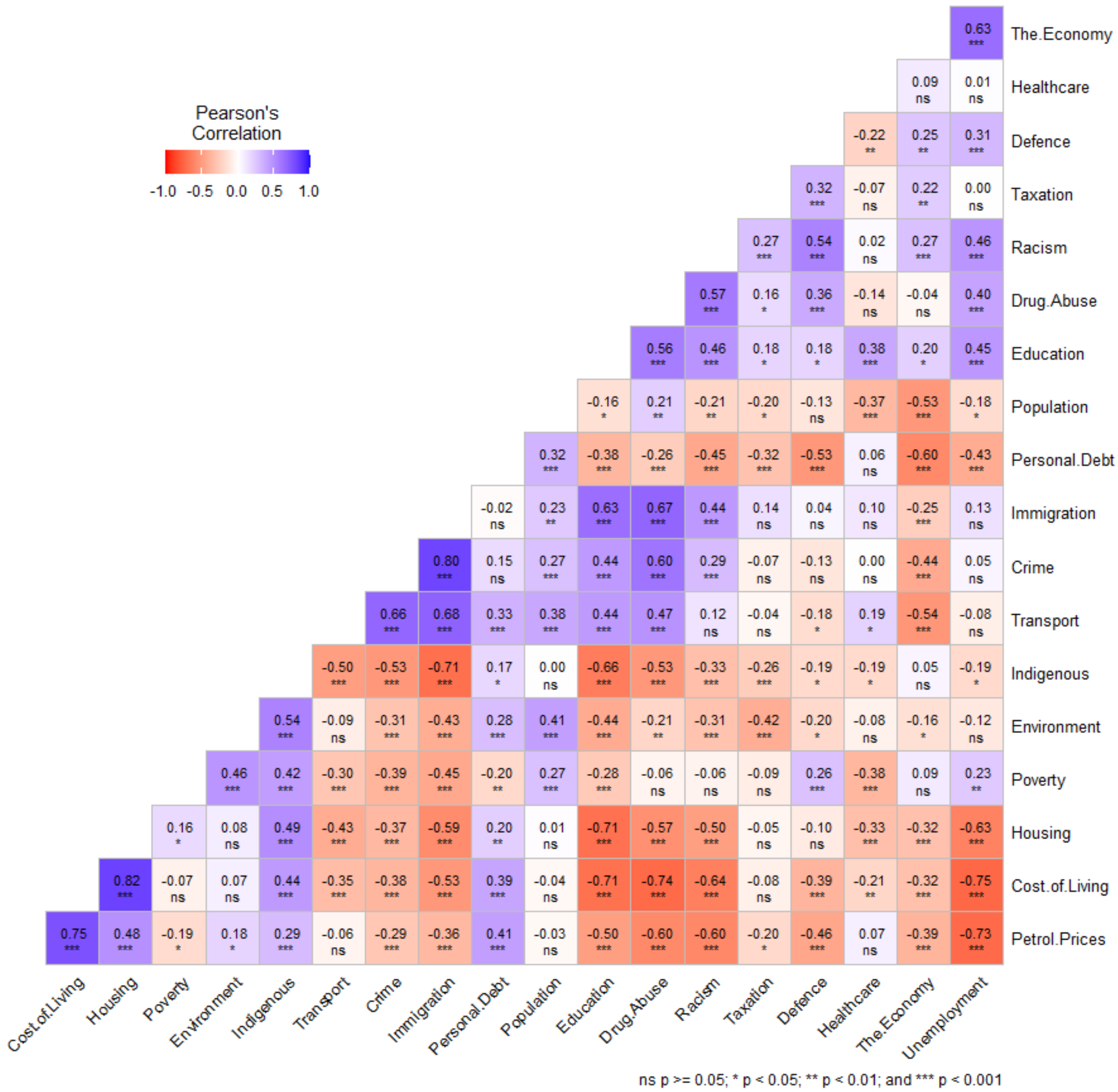

Figure 2: Pearson's correlation matrix with coefficients and significance tests

The results of the 36 simple linear and polynomial regressions of each individual issue on the 'Unemployment' issue are summarised in Table 2 below, from which I find that the national issues with the most statistically significant relationships with the 'Unemployment' issue (p-values of <2.2e-16) are 'Cost of Living', 'The Economy', 'Housing', and 'Petrol Prices'.

Predictor	Model	Estimator		Std. Error	t-value	p-value	Significance	Multiple R^2	Adjusted R^2	F-statistic	Model p-value
Cost of Living	Linear	Cost of Living	-0.48	0.03336	-14.520	<2e-16	***	0.5609	0.5583	210.8 on 1 and 165 D	<2.2e-16
	Polynomial	Cost of Living	-1.75	0.221948	-7.884	4.19E-13	***	0.6347	0.6303	142.5 on 2 and 164 DF	<2.2e-16
		Cost of Living^2	0.01	0.002559	5.757	4.12E-08	***	0.6347	0.6303	142.5 on 2 and 164 DF	<2.2e-16
Housing	Linear	Housing	-0.69	0.06585	-10.47	<2e-16	***	0.3991	0.3955	109.6 on 1 and 165 DF	<2.2e-16
	Polynomial	Housing	-1.77	0.431256	-4.113	6.15E-05	***	0.4219	0.4149	59.85 on 2 and 164 DF	<2.2e-16
		Housing^2	0.02	0.007653	2.544	0.0119	*	0.4219	0.4149	59.85 on 2 and 164 DF	<2.2e-16
Healthcare	Linear	Healthcare	0.02	0.12062	0.189	0.851		0.0002159	-0.005843	0.0356 on 1 and 165 DF	0.8505
	Polynomial	Healthcare	-0.04	1.248902	-0.034	0.973		0.0002325	-0.01196	0.01907 on 2 and 164 DF	0.9811
		Healthcare^2	0.00	0.01681	0.052	0.958		0.0002325	-0.01196	0.01907 on 2 and 164 DF	0.9811
The Economy	Linear	The Economy	0.59	0.05631	10.497	<2e-16	***	0.4004	0.3968	110.2 on 1 and 165 DF	<2.2e-16
	Polynomial	The Economy	-1.50	0.364067	-4.13	5.76E-05	***	0.5028	0.4968	82.93 on 2 and 164 DF	<2.2e-16
		The Economy^2	0.03	0.005214	5.812	3.13E-08	***	0.5028	0.4968	82.93 on 2 and 164 DF	<2.2e-16
Crime	Linear	Crime	0.08	0.12737	0.609	0.543		0.002242	-0.003805	0.3707 on 1 and 165 DF	0.5435
	Polynomial	Crime	2.06	0.8286	2.482	0.0141	*	0.03654	0.02479	3.11 on 2 and 164 DF	0.04725
		Crime^2	-0.04	0.01823	-2.416	0.0168	*	0.03654	0.02479	3.11 on 2 and 164 DF	0.04725
Immigration	Linear	Immigration	0.18	0.1071	1.675	0.0957	.	0.01673	0.01077	2.807 on 1 and 165 DF	0.09575
	Polynomial	Immigration	2.47	0.55631	4.432	1.71E-05	***	0.1114	0.1006	10.28 on 2 and 164 D	6.22E-05
		Immigration^2	-0.07	0.01744	-4.18	4.73E-05	***	0.1114	0.1006	10.28 on 2 and 164 D	6.22E-05
Poverty	Linear	Poverty	0.75	0.2463	3.046	0.0027	**	0.05325	0.04751	9.28 on 1 and 165 DF	0.002698
	Polynomial	Poverty	2.16	2.14151	1.01	0.314		0.05578	0.04427	4.844 on 2 and 164 DF	0.009035
		Poverty^2	-0.05	0.08078	-0.664	0.508		0.05578	0.04427	4.844 on 2 and 164 DF	0.009035
Environment	Linear	Environment	-0.17	0.1092	-1.557	0.121		0.01448	0.008503	2.424 on 1 and 165 DF	0.1214
	Polynomial	Environment	-1.27	0.47872	-2.656	0.00869	**	0.04688	0.03525	4.033 on 2 and 164 DF	0.01951
		Environment^2	0.03	0.01185	2.361	0.01939	*	0.04688	0.03525	4.033 on 2 and 164 DF	0.01951
Petrol Prices	Linear	Petrol Prices	-1.08	0.07771	-13.89	<2e-16	***	0.539	0.5362	192.9 on 1 and 165 DF	<2.2e-16
	Polynomial	Petrol Prices	-2.36	0.27477	-8.588	6.57E-15	***	0.5965	0.5915	121.2 on 2 and 164 DF	<2.2e-16
		Petrol Prices^2	0.05	0.01028	4.833	3.07E-06	***	0.5965	0.5915	121.2 on 2 and 164 DF	<2.2e-16
Personal Debt	Linear	Personal Debt	-1.48	0.243	-6.095	7.49E-09	***	0.1838	0.1788	37.15 on 1 and 165 DF	7.49E-09
	Polynomial	Personal Debt	-1.54	1.331976	-1.158	0.249		0.1838	0.1738	18.46 on 2 and 164 DF	5.87E-08
		Personal Debt^2	0.00	0.069868	0.047	0.963		0.1838	0.1738	18.46 on 2 and 164 DF	5.87E-08
Population	Linear	Population	-0.61	0.2559	-2.384	0.0183	*	0.03329	0.02743	5.682 on 1 and 165 DF	0.01827
	Polynomial	Population	-1.55	1.26668	-1.225	0.222		0.03668	0.02493	3.122 on 2 and 164 DF	0.04671
		Population^2	0.05	0.06286	0.759	0.449		0.03668	0.02493	3.122 on 2 and 164 DF	0.04671
Taxation	Linear	Taxation	0.02	0.37623	0.058	0.954		2.01E-05	-0.00604	0.003 on 1 and 165 DF	0.9542
	Polynomial	Taxation	-5.60	2.1535	-2.6	0.01018	*	0.04105	0.02936	3.51 on 2 and 164 DF	0.03215
		Taxation^2	0.33	0.1235	2.649	0.00886	**	0.04105	0.02936	3.51 on 2 and 164 DF	0.03215
Education	Linear	Education	0.89	0.1381	6.468	1.08E-09	***	0.2022	0.1974	41.83 on 1 and 165 DF	1.08E-09
	Polynomial	Education	3.15	0.80054	3.932	0.000124	***	0.2401	0.2308	25.9 on 2 and 164 DF	1.67E-10
		Education^2	-0.08	0.02807	-2.857	0.004828	**	0.2401	0.2308	25.9 on 2 and 164 DF	1.67E-10
Drug Abuse	Linear	Drug Abuse	0.84	0.1519	5.55	1.12E-07	***	0.1573	0.1522	30.8 on 1 and 165 DF	1.12E-07
	Polynomial	Drug Abuse	3.59	0.72543	4.953	1.80E-06	***	0.2278	0.2184	24.19 on 2 and 164 DF	6.20E-10
		Drug Abuse^2	-0.11	0.02943	-3.87	0.000157	***	0.2278	0.2184	24.19 on 2 and 164 DF	6.20E-10
Defence	Linear	Defence	0.59	0.1435	4.119	6.01E-05	***	0.09322	0.08773	16.96 on 1 and 165 DF	6.01E-05
	Polynomial	Defence	0.43	0.543941	0.787	0.432		0.09376	0.08271	8.484 on 2 and 164 DF	0.000312
		Defence^2	0.01	0.025914	0.31	0.757		0.09376	0.08271	8.484 on 2 and 164 DF	0.000312
Transport	Linear	Transport	-0.31	0.2847	-1.078	0.283		0.006992	0.0009738	1.162 on 1 and 165 DF	0.2827
	Polynomial	Transport	6.04	1.6983	3.555	0.000493	***	0.08679	0.07566	7.793 on 2 and 164 DF	0.000584
		Transport^2	-0.42	0.1097	-3.786	0.000215	***	0.08679	0.07566	7.793 on 2 and 164 DF	0.000584
Indigenous Issues	Linear	Indigenous Issues	-1.16	0.4608	-2.515	0.0128	*	0.03693	0.03109	6.327 on 1 and 165 DF	0.01285
	Polynomial	Indigenous Issues	-10.93	2.6957	-4.056	7.69E-05	***	0.1103	0.09941	10.16 on 2 and 164 DF	6.91E-05
		Indigenous Issues^2	1.20	0.3252	3.677	0.00032	***	0.1103	0.09941	10.16 on 2 and 164 DF	6.91E-05
Racism	Linear	Racism	2.03	0.3072	6.612	5.03E-10	***	0.2095	0.2047	43.72 on 1 and 165 DF	5.03E-10
	Polynomial	Racism	6.77	1.2222	5.537	1.20E-07	***	0.2795	0.2707	31.81 on 2 and 164 DF	2.13E-12
		Racism^2	-0.35	0.0866	-3.992	9.87E-05	***	0.2795	0.2707	31.81 on 2 and 164 DF	2.13E-12

