Mood misattribution and external factors: The effect of short-term temperature changes on presidential approval in Ecuador

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1 Introduction

Whether voters can truly capture a realistic appraisal of the state of the world at the polls remains a core research topic in the study of politics. In an ideal scenario, individuals will be able to adequately judge the strengths and weaknesses of politicians, punishing poor performers and providing incentives for new leaders to perform competently while in office. This well known argument of *voter rationality* by Key (1960) builds the foundation of retrospective voting, which models citizens as rational observers of government past-performance (Ferejohn, 1986; A. Healy & Malhotra, 2013). An adequate system of retrospective voting has can to efficient political outcomes, where politicians who underperform leave office resulting in greater democratic accountability (Besley, 2006; Persson & Tabellini, 2002).

However, modern researchers have challenged the view that voters can adequately appraise the performance of a politician, finding a variety of biases in the way voters attribute responsibility to political leaders, which challenges the foundational basis of the perfect retrospective voter (A. Healy & Malhotra, 2013). In this paper, I contribute to this stream of the literature by focusing on how seemingly irrelevant events can affect presidential approval.

By merging the AmericasBarometer (AB) public opinion survey data with CPC Global Unified temperature data from Ecuador, I leverage variation from an ordinary yet impactful natural experiment: short-term temperature changes. Given that daily temperature changes can be assumed to be random and exogenous to political behaviour, I can consistently estimate the impact of daily temperature changes on presidential approval ratings. The core result of the paper is that higher temperatures have a negative and statistically significant relationship with presidential approval, which suggests that voters commit attribution errors when evaluating politicians. I ascribe this result to mood misattributions, where the weather affects the mood of individuals negatively (Barrington-Leigh & Behzadnejad, 2017; Keller et al., 2005; Lignier et al., 2023), and in turn individuals search externally for factors to validate their mood (Bower, 1981; Schwarz & Clore, 1983).

Other research has found evidence of cognitive biases in voters' perceptions of politicians (Beck, 1982; Hart & Matthews, 2023; Kahneman & Tversky, 1982; Tilley & Hobolt, 2011), yet few papers studied the impact of random events (Achen & Bartels, 2017; A. J. Healy et al., 2010; A. Healy & Malhotra, 2010). Weather-related events have been used in quasiexperimental studies to draw causal statements about voter behaviour (Bassi, 2019; Bastos & Miller, 2013; A. Healy & Malhotra, 2009; Liao & Ruiz Junco, 2022; Visconti, 2022), but their direct effect on performance ratings and the implications for retrospective voting are yet to be understood.

Understanding how voters misattribute their mood to political leaders is a question whose importance has been well established by the literature. Extending the applicability of retrospective voting models based on cognitive biases to the context of a developing country in the tropics like Ecuador holds additional importance. Significant mood misattributions like the one I find may partially explain democratic accountability crises, as voters may persistently fail to evaluate incumbent performance and fail to provide good incentives for political leaders. Further, understanding what factors outside the common variables may be a better way to understand the modern issues the region faces.

The rest of the paper proceeds as follows. In the next section, I review the theory which informed the paper's empirical approach. Section 3 presents the empirical approach. In section 4, I present the paper's results. Section 5 concludes.

2 Theory

Economic voting research has long discussed if the economy truly explains voting behaviour, or if the economy is seen through partisan lens (Lewis-Beck, 2006; Lewis-Beck et al., 2008; Wlezien et al., 1997). Difficult identification challenges emerge from this type of performance models, given that multiple factors are endogenous to the public's perceptions of the economy and vote choice (Anderson, 2007; Kiewiet & Rivers, 1984). Most retrospective voting research in Latin America has focused on economic voting too, as well as on populism and the recent rise of leftist parties and populism (Benton, 2005; Lee, 2014; Murillo et al., 2010; Wiesehomeier & Doyle, 2013). The literature also finds no clear conclusions, with some evidence for Latin American voters behaving similar to developed country voters (Singer & Carlin, 2011). However, Veiga (2013) finds that usual macroeconomic variables are not reliable predictors of vote choice on Latin American countries. Regarding leftist parties and populism, evidence has shown that the early 2000's *pink tide* in Latin America may have been a result of retrospective voting and discontent with establishment parties (Wiesehomeier & Doyle, 2013).