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Table 2: Summary of linear and non-linear regressions of each National Issue on the 'Unemployment' Issue

However, the only predictor variables which yield Adjusted R-squared values of approximately 0.50 or greater are the "Cost of Living" issue (0.63 in polynomial model, 0.56 in the simple linear model), the "Petrol Prices" issue (0.59 in the polynomial model, 0.54 in the simple linear model), and "The Economy" issue (0.4968 in the polynomial model). We will therefore focus on the "Cost of Living" and "Economy" issues.

Unemployment **and** ***The Economy***

The simple linear model of "The Economy" issue on the "Unemployment" issue yields a coefficient of 0.59. However, the better fit is given by the polynomial model, with a higher Adjusted R-squared of 0.4968 compared to the linear model's 0.3968.

Table 3: Regression outputs of 'The Economy' issue on the 'Unemployment' issue

	Dependent variable:	
	Unemployment issue	
	(Simple Linear)	(Polynomial)
'The Economy' issue	0.591^{***}	-1.504^{***}
	(0.056)	(0.364)
('The Economy' issue)^2		0.030^{***}
		(0.005)
Constant	0.637	33.932^{***}
	(1.832)	(5.968)
Observations	167	167
R^2	0.400	0.503
Adjusted R^2	0.397	0.497
Residual Std. Error	6.694 (df = 165)	6.114 (df = 164)
F Statistic	110.189^{***} (df = 1; 165)	82.931^{***} (df = 2; 164)
Note:		*p<0.1; **p<0.05; ***p<0.01

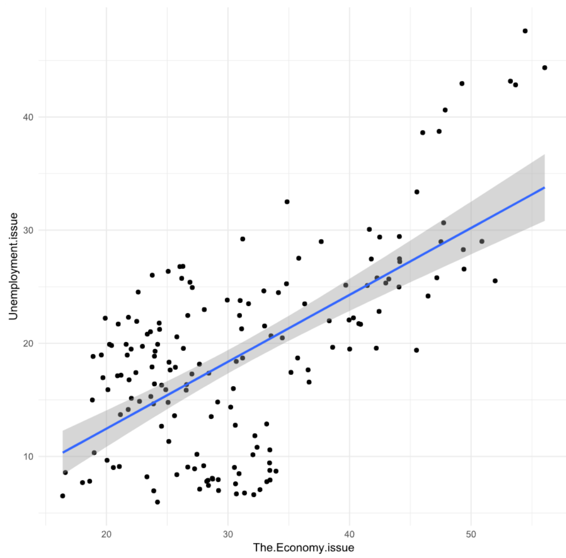

Figure 3:
Simple linear regression

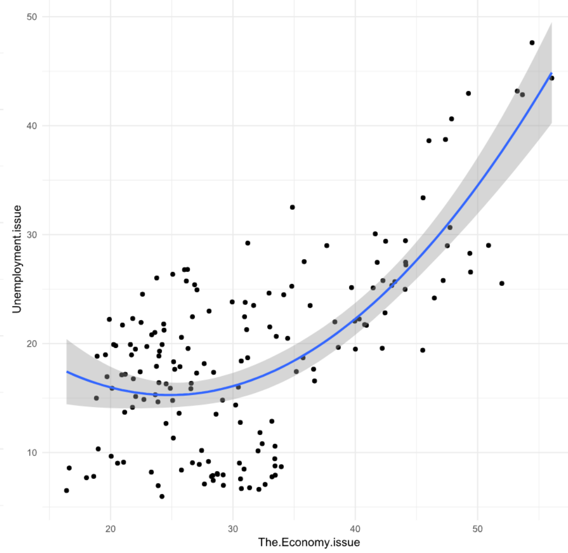

Figure 4:
Polynomial regression

Figure 5: Regression models of voter prioritisation of 'The Economy' issue and 'Unemployment' issue

We can therefore conclude that voter anxiety about unemployment is closely linked to voter anxiety about the economy in general, and that voter anxiety about both issues broadly moves in tandem.

Unemployment **and** ***Cost of Living***

The simple linear regression of the "Cost of Living" issue on the "Unemployment" issue yields a coefficient of -0.48, while the polynomial regression model yields a substantially better fit with a higher Adjusted R-squared.

Table 4: Regression outputs of 'Cost of Living' issue on the 'Unemployment' issue

	Dependent variable:	
	Unemployment issue	
	(Simple Linear)	(Polynomial)
Cost of Living issue	-0.484^{***}	-1.750^{***}
	(0.033)	(0.222)
(Cost of Living issue)^2		0.015^{***}
		(0.003)
Constant	36.046^{***}	59.703^{***}
	(1.250)	(4.266)
Observations	167	167
R^2	0.561	0.635
Adjusted R^2	0.558	0.630
Residual Std. Error	5.728 (df = 165)	5.241 (df = 164)
F Statistic	210.780^{***} (df = 1; 165)	142.488^{***} (df = 2; 164)
Note:		*p<0.1; **p<0.05; ***p<0.01

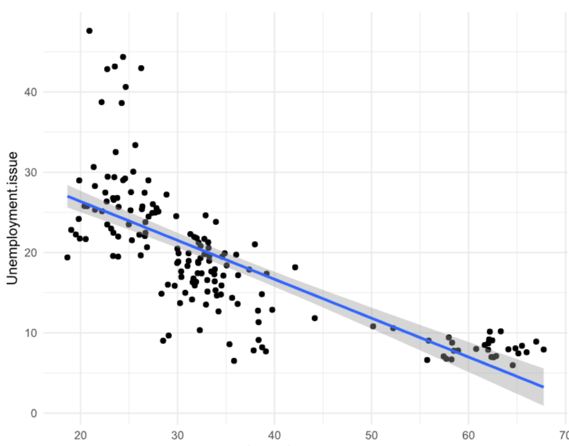

Figure 6:
Simple linear regression

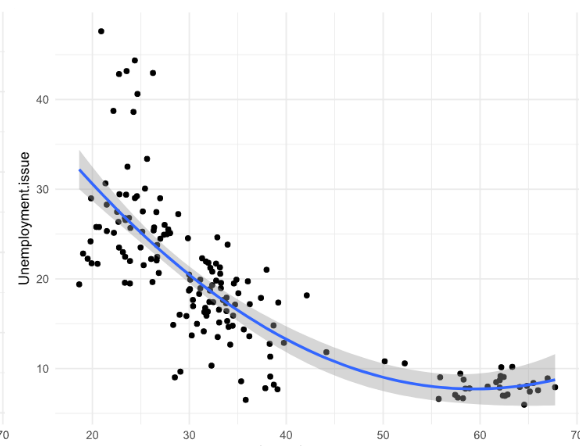

Figure 7:
Polynomial regression

Figure 8: Regression models of voter prioritisation of 'Cost of Living' issue and 'Unemployment' issue

Returning to the paper's first hypothesis, given the inverse relationship between the percentage of Australians who select "Cost of Living" as a top-three national issue and the percentage of Australians who select "Unemployment" as a top-three national issue and the p-value of $<2.2e-16$, we can therefore reject the null hypothesis and infer that rising voter anxiety about cost of living contributed to the fall in voter anxiety about unemployment, supporting the "political crowding out" hypothesis.

Indeed, Figure 9 illustrates voter prioritisation of the "Cost of Living" and "Unemployment" issues have typically adjusted in divergent directions across the time series, with the exception of approximately mid-2013 to June 2017 (and particularly June 2015 to March 2017, when the moving 12-month Pearson's correlation coefficient changed from negative to positive—see Figure 10). Moreover, cost-of-living anxiety eclipsed unemployment anxiety in June 2021 while headline inflation overshot the target band, rising from 1.1 per cent in the year-to-March 2021 to 3.8 per cent in the year-to-June 2021.

A follow-up paper will conduct a Principal Component Analysis (PCA) to determine how much of the collapse in voters' prioritisation of the "Unemployment" issue was driven by rising cost-of-living anxiety and inflation, and how much was driven by the fall in the unemployment rate at the time—noting that the Adjusted R-squared of the polynomial regression model above indicates that 63 per cent of the "Unemployment" issue observations in the Ipsos polling data can be explained by changes in the share of voters prioritising the "Cost of Living" issue.

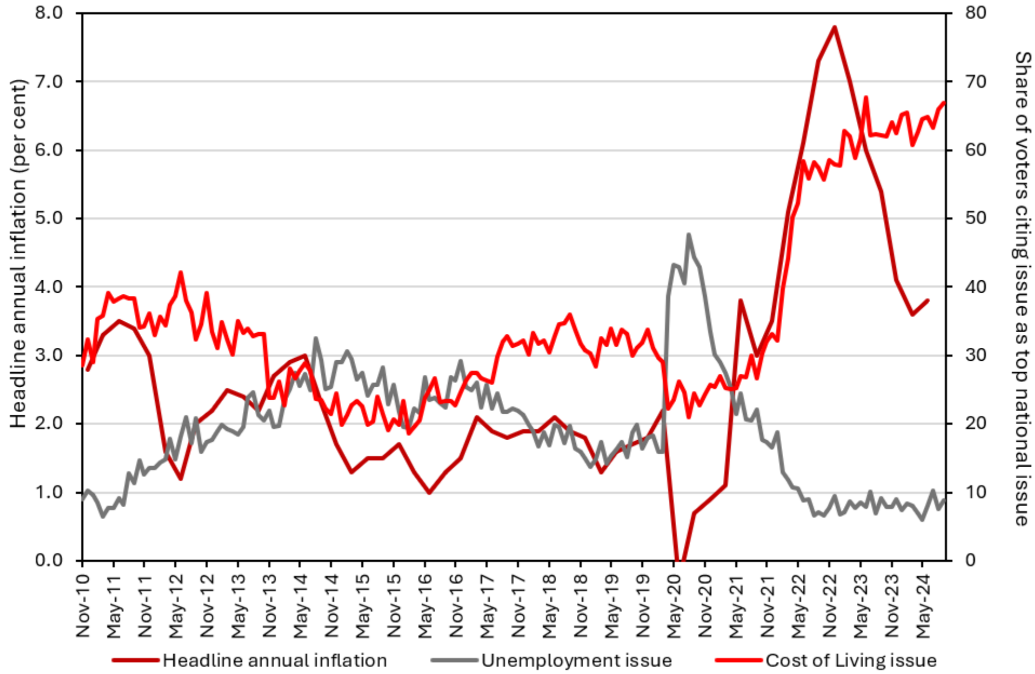

Figure 9: Inflation and share of voters citing cost of living or unemployment as top issues, 2010-2024

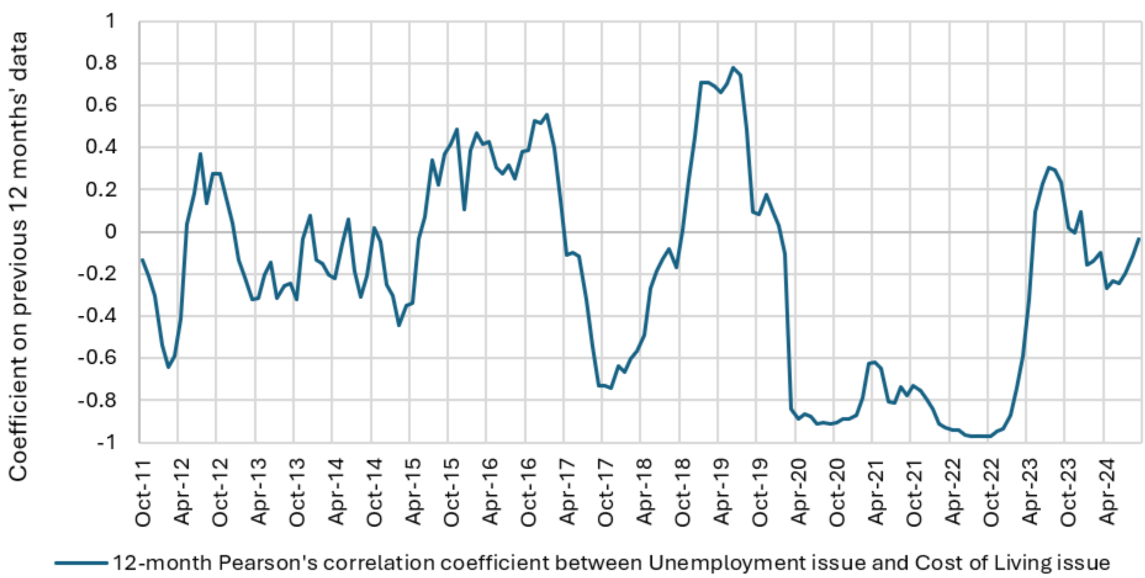

Figure 10: 12-month moving Pearson's correlation coefficient: 'Unemployment' issue and 'Cost of Living' issue

Political echoes of the Phillips Curve?

The inverse relationship between the percentage of Australians who select "Cost of Living" as a top-three national issue and the percentage of Australians who select "Unemployment" as a top-three national issue bears a resemblance of an almost Phillips Curve-like relationship.

Indeed, replotting Figure 7 with "Unemployment" issue anxiety on the x-axis and "Cost of Living" issue anxiety on the y-axis (consistent with conventional graphical treatments of the Phillips Curve), we observe an apparent trade-off between voters' prioritisation of the "Cost of Living" issue and voters' prioritisation of the "Unemployment" issue, or a "Political Phillips Curve".

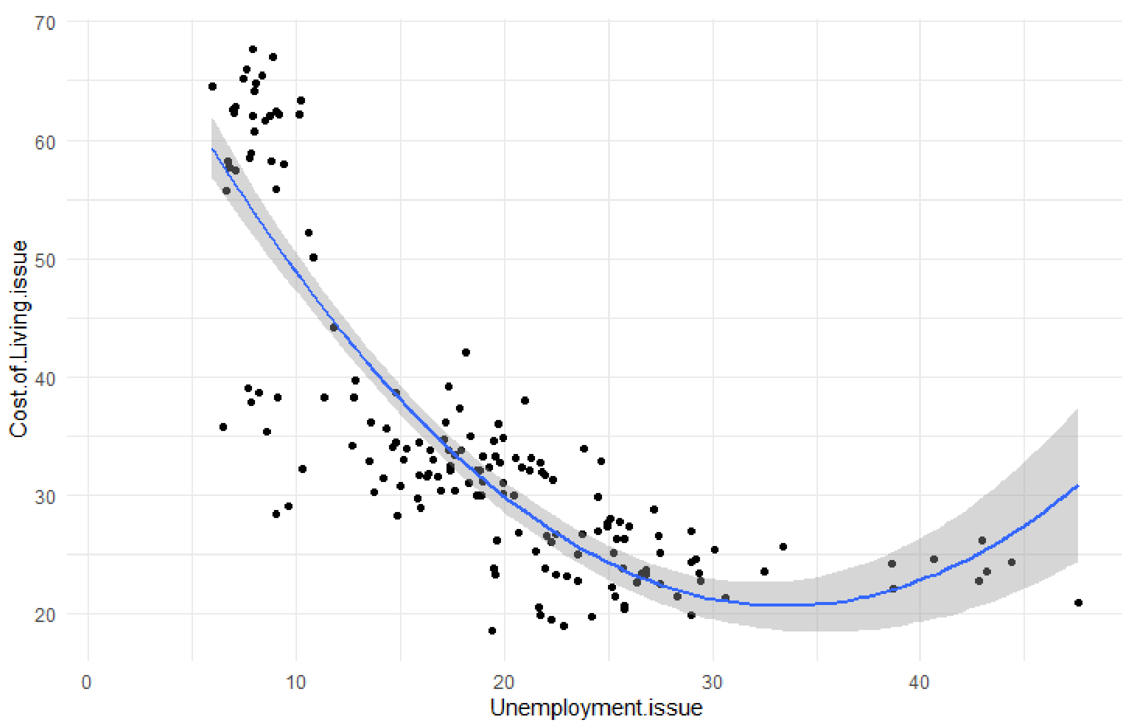

Figure 11: The 'Political Phillips Curve'

The 'Political Phillips Curve' regression model output is given in Table 5.

Table 5: 'Political Phillips Curve' regression output

	Dependent variable:
	Cost of Living issue
Unemployment issue	-3.425^{***}
	(0.223)
(Unemployment issue)^2	0.051^{***}
	(0.005)
Constant	77.969^{***}
	(2.351)
Observations	167
R^2	0.740
Adjusted R^2	0.736
Residual Std. Error	6.843 (df = 164)
F Statistic	232.817^{***} (df = 2; 164)
Note:	*p<0.1; **p<0.05; ***p<0.01

Potentially interesting future research might include exploring:

- the relationship between the Political Phillips Curve and the inflations expectations literature (noting Rudd [2021]'s empirical and theoretical critique of the inflation expectations hypothesis); and

- whether the Political Phillips Curve is steeper or flatter than the traditional, i.e. economic, Phillips Curve (noting the difficulty in estimating the Phillips Curve [Bishop and Greenland 2021; Debelle and Vickery 1997] and the debate over both its historical interpretation [Forder 2014] and its very existence [Fields and Rochon 2024; Hooper, Mishkin and Sufi 2019])[1].

[1] If indeed the traditional Phillips Curve does exist, Mitchell (2020) points out it is possible for policy reform to "flatten the Phillips Curve" and eliminate any hypothetical trade-off between unemployment and inflation.

While noting the difficulties in estimating the Phillips Curve, a very basic exercise in plotting a 'naive' Philips Curve based on observed headline inflation and unemployment rates during the November 2010 – September 2024 period covered by the Ipsos Issues Monitor serves to illustrate the question of whether the Political Phillips Curve is steeper or flatter than the "actual" Phillips Curve, and the questions this poses for both macroeconomic theory and policy, and positive political economy.

However, care must be taken to avoid over-inferring conclusions from the Political Phillips Curve. The curve does not mean unemployment does not matter to voters, and certainly should not be interpreted as such by policymakers. On the contrary, as Part 2 illustrates, voters are acutely sensitive to even the smallest change in national unemployment rates. Nor does the Political Phillips Curve *necessarily* mean voters *perceive* there to be a policy trade-off between inflation and unemployment. Indeed, notwithstanding estimation difficulties and existential debates around the actual Phillips Curve, the political curve may in fact be *flatter* as suggested by Figure 12.

All the Political Phillips Curve illustrates is that from the period 2010 to 2024, when the percentage of Australians selecting 'Unemployment' as a top-three national issue is relatively high, the percentage of Australians selecting 'Cost of Living' as a top-three national issue is typically low, and vice-versa.

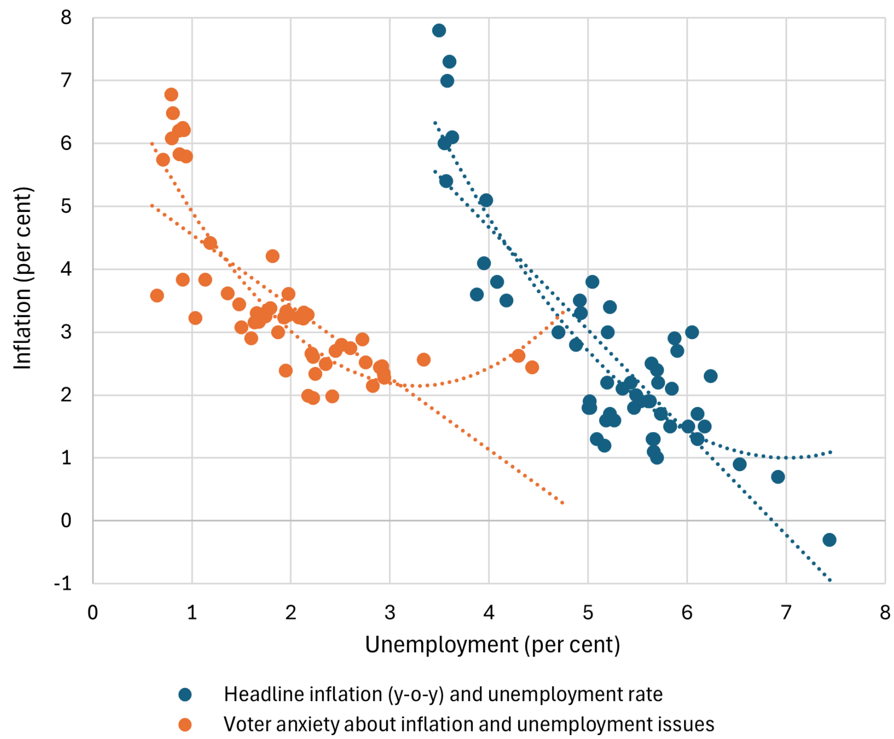

Figure 12: Percentage of voters citing issue as top-three issue, and unemployment rate and inflation rate, 2010-2024. Note Ipsos National Issues Monitor data has been scaled by 0.1 for greater visibility on plot. Linear and non-linear trendlines are tentative ('naive') economic and Political Phillips Curves.

Part 2: Identifying drivers of cost-of-living anxiety

Having determined that rising voter anxiety about cost of living contributed to the collapse in voter anxiety about unemployment, we turn to the paper's second hypothesis: did rising inflation itself contribute to the latter? To test the hypothesis, I ran 26 polynomial and simple linear regressions of 13 key ABS inflation indicators on voter anxiety about cost of living. For brevity, the Adjusted R-squared and p-values are summarised in Table 6, ranked from largest to smallest Adjusted R-squared.