The literature on presidential approval is adjacent to economic voting, since it has mostly focused on estimating *popularity functions* to determine the relationship between presidential popularity and other variables (Berlemann & Enkelmann, 2014). Macroeconomic variables such as inflation and unemployment have been found to significantly affect presidential approval in some cases, however, no definitive results have been found. Results are highly dependent on context, and on the researcher's choice of variables, model specification, frequency, time frame, among others. (Donovan et al., 2020) show that presidential approval is also impacted by the public's partisan identity. Recent findings show that perceptions of corruption can act as significant predictors of presidential approval (Jung & Oh, 2020), especially in Latin America, where other work has shown a reduced importance of standard economic variables (Cerda & Vergara, 2023).

The debate which retrospective voting has gave rise to has incentivized the use of advanced causal inference and experimental techniques to overcome identification challenges. This renewed approach has allowed for a more precise understanding of the mechanisms behind retrospective voting, which involves the evolving literature on the mistakes that voters make when evaluating politicians' performance. This has went beyond the mere lack of knowledge about economic information, which is typically trivial considering that a voter need only consult his own economic situation. Rather, recent research has found that citizens tend to commit errors consistent with decision-making beyond political life.

Events that are irrelevant are one type of such biases. Though disputed, Achen & Bartels (2017) famously presented evidence of shark attacks impacting Woodrow Wilson's vote share in 1916. Further, A. J. Healy et al. (2010) find that football games can positively impact the vote share of incumbents, results also consistent with irrelevant events impacting voting behaviour. Events that politicians have no control upon can impact their electoral outcomes if voters are assumed to be affected by mood in their performance judgments, a well-documented phenomenon in other fields. In an experimental setting, Schwarz & Clore (1983) show how inducing positive moods led subjects to report more feelings of satisfaction relative to subjects which were induced negative moods. Most importantly, it was shown that *people in bad moods were more likely to search for information to explain their mood* relative to those in a happy mood. This is direct evidence for attribution errors: if an outside circumstance induces a negative mood, people may be more likely to attribute their mood to search for information that confirms their mood, rather than the other way around. Additionally, Bower (1981) show that people who were induced a mood were more likely to recall information that was congruent with their mood. This can confirm misattribution errors in voters, who may be more likely to recall negative information about politicians if they are in a bad mood, and vice versa.

Fields other than political science have studied weather extensively, mostly showing significant impacts across a range of variables. Notably, Keller et al. (2005) find that pleasant weather (higher temperature or barometric pressure) has a positive impact on mood for U.S.

subjects. Kämpfer & Mutz (2013) and Kämpfer & Mutz (2013) find conflicting results of the impact of sunnier days on life satisfaction using survey data from Germany. Lucas & Lawless (2013) does not find reliable evidence of weather impacting life satisfaction using U.S. survey data. In Canada, Barrington-Leigh (2008) finds a positive effect of sunnier days on trust in neighbours using Canadian survey data. Further, Barrington-Leigh & Behzadnejad (2017) find that temporary rainfall variations have a significant, yet small negative impact in life satisfaction, especially for individuals with poor health and women. Lignier et al. (2023) find that higher temperatures in prolonged dry temperatures have a negative impact on life satisfaction in Australia. Beyond life satisfaction, Deller & Michels (2022) show that cloudy days have a significant impact on the way that managers evaluate subordinates across field experiments in the United States. Additionally, Quijano-Ruiz (2023), using the same CPC daily weather data for Ecuador, finds an effect of daily temperature changes on self-rated health for female survey respondents only.

The causal mechanism this paper draws from Schwarz & Clore (1983) and Bower (1981). Weather impacts mood, which then causes citizens to attribute their moods to external circumstances. If citizens consider higher temperatures to be "bad weather", their mood can be negatively impacted, making them more likely to negatively evaluate the president as a result of their discomfort. According to the theory, voters will attribute their mood to a external situation (the question being asked by the interviewer, which in this case relates to the president) and may even justify it by searching for negative events that confirm their mood, as proposed by Bower (1981).

In summary, retrospective voting literature has had an economic focus, which underscores the importance of controlling for economic perceptions in any formal empirical model of political behaviour. The Latin American context has shown some degree of resemblance to developed countries, but also some differences, notably in how certain ideological factors may moderate political behaviour to larger extent than developed countries. Presidential approval rating is extensive and has provided many recommendations for the estimation of popularity functions, notably, incorporating data at many frequencies and aggregations. However, this may not be possible or applicable in all contexts due to data availability. My theory on the impact of weather on presidential approval is supported by a growing literature on the impact of weather on mood and life satisfaction, which has shown mostly significant impacts of "better" weather across several variables. The causal mechanism I draw from is supported by psychological theory, which has shown that mood can impact the way that individuals process information, and how they attribute their mood to external circumstances.