Inflation indicator	Period	Model	Adjusted R^2	p-value
Underlying inflation: Weighted Median s.a.	Year-on-year	Polynomial	0.7605	<2.2e-16
Underlying inflation: Weighted Median s.a.	Year-on-year	Simple linear	0.7489	<2.2e-16
Underlying inflation: Trimmed Mean s.a.	Year-on-year	Polynomial	0.6977	<2.2e-16
Underlying inflation: Trimmed Mean s.a.	Year-on-year	Simple linear	0.6936	<2.2e-16
Monthly CPI inflation, original	Year-on-year	Polynomial	0.6164	1.65e-15
Headline (CPI) inflation, original	Year-on-year	Simple linear	0.6076	<2.2e-16
Headline (CPI) inflation, original	Year-on-year	Polynomial	0.6053	<2.2e-16
CPI inflation, s.a.	Year-on-year	Simple linear	0.6017	<2.2e-16
CPI inflation, s.a.	Year-on-year	Polynomial	0.5992	<2.2e-16
Monthly CPI inflation, original	Year-on-year	Simple linear	0.5838	3.52e-15
Non-discretionary inflation, original	Year-on-year	Polynomial	0.5642	<2.2e-16
Non-discretionary inflation, original	Quarter-on-quarter	Polynomial	0.5642	<2.2e-16
Underlying inflation: Weighted Median s.a.	Quarter-on-quarter	Polynomial	0.5527	<2.2e-16
Non-discretionary inflation, original	Year-on-year	Simple linear	0.5483	<2.2e-16
Underlying inflation: Weighted Median s.a.	Quarter-on-quarter	Simple linear	0.5387	<2.2e-16
Underlying inflation: Trimmed Mean s.a.	Quarter-on-quarter	Simple linear	0.4601	<2.2e-16
Underlying inflation: Trimmed Mean s.a.	Quarter-on-quarter	Polynomial	0.4601	<2.2e-16
Discretionary inflation, original	Year-on-year	Polynomial	0.4139	<2.2e-16
Discretionary inflation, original	Year-on-year	Simple linear	0.3802	<2.2e-16
CPI inflation, s.a.	Quarter-on-quarter	Polynomial	0.2408	8.62e-11
Headline (CPI) inflation, original	Quarter-on-quarter	Polynomial	0.2313	2.36e-10
CPI inflation, s.a.	Quarter-on-quarter	Simple linear	0.217	1.95e-10
Headline (CPI) inflation, original	Quarter-on-quarter	Simple linear	0.2085	4.79e-10
Non-discretionary inflation, original	Quarter-on-quarter	Simple linear	0.1485	2.08e-07
Discretionary inflation, original	Quarter-on-quarter	Polynomial	0.121	1.15e-05
Discretionary inflation, original	Quarter-on-quarter	Simple linear	0.118	3.99e-06

Table 6: Summary of regression outputs of inflation indicators on ‘Cost of Living’ Issue anxiety

Interestingly, from these results public anxiety about cost of living appears to be more sensitive to seasonally adjusted underlying inflation than either the Monthly CPI Indicator or headline (original) inflation, which in turn is a better predictor than its seasonally adjusted variant.

In addition, recall from Figure 9 that cost of living anxiety has remained elevated despite headline inflation falling from a peak of peak of 7.8 per cent in the year-to-December 2022 and making substantial progress back towards the central bank's target band of 2-3 per cent. This "stickiness" in voter prioritisation of the "Cost of Living" issue may well be a function of the elevated price level.

From here, I build a multiple linear and polynomial regression model to explain relative public anxiety about cost of living using the four inflation indicators with the highest Adjusted R-squared values (seasonally adjusted annual Weighted Median inflation, seasonally adjusted annual Trimmed Mean inflation, annualised Monthly CPI inflation, and annual headline inflation). This **Cost of Living Anxiety Explanatory Model 1.0** takes the form from Equation 1:

$$y = \alpha + \beta_{CPI} x_{CPI} + \beta_{WM} x_{WM} + \beta_{WM^2} x_{WM}^2 + \beta_{TM} x_{TM} + \beta_{TM^2} x_{TM}^2 + \beta_{MCPI} x_{MCPI} + \beta_{MCPI^2} x_{MCPI}^2 + \epsilon \quad (3)$$

The regression output summarised in Table 7 therefore means the model is solved as

$$y = 13.8 - 5.19 x_{CPI} - 7.89 x_{WM} - 2.33 x_{WM}^2 + 17.68 x_{TM} - 1.89 x_{TM}^2 + 5.53 x_{MCPI} - 0.4 x_{MCPI}^2 + \epsilon \quad (4)$$

Table 7: Combined Cost of Living model output

	Dependent variable:
	Cost of Living issue
Headline annual inflation, original	-5.186^{***}
	(1.644)
Annual Weighted Median inflation, seasonally adjusted	-7.891
	(7.327)
(Annual Weighted Median inflation, seasonally adjusted)^2	2.329^{**}
	(0.977)
Annual Trimmed Mean inflation, seasonally adjusted	17.680^{**}
	(7.274)
(Annual Trimmed Mean inflation, seasonally adjusted)^2	-1.889^{**}
	(0.828)
Annualised Monthly CPI inflation, original	5.534^{**}
	(2.539)
(Annualised Monthly CPI inflation, original)^2	-0.397
	(0.242)
Constant	13.799^{***}
	(3.560)
Observations	70
R^2	0.929
Adjusted R^2	0.921
Residual Std. Error	4.465 (df = 62)
F Statistic	115.196^{***} (df = 7; 62)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

For good measure, to mitigate the risk of overfitting, we first check for multicollinearity and then apply shrinkage methods by performing a Ridge regression and a Lasso regression. The high Variance Inflation Factors returned in Table 8 suggest a high degree of multicollinearity.

Headline	Weighted Median	(Weighted Median)^2	
48.720	533.402	424.938	
Trimmed Mean	**(Trimmed Mean)^2**	**Monthly CPI**	**(Monthly CPI)^2**
663.306	482.439	114.816	66.688

Table 8: Variance Inflation Factors (Multicollinearity Check)

Since Ridge and Lasso regressions cannot be performed using predictor variables with missing data, and annualised Monthly CPI inflation data is only available from September 2018 onwards while the target variable (Ipsos National Issues Monitor) data begins in November 2010, I remove Monthly CPI from the model. This revised **Cost of Living Anxiety Explanatory Model 2.0** is given by:

$$y = \alpha \ + \beta_{CPI} x_{CPI} \ + \beta_{WM} x_{WM} \ + \beta_{WM^2} x_{WM}^2 \ + \beta_{TM} x_{TM} \ + \beta_{TM^2} x_{TM}^2 + \epsilon$$

Ridge and Lasso regressions are then performed to shrink the coefficients and mitigate multicollinearity. A robustness check of the Mean Squared Error (MSE) of the four single predictor variable models with highest Adjusted R-squared values against the MSE of four multiple-predictor variable models yields the output summarised in the table below. Table 9 includes Cost of Living Anxiety Explanatory Models 1.0 (four predictor variables), 2.0 (three predictor variables without shrinkage), 2.1 (Ridge), and 2.2 (Lasso).

Model	Mean Squared Error
Headline inflation (simple linear) model	63.348442
Weighted Median inflation (polynomial) model	38.45273
Trimmed Mean inflation (polynomial) model	48.52805
Monthly CPI inflation (polynomial) model	95.08902
Cost of Living Explanatory Model 1.0	17.66053
Cost of Living Explanatory Model 2.0	29.17126
Cost of Living Explanatory Model 2.1 (Ridge)	39.05410
Cost of Living Explanatory Model 2.2 (Lasso)	29.19465

Table 9: Robustness checks of combined-variable Cost of Living Model compared with single-variable models

With the lowest MSE of the two shrinkage method models, the best-fitting model is therefore the Lasso regression model, **Cost of Living Anxiety Explanatory Model 2.2**, which is solved as

$$y = 26.85 + 2.13x_{CPI} \ + -13.28x_{WM} \ + 4.66x_{WM}^2 \ + 7.71x_{TM} \ + -2.47x_{TM}^2 + \epsilon \quad (5)$$

While this model (2.2) addresses multicollinearity, the substantially smaller MSE for Cost of Living Model Explanatory Model 1.0 suggests that even with a high degree of multicollinearity, Model 1.0 is still a robust alternative..

Part 3: Models of public anxiety about unemployment

Labour market explanatory variables

Key results of the nine regressions of labour market indicators on 'Unemployment' Issue anxiety are summarised below in Table 10.

Labour market indicator	**Model**	**Adjusted R^2**	**p-value**
Unemployment rate (trend)	**Polynomial**	**0.8547**	<2.2e-16
Unemployment rate (seasonally adjusted)	**Polynomial**	**0.8253**	<2.2e-16
Underutilisation rate (trend)	**Polynomial**	**0.8109**	<2.2e-16
Underutilisation rate (trend)	Linear	0.8092	<2.2e-16
Underutilisation rate (seasonally adjusted)	**Polynomial**	**0.8035**	<2.2e-16
Underutilisation rate (seasonally adjusted)	Linear	0.8024	<2.2e-16
Underutilisation rate (original)	**Polynomial**	**0.7661**	<2.2e-16
Underutilisation rate (original)	Linear	0.7624	<2.2e-16
Unemployment rate (seasonally adjusted)	Linear	0.7617	<2.2e-16
Employment to population ratio (seasonally adjusted)	**Linear**	**0.7617**	<2.2e-16
Unemployment rate (trend)	Linear	0.7552	<2.2e-16
Employment to population ratio (trend)	**Polynomial**	**0.7313**	<2.2e-16
Employment to population ratio (seasonally adjusted)	Polynomial	0.7198	<2.2e-16
Unemployment rate (original)	**Polynomial**	**0.6955**	<2.2e-16
Employment to population ratio (trend)	Linear	0.693	<2.2e-16
Unemployment rate (original)	Linear	0.6633	<2.2e-16
Employment to population ratio (original)	**Polynomial**	**0.657**	<2.2e-16
Employment to population ratio (original)	Linear	0.6318	<2.2e-16

Table 10: Adjusted R-squared and p-values of ‘Unemployment’ Issue models

A number of inferences can be made from the Adjusted R-squared values of the nine models. Firstly, voter prioritisation of the "Unemployment" issue appears to be far better explained by underlying (trend) movements in unemployment rates and by non-seasonal factors than seasonal factors. The original unemployment rate polynomial model's Adjusted R-squared value is significantly lower (0.70) than those of either the trend unemployment rate polynomial model (0.85) or the seasonally adjusted unemployment rate polynomial model (0.83).

Secondly, while the trend and seasonally adjusted underutilisation rate (polynomial) models fit the polling data relatively well, their inclusion of underemployment factors do not improve upon the goodness-of-fit of the unemployment-only models, suggesting that unemployment itself—and not the broader dimensions of underutilisation such as underemployment—is the driving factor behind households' anxiety about the labour market.

Thirdly, the employment-to-population ratio, which to an extent captures "hidden" unemployment in the form of workers who have given up looking for work, is a substantially worse fit than the other two employment indicators.

This suggests the phenomenon of "hidden" or "unofficial" unemployment is not a larger driver of household unemployment anxiety than the headline or "official" unemployment rate.

Results from the four best-fitting models are presented below (trend unemployment rate polynomial model, seasonally adjusted unemployment rate polynomial model, trend underutilisation rate polynomial model, and seasonally adjusted underutilisation rate polynomial model).

Table 11: Polynomial regression model of unemployment anxiety and trend unemployment rate

	Dependent variable:
	Unemployment issue
Unemployment rate, trend	-23.119^{***}
	(3.015)
(Unemployment rate, trend)^2	3.186^{***}
	(0.299)
Constant	50.629^{***}
	(7.464)
Observations	166
R^2	0.856
Adjusted R^2	0.855
Residual Std. Error	3.281 (df = 163)
F Statistic	486.427^{***} (df = 2; 163)
Note:	*p<0.1; **p<0.05; ***p<0.01

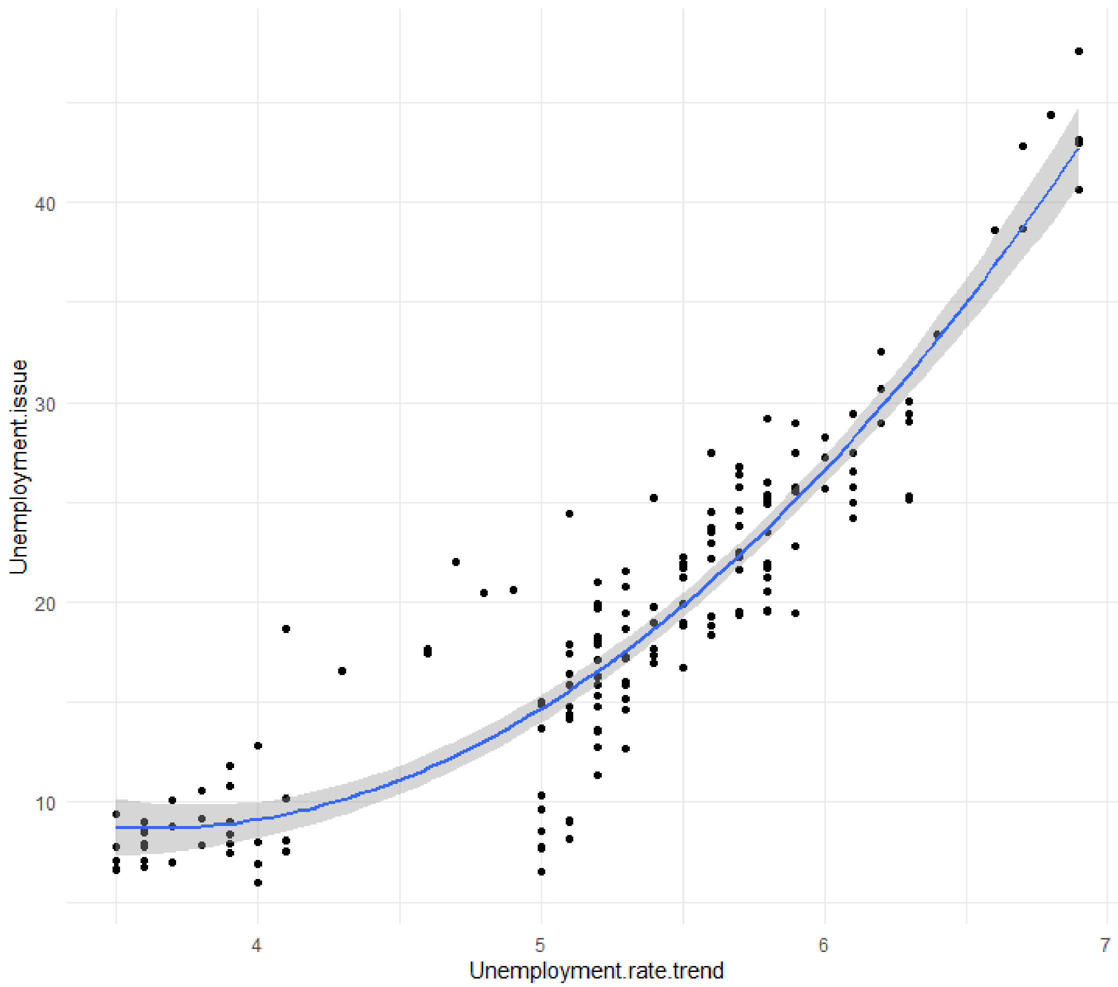

Figure 13: Polynomial regression of trend unemployment rate on 'Unemployment' issue anxiety

Table 12: Polynomial regression model of unemployment anxiety and seasonally adjusted unemployment rate

	Dependent variable:
	Unemployment issue
Unemployment rate, seasonally adjusted	-13.647^{***}
	(2.854)
(Unemployment rate, seasonally adjusted)^2	2.189^{***}
	(0.279)
Constant	28.914^{***}
	(7.199)
Observations	166
R^2	0.828
Adjusted R^2	0.826
Residual Std. Error	3.594 (df = 163)
F Statistic	391.894^{***} (df = 2; 163)
Note:	*p<0.1; **p<0.05; ***p<0.01

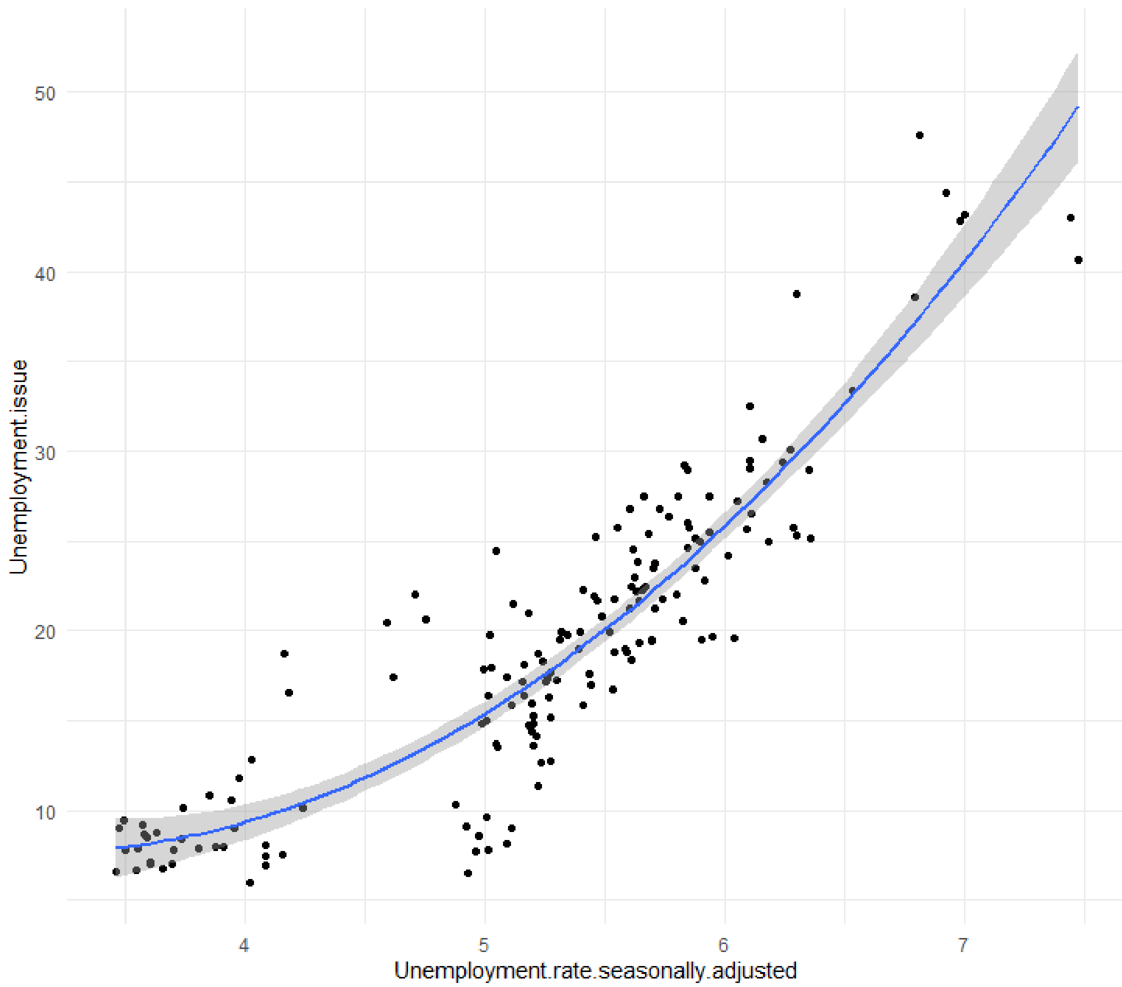

Figure 14: The 'seahorse' graph: polynomial regression of seasonally adjusted unemployment rate on 'Unemployment' issue anxiety

Table 13: Polynomial regression model of trend underutilisation rate and 'Unemployment' issue anxiety

	Dependent variable:
	Unemployment issue
Underutilisation rate, trend	2.170^{*}
	(1.148)
(Underutilisation rate, trend)^2	0.066
	(0.042)
Constant	-20.776^{***}
	(7.778)
Observations	166
R^2	0.813
Adjusted R^2	0.811
Residual Std. Error	3.744 (df = 163)
F Statistic	354.678^{***} (df = 2; 163)
Note:	*p<0.1; **p<0.05; ***p<0.01

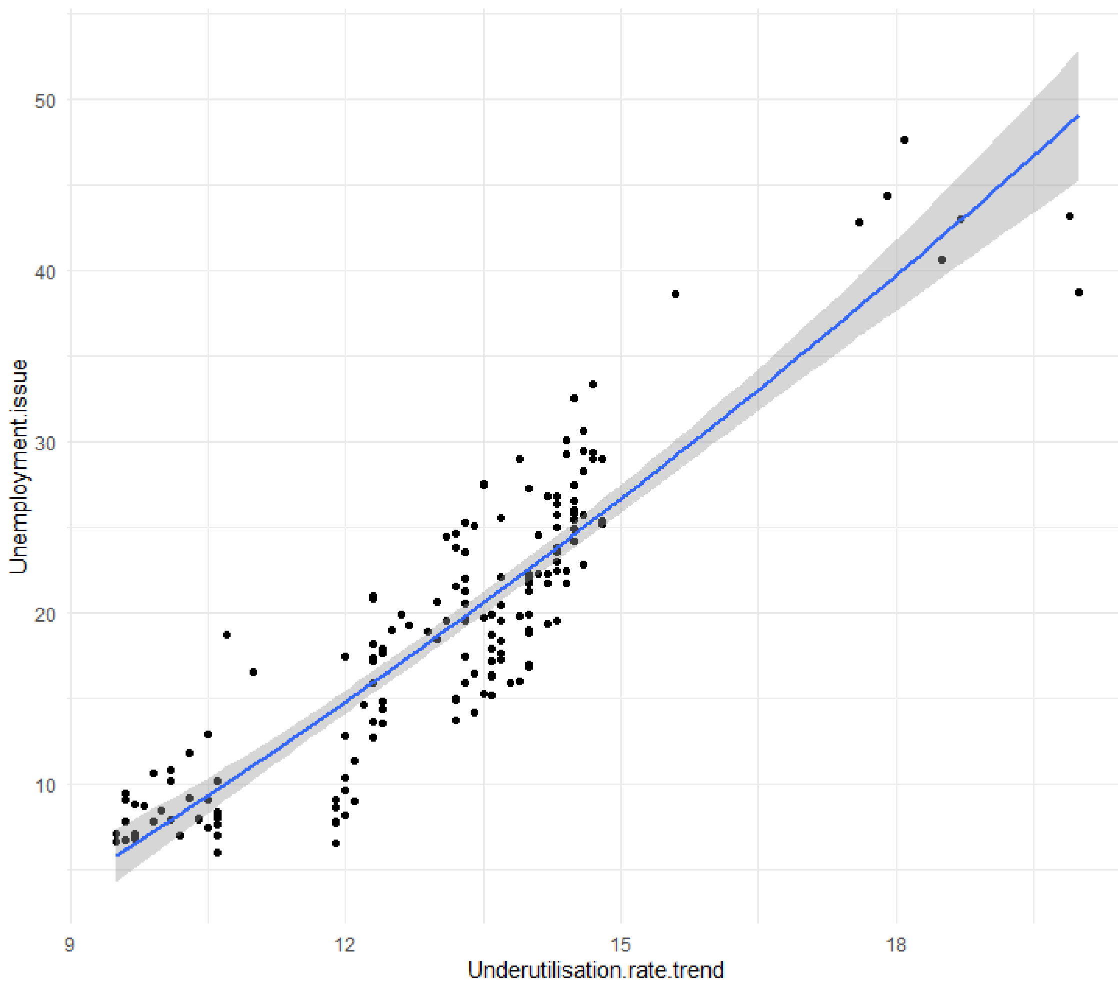

Figure 15: Polynomial regression of trend underutilisation rate on 'Unemployment' issue anxiety