3 Empirical Approach

3.1 Data

My data are composed of a pooled cross section of the AmericasBarometer (AB) merged with daily CPC Global Unified temperature, based on interview date and cantons in Ecuador[1]. The AB is a public opinion survey conducted by the Latin American Public Opinion Project (LAPOP), which has conducted biennial survey waves in Ecuador and other countries from 2004 to 2023. I use the subscriber LAPOP datasets available through Universidad San Francisco de Quito's research affiliation with LAPOP, focusing on the eight survey waves carried out between 2008 to 2023[2]. The surveys are based on a multi-stage national probability design, representative at the national level, except for 2021, where the survey switched to a random-digit-dialing design due to the COVID-19 pandemic.

The explained variable of interest is presidential job approval, which the AmericasBarometer measures as in a 1-5 scale in the question: "Speaking in general of the current administration, how would you rate the job performance of President [NAME]" (LAPOP, n.d.-a) (p.14), where 1 represents a very good performance and 5 terrible performance. This question is similarly similarly to the classic Gallup presidential approval question, which the literature has used extensively (Berlemann & Enkelmann, 2014) and has not been found to significantly deviate from other presidential popularity measures. I dichotomize the variable following LAPOP re-

[1] 1
[2] 2

search reports (Layton et al., 2016), where responses greater than 3 are considered as approval for the incumbent president.

Table 1 below displays descriptive statistics for the variables used in the empirical analysis. I collect opinion on personal economic situations and on country economic situation, also measured on a 1-5 scale, where 1 represents a very good situation and 5 a terrible situation. Political ideology is represent in a 0-10 scale, where 0 represents the “extreme left” and 10 the “extreme right”. I include 1-7 scales for trust in police, local government, political pride, and support for democracy where 0 represents no trust or support and 7 complete the opposite. Corruption perceptions are collected by the AB as a 1-4 scale, where 1 represents “corruption not generalized” and 4 “very generalized” (p. 22). (LAPOP, n.d.-a) I dichotomize this variable taking values greater than 1 as perceiving corruption. Corruption tolerance is measured as tolerance to paying a bribe, where 0 is not justified, and 1 is justified. The empirical analysis also includes socioeconomic controls, where labour market status includes three categories: employed, not in the labour force, and unemployed. Not being in the labour force includes retired, students, homemakers, and those not working. Education is a categorical variable for highest educational degree attained, including levels for no education, primary, secondary, and higher education (college, university or higher are lumped together).

Table 1: Descriptive statistics for the matched AB data and weather variables

		N	Percent	Missing (%)	Mean	Std. dev.	Min	Median	Max	Percent
Education	None	183	1.10	100						1.10
	Primary	3748	22.48	100						22.48
	Secondary	7610	45.64	100						45.64
	Superior	3441	20.64	100						20.64
Female	Male	7286	43.69	100						43.69
	Female	6065	36.37	100						36.37
Labour market status	Employed	7887	47.30	100						47.30
	Not in Labour Force	5559	33.34	100						33.34
	Unemployed	1577	9.46	100						9.46
Worse perception of personal economy	Better or Same	10010	60.03	100						60.03
	Worse	6415	38.47	100						38.47
Worse perception of country economy	Better or Same	7744	46.44	100						46.44
	Worse	5711	34.25	100						34.25
Perception of corruption	Not Corrupt	4667	27.99	100						27.99
	Corrupt	6230	37.36	100						37.36
Tolerance to bribes	Not Tolerant	10580	63.45	100						63.45
	Tolerant	2688	16.12	100						16.12
	Presidential approval	14997	100.00	10	0.49	0.50	0.00	0.00	1.00	100.00
	Daily minimum temperature (C)	15749	100.00	6	16.35	6.57	−2.17	18.27	27.78	100.00
	Daily maximum temperature (C)	15749	100.00	6	24.40	4.86	8.40	25.28	34.34	100.00
	Daily average temperature (C)	15749	100.00	6	20.37	5.51	4.55	21.97	29.28	100.00
	Daily precipitation (mm)	15820	100.00	5	5.20	8.55	0.00	2.06	236.47	100.00
	Age (years)	16649	100.00	0	37.93	15.67	16.00	35.00	96.00	100.00
	Ideology score (0-10)	9222	100.00	45	5.35	2.46	1.00	5.00	10.00	100.00
	Political pride score	14899	100.00	11	4.12	1.79	1.00	4.00	7.00	100.00
	Trust in police score (0-7)	13589	100.00	19	3.97	1.79	1.00	4.00	7.00	100.00
	Trust in local government score (0-7)	15055	100.00	10	3.94	1.77	1.00	4.00	7.00	100.00