Table 14: Polynomial regression of seasonally adjusted underutilisation rate on 'Unemployment' issue

	Dependent variable:
	Unemployment issue
Underutilisation rate, seasonally adjusted	2.332^{**}
	(1.133)
(Underutilisation rate, seasonally adjusted)^2	0.056
	(0.041)
Constant	-21.268^{***}
	(7.701)
Observations	166
R^2	0.806
Adjusted R^2	0.803
Residual Std. Error	3.816 (df = 163)
F Statistic	338.290^{***} (df = 2; 163)
Note:	*p<0.1; **p<0.05; ***p<0.01

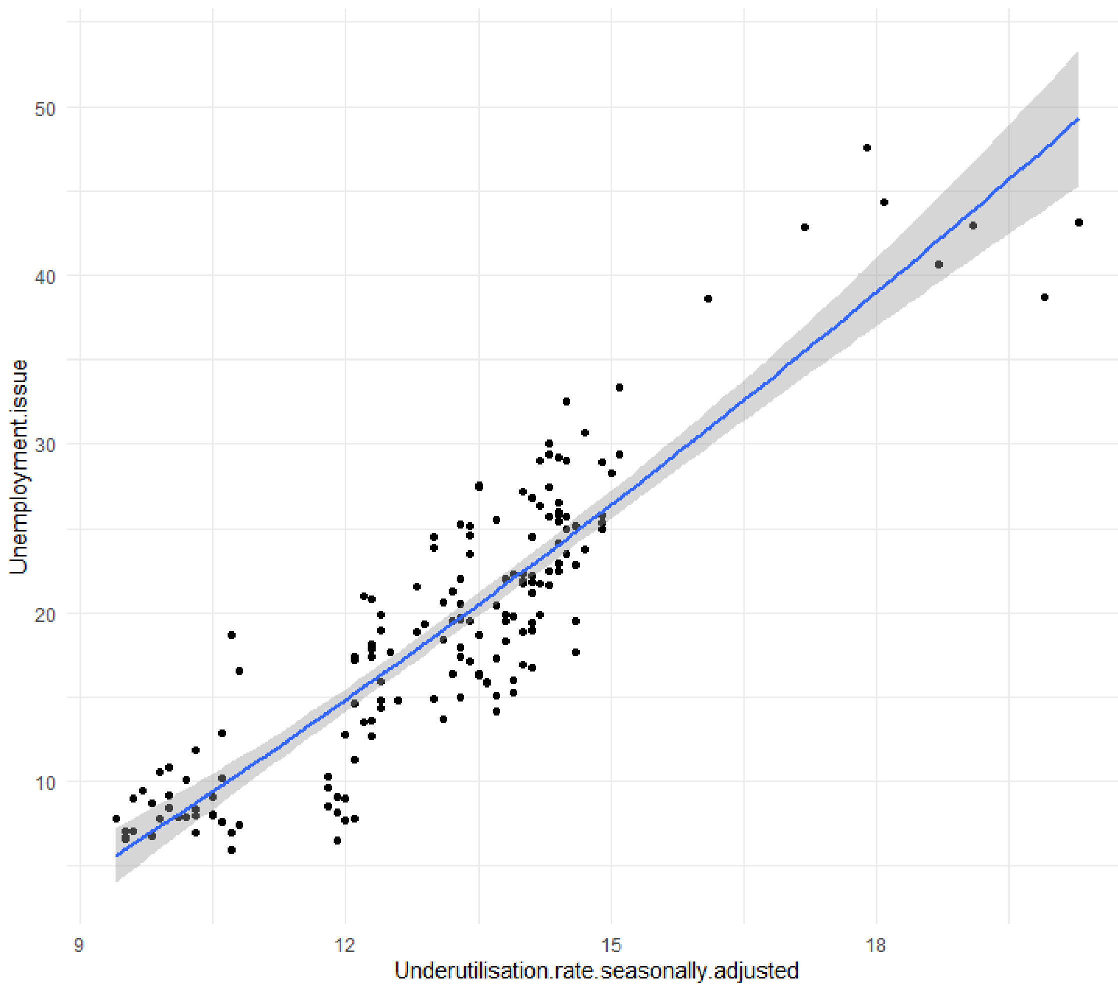

Figure 16: Polynomial regression of seasonally adjusted underutilisation rate on 'Unemployment' issue anxiety

Predicting voter responses to rising unemployment rates

Returning to RQ 1.a., there is a clear relationship between business cycles and voters' policy priorities. Unemployment rates above (below) their pre-pandemic decade average (5.5 per cent) are typically associated with above (below) pre-pandemic average levels of voter anxiety about unemployment (20 per cent), as illustrated in Figure 17. The collapse in unemployment rates in late 2021 and subsequent three years of low unemployment rates drove a collapse in voters' prioritisation of the 'Unemployment' issue, compounded by rising inflation and voters' priorities shifting towards cost of living (as illustrated earlier in Figure 9).

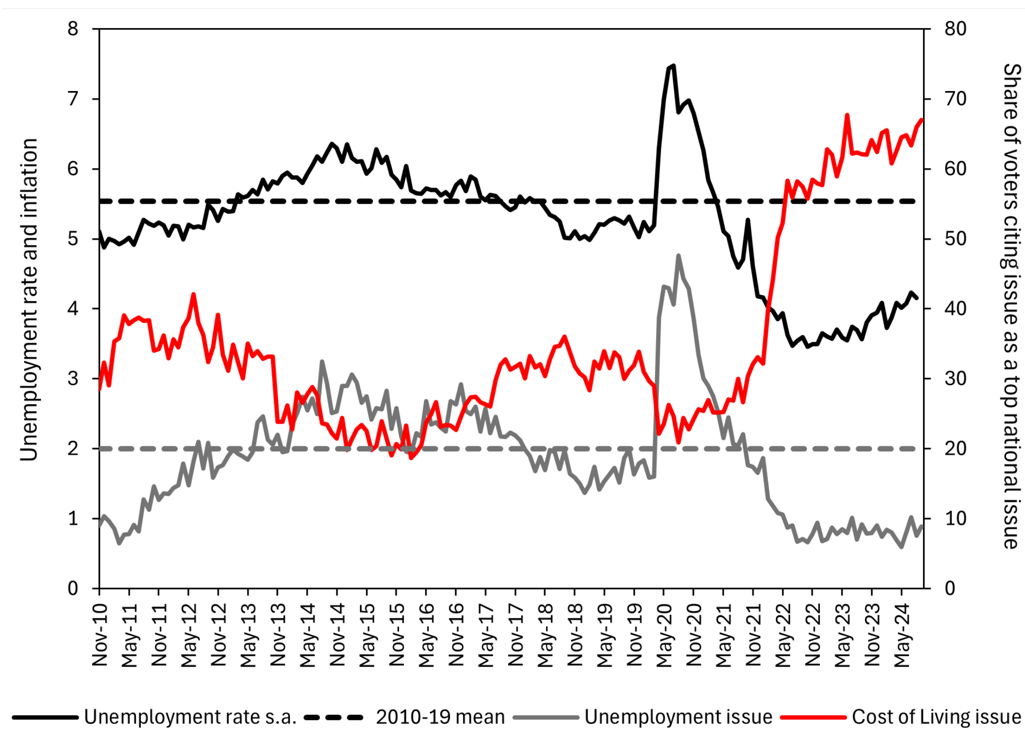

Figure 17: Unemployment rate, 'Unemployment' and 'Cost of Living' Issues, 2010-24

We can quantify the impact of a 1 percentage point rise in unemployment rates on public sentiment accordingly:

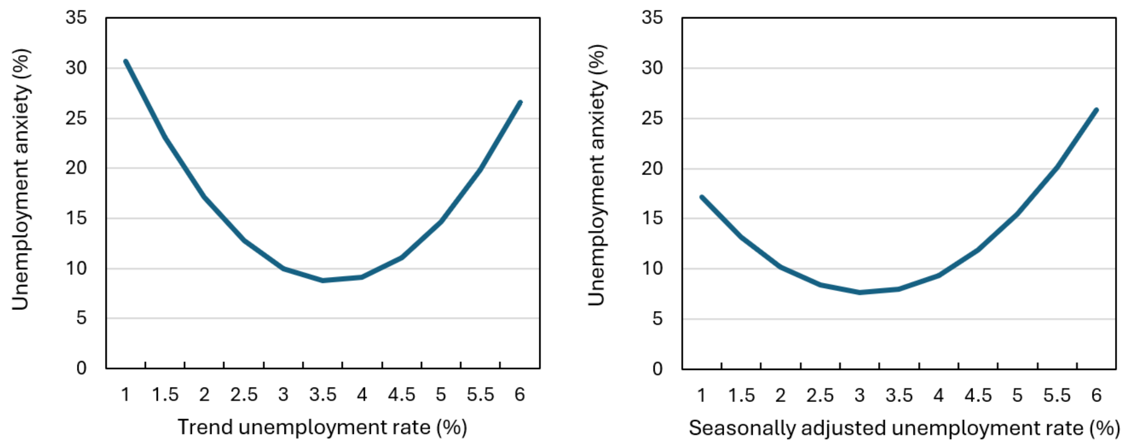

Figure 18: Polynomial model predictions of unemployment anxiety at 1-6 per cent unemployment rates

Trend unemployment rate, per cent	*1.0*	*1.5*	*2.0*	*2.5*	*3.0*	*3.5*	*4.0*	*4.5*	*5.0*	*5.5*	*6.0*
Unemployment anxiety (based on trend UR), per cent	30.7	23.1	17.1	12.7	9.9	8.7	9.1	11.1	14.7	19.8	26.6
Seasonally adjusted unemployment rate, per cent	*1.0*	*1.5*	*2.0*	*2.5*	*3.0*	*3.5*	*4.0*	*4.5*	*5.0*	*5.5*	*6.0*
Unemployment anxiety (based on s.a. UR), per cent	17.2	13.1	10.2	8.4	7.6	7.9	9.4	11.9	15.4	20.1	25.9

Table 15: Estimated effect of percentage point changes in unemployment rates on voter prioritisation of the 'Unemployment' issue

Turning to RQ 1.b., "can we predict how voters' policy priorities will adjust in response to rising unemployment rates and falling inflation?", we first solve Equation 2 using the output from the polynomial regression model (Table 12), such that Equation 2 (the **Unemployment Issue Anxiety Prediction Model**) is solved as

$$y = 28.91 + -13.65x_{URSA} + 2.19x^2_{URSA} + \epsilon \tag{6}$$

and then plug the Reserve Bank August 2024 *Statement on Monetary Policy* and latest Treasury forecasts for the seasonally adjusted unemployment rate into the polynomial regression model from Equation 2, and do the same for the cost of living anxiety model with the official forecasts for headline and annual trimmed mean inflation.

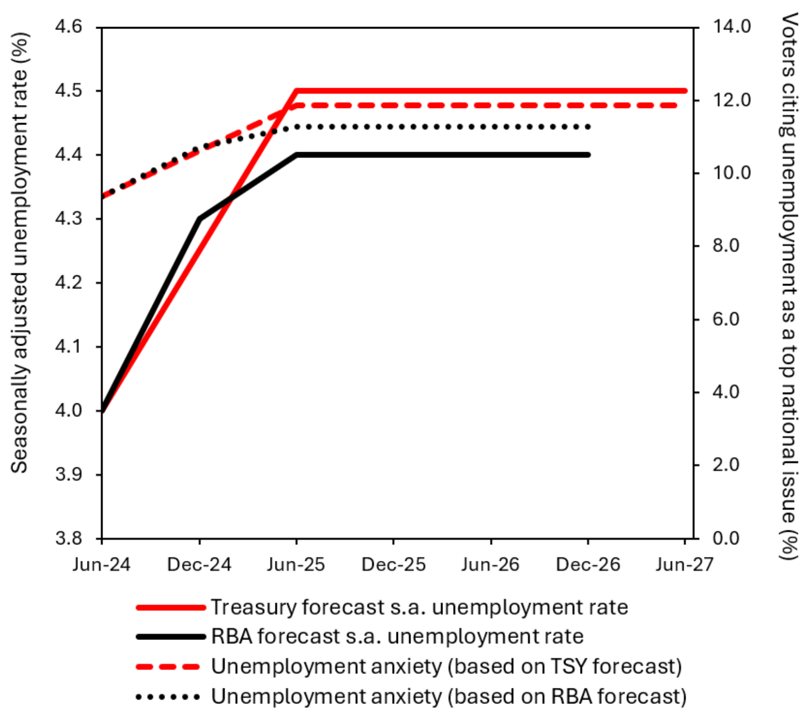

Figure 19: Official forecasts for the seasonally adjusted unemployment rate, and predicted unemployment anxiety

Variable	Jun-24	Dec-24	Jun-25	Dec-25	Jun-26	Dec-26	Jun-27
Treasury forecast UE rate	4.0	-	4.5	-	4.5	-	4.5
RBA forecast UE rate	4.0	4.3	4.4	4.4	4.4	4.4	-
U.E. anxiety based on TSY forecast	9.4	-	11.9	-	11.9	-	11.9
U.E. anxiety based on RBA forecast	9.4	10.7	11.3	11.3	11.3	11.3	-

Table 16: Official forecasts for the seasonally adjusted unemployment rate, and predicted public anxiety about unemployment (per cent)

Given the official forecasts do not include forecasts for weighted median inflation, we must adjust the earlier Cost of Living model to a headline-plus-annual-trimmed-mean-inflation linear and polynomial regression model for the Reserve Bank forecasts and use the earlier headline-inflation-only simple linear regression model for the Treasury forecasts. **Cost of Living Anxiety Prediction Model 1** is therefore

$$y = \alpha \ + \beta_{CPI} x_{CPI} \ + \epsilon$$

Per our results earlier, solving the model therefore yields

$$y = 18.83 + 5.87 x_{CPI} \ + \epsilon \tag{7}$$

where $\epsilon \sim N(0,\, 8.01)$. The adjusted **Cost of Living Issue Anxiety Prediction**

Model 2.0 (using RBA forecasts) is

$$y = \alpha \ + \beta_{CPI} x_{CPI} \ + \beta_{TM} x_{TM} \ + \beta_{TM^2} x_{TM}^2 \ + \epsilon \tag{8}$$

which is solved as

$$y = 9.48 + 0.14 x_{CPI} \ + 11.28 x_{TM} \ + -0.49 x_{TM}^2 \ + \epsilon \tag{9}$$

where $\epsilon \sim N(0, 7.05)$, using the regression output summarised in the Table 17 below.

Table 17: Cost of Living Issue Anxiety Prediction Model 2

	Dependent variable:
	Cost of Living issue
Headline annual inflation, original	0.135
	(0.906)
Annual Trimmed Mean inflation, seasonally adjusted	11.282***
	(2.316)
(Annual Trimmed Mean inflation, seasonally adjusted)^2	−0.486*
	(0.273)
Constant	9.482***
	(3.107)
Observations	164
R^2	0.701
Adjusted R^2	0.696
Residual Std. Error	7.052 (df = 160)
F Statistic	125.302*** (df = 3; 160)
Note:	*p<0.1; **p<0.05; ***p<0.01

Both of these Cost of Living prediction models however yield predicted results substantially below observed results:

	Jun-24	Jul-24	Aug-24	Sep-24	Dec-24	Jun-25	Dec-25	Jun-26	Dec-26	Jun-27
Treasury forecast headline inflation	3.5					2.8		2.8		2.5
Cost of Living Issue based on TSY forecast	39.4					35.0		35.0		33.5
RBA forecast headline inflation	3.8				3.0	2.8	3.7	3.2	2.6	
RBA forecast annual trimmed mean inflation	3.9				3.5	3.1	2.9	2.7	2.6	
Cost of Living Issue based on RBA forecast	46.6				43.4	40.2	38.6	36.8	35.9	
Actual Cost of Living Issue	65	63	66	67						

Table 18: Model predictions of Cost of Living anxiety

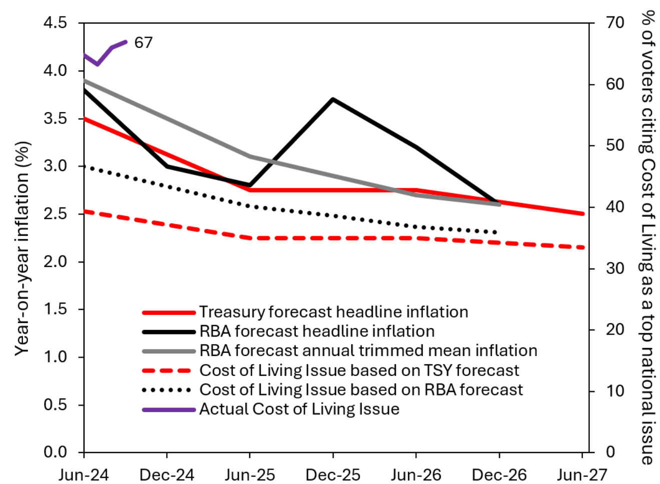

Figure 20: Official forecasts for the seasonally adjusted unemployment rate, and predicted unemployment anxiety

Applying shrinkage methods to Prediction Model 2.0 to address multicollinearity do not improve predictive accuracy either. A Ridge regression variant of the model **Prediction Model 2.1**, solved as

$$y = 18.2 + 1.33x_{CPI} + 4.28x_{TM} + 0.22x_{TM}^2 + \epsilon \tag{10}$$

yields a predicted Cost of Living Issue value of 43.3 per cent for June 2024 (compared to an actual observed value of 65 per cent) given headline annual inflation of 3.8 per cent and annual trimmed mean inflation of 3.9 per cent. A Lasso regression variant of the model, **Prediction Model 2.2**, solved as

$$y = 14.94 + 0.09x_{CPI} + 7.59x_{TM} + \epsilon \tag{11}$$

where the coefficient of x_{TM}^2 has been shrunk to zero, yields a predicted Cost of Living Issue value of 44.9 per cent.

The persistent stickiness of Cost of Living anxiety throughout 2023 and 2024 despite the observed falls in headline and underlying inflation could potentially be explained by the elevated price level. From this, we could speculate that short of an outright deflation episode, a sustained period of low inflation will be required to bring down public anxiety about Cost of Living. Moreover, it suggests that the adjustment of voters' policy priorities in response to a rise in unemployment rates and continued decline in inflation could well take the form of an outward shift in the Political Phillips Curve, rather than movement down along the Political Phillips Curve.

We therefore conclude that while we can predict how voters' policy priorities will adjust in response to rising unemployment rates, we cannot predict with comparable certainty how voters' policy priorities will adjust in response to falling inflation.

Part 4: Nowcasting the unemployment rate

Model solutions and nowcast results

To use our models of public anxiety from the previous section to nowcast the unemployment rate, we simply take our models of unemployment anxiety and the seasonally adjusted unemployment rate and switch the predictor variable and the target variable.

Outputs of the simple linear regression from **Nowcast Model 1** and the polynomial regression from **Nowcast Model 2** in Table 19 below solve the models as

$$y_{URSA} = 3.54 + 0.09x_{UA} \ + \epsilon \tag{12}$$

where $\epsilon \sim N(0,\, 0.426)$

and

$$y_{URSA} = 3.02 + 0.145x_{UA} \ + -0.001x_{UA}^2 \ + \epsilon \tag{13}$$

where $\epsilon \sim N(0,\, 0.403)$

Table 19: Summary of Nowcast Model regressions

	Dependent variable:	
	Unemployment rate, seasonally adjusted	
	(Nowcast Model 1)	(Nowcast Model 2)
Unemployment issue	0.088^{***}	0.145^{***}
	(0.004)	(0.013)
(Unemployment issue)^2		-0.001^{***}
		(0.0003)
Constant	3.543^{***}	3.020^{***}
	(0.081)	(0.140)
Observations	166	166
R^2	0.763	0.789
Adjusted R^2	0.761	0.786
Residual Std. Error	0.426 (df = 164)	0.403 (df = 163)
F Statistic	527.235^{***} (df = 1; 164)	304.348^{***} (df = 2; 163)
Note:		*p<0.1; **p<0.05; ***p<0.01

Using the August 2024 Ipsos unemployment issue value of 7.58 per cent in the Nowcast Model 1 yields a predicted seasonally adjusted unemployment rate of 4.212267 per cent. Using the September 2024 Ipsos unemployment issue value of 8.91 per cent in the model yields a predicted seasonally adjusted unemployment rate of 4.32993 per cent.

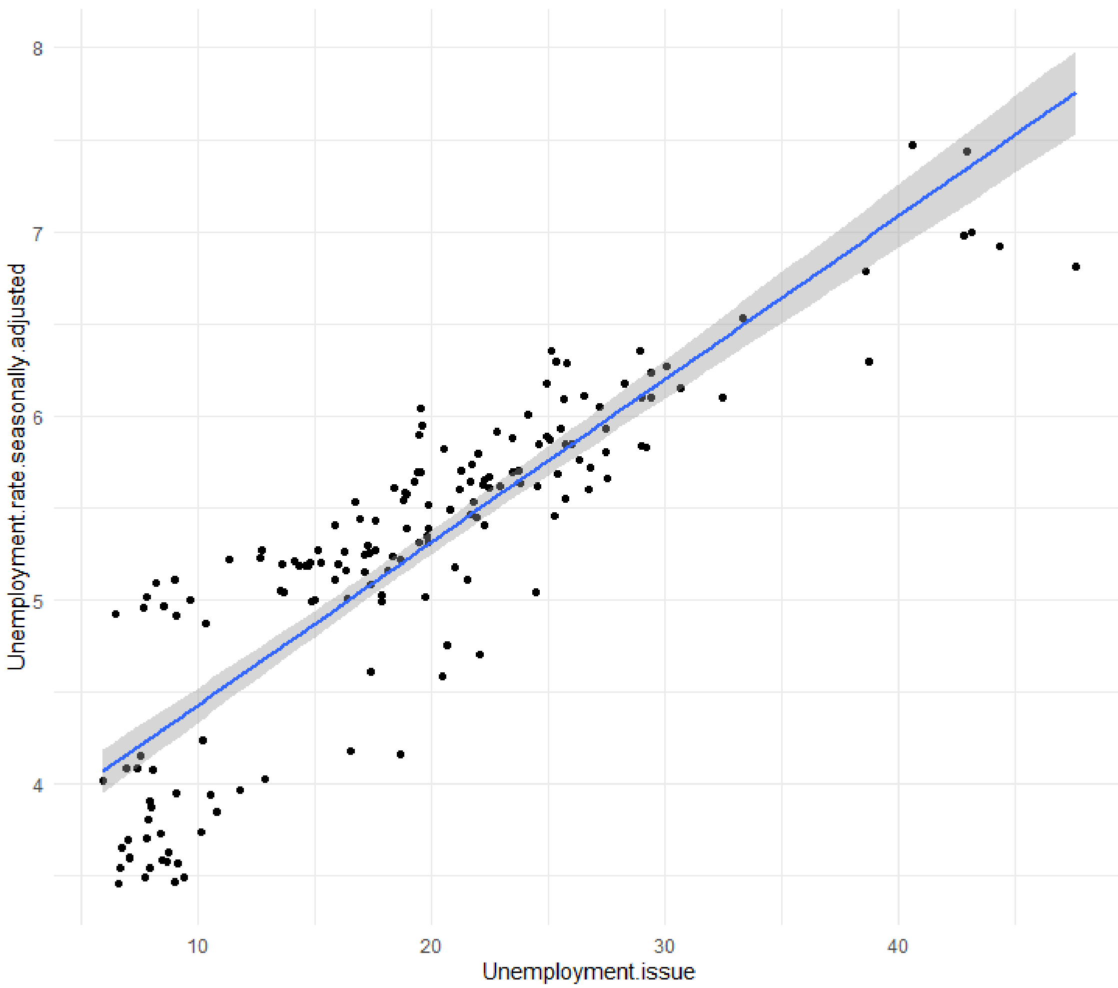

Figure 21: Nowcast Model 1 (simple linear regression model)

Using the August 2024 and September 2024 Ipsos unemployment issue values in the Nowcast Model 2 yields seasonally adjusted unemployment rates of 4.04646 (August 2024) and 4.211284 (September 2024).

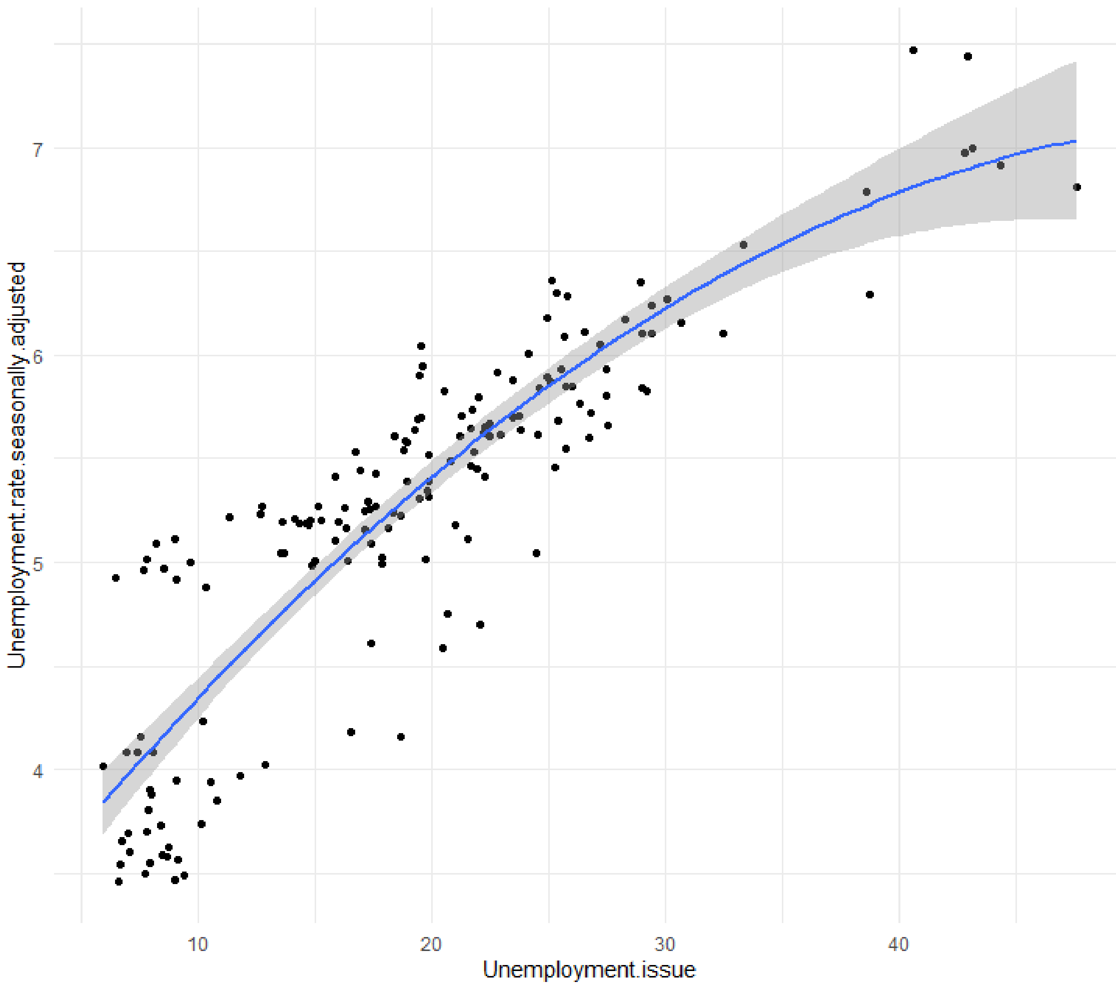

Figure 22: Nowcast Model 2 (polynomial regression model)

Table 20 below compares each nowcast model's predictions against the actual results from the September 2024 ABS Labour Force Survey, released 17 October 2024:

Month	*August 2024*	*September 2024*
Actual	4.143259	4.0673634
Nowcast Model 1	4.212267	4.32993
Nowcast Model 2	4.04646	4.211284
Model 1 difference	0.069008	0.2625666
Model 2 difference	-0.096799	0.1439206

Table 20: Model nowcasts and actuals

Conclusion to Research Question 2

While the results of this nowcasting experiment are disappointing, the narrow differences in the nowcast for August 2024 do suggest that the application of more advanced econometric techniques such as machine learning in future research could prove fruitful. The substantially larger differences in the nowcast for September 2024 are likely a product of the divergence between unemployment anxiety for that month (up 1.33 percentage points to 8.91 per cent) and the unemployment rate (down 0.76 percentage points to 4.07 per cent).

Revisions to the Labour Force Survey results also pose a challenge. For instance, the September 2024 Labour Force Survey revised the August 2024 seasonally adjusted unemployment rate from 4.1559749 to 4.143259—a -0.0127159 percentage point revision, but enough to revise the rounded figure from 4.2 per cent (just within Nowcast Model 1's prediction) to 4.1 per cent. This points to the difficulty in nowcasting figures to 0.1 percentage point precision, especially when the figures themselves are subject to revision.

A question of lagging?

This then leads to the final question to be addressed: is voter anxiety about unemployment (as a national issue) more a reaction to the official statistics announced by the news media (an "announcement effect"), or is it more a function of observed labour market conditions in voters' own circumstances, local communities, and social networks? In other words, is an increase in voter anxiety about unemployment in a given reference month driven more by news headlines, or is it driven more by their own observations and experiences of economic conditions?

To answer this, a two-month lag is applied to the seasonally adjusted unemployment rate polynomial regression model (Equation 2), so that

$$y_t = \alpha \ + \beta_1 x_{t-2} \ + \beta_2 x_{t-2}^2 \ + \epsilon \tag{14}$$

where y_t is the share of voters in the reference month citing 'Unemployment' as a top-three national issue, x_{t-2} is the most recently *announced* unemployment rate (i.e. the unemployment rate of two months' prior), and β_1 and β_2 are the coefficients.

Table 21: Summary of output, lagged and non-lagged polynomial regression models

	Dependent variable:	
	Unemployment.issue	
	(Non-lagged model)	(Lagged model)
Current unemployment rate	-13.647^{***}	
	(2.854)	
(Current unemployment rate)^2	2.189^{***}	
	(0.279)	
Two-month lagged unemployment rate		-9.315^{***}
		(3.348)
(Two-month lagged unemployment rate)^2		1.746^{***}
		(0.327)
Constant	28.914^{***}	18.632^{**}
	(7.199)	(8.453)
Observations	166	166
R^2	0.828	0.762
Adjusted R^2	0.826	0.759
Residual Std. Error (df = 163)	3.594	4.228
F Statistic (df = 2; 163)	391.894^{***}	260.493^{***}
Note:		*p<0.1; **p<0.05; ***p<0.01

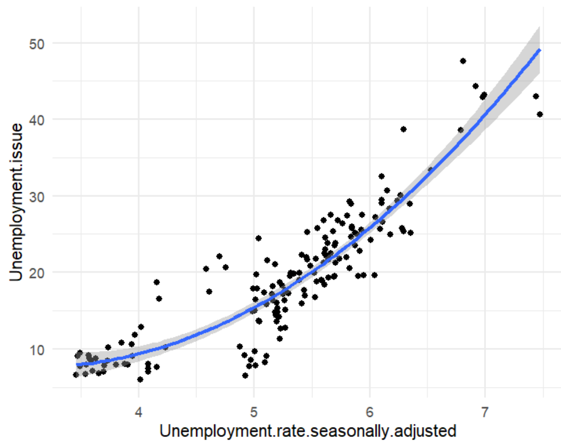

Figure 23:
Non-lagged regression

Figure 24:
Two-month lagged regression

Figure 25: Polynomial regression models, lagged and non-lagged

The lower Adjusted R-squared value (0.759) and higher Residual Standard Error (4.228) in the two-month lagged model compared to the non-lagged model (0.826 and 3.594 respectively) suggests the lagged model is a worse fit. Combined with the lower absolute values of the coefficients in the lagged model, this suggests that voters are less sensitive to the latest official unemployment rate (from two months prior to the reference month) than they are to the as-yet unannounced unemployment rate of the reference month. The lagged model also is less robust, with a higher MSE.

Model	**Mean Squared Error**
Non-lagged model	12.68086
Two-month lagged model	17.55309

Table 22: Robustness check of lagged and non-lagged models

These suggest that the “announcement effect” is weaker than the “organic” effect, suggesting voters are responding to changes in labour market conditions on the ground in real time, and lending credence to the possibility of using Ipsos polling data to nowcast the unemployment rate.

Conclusion

Returning to Research Question 1, "how do macroeconomic variables affect which issues voters care about?", inflation and labour market conditions have a significant effect on voters' policy priorities. Public anxiety about cost of living is more affected by year-on-year inflation than quarter-on-quarter inflation and is more affected by underlying (weighted median and trimmed mean) inflation than headline inflation and annualised Monthly CPI inflation. Public anxiety about unemployment is particularly affected by the trend unemployment rate, the seasonally adjusted unemployment rate, the trend underutilisation rate and the seasonally adjusted underutilisation rate, and is less sensitive to the employment-to-population ratio.

Regarding Research Question 2, basic regression models fail to accurately nowcast the unemployment rate using polling data. However, the margin of error is small. Moreover, the unemployment rate of a given reference month (such as September) is a far better fit for the share of voters nominating 'Unemployment' as a top-three national issue in that same reference month (September) than the unemployment rate of two months prior (July), even though voters do not know what the official unemployment rate will be for the reference month (September) at the time they are being surveyed. In other words, the as-yet-unknown contemporaneous unemployment rate is a better predictor of voter anxiety about unemployment than the latest known unemployment rate. This suggests that more sophisticated nowcasting models could have more success in nowcasting the unemployment rate using polling data.

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