Note: Descriptive statistics for variables used in the empirical analysis. For categorical variables, the percent of observations in the category out of the total sample is presented. For numerical (either ordinal or continuous) variables, the mean, standard deviation, minimum and maximum are presented. For both, the number of observations and the percentage of missing values.

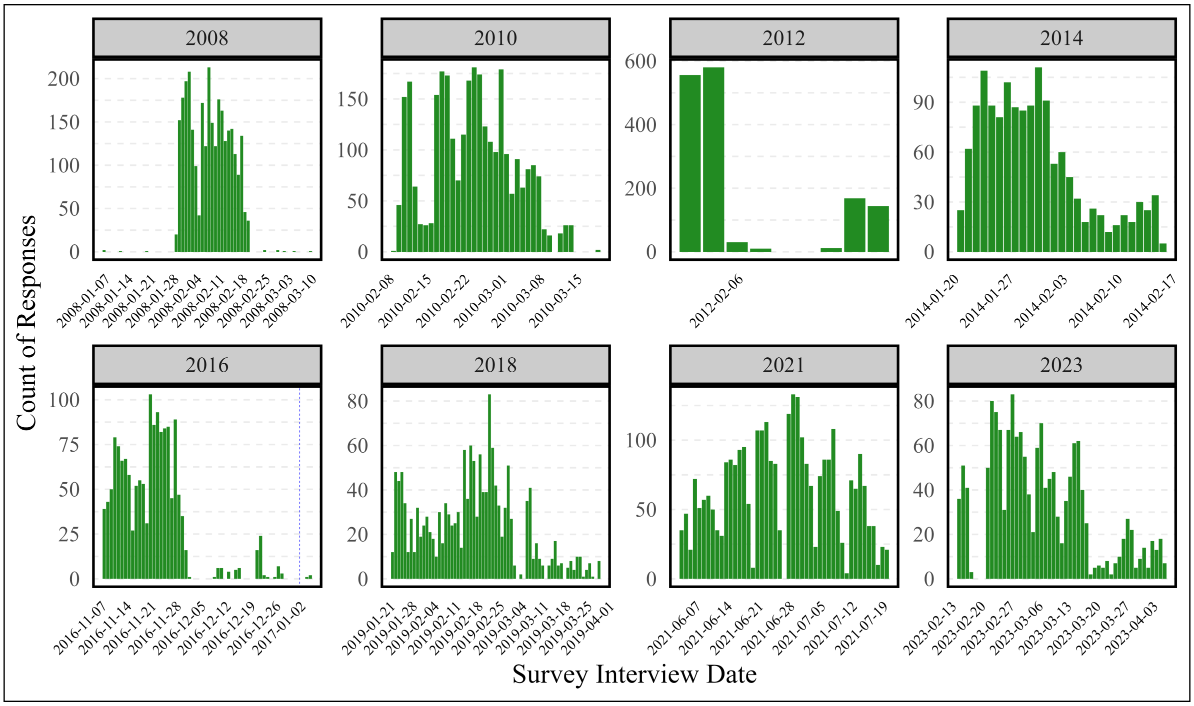
I extract daily minimum and maximum temperature and precipitation data from the CPC Global Unified Temperature datasets (National Oceanic and Atmospheric Administration (NOAA) Physical Sciences Laboratory (PSL), 2024). These data are prepared by the U.S. government National Oceanic and Atmospheric Administration (NOAA) and emerge from satellite imaging of the Earth surface. While daily weather data would typically be available from every country's meteorological authority[3], publicly available meteorological data from weather stations lacks the frequency and geospatial granularity required for this type of analysis.

The temperature data from NOAA is of lower quality than that of a typical meteorological authority, given that this data is global gridded GTS data (0.5°×0.5°) for temperature and gauge-based for precipitation. However, I follow Quijano-Ruiz (2023) and compute weighted mean minimum and maximum temperatures for each canton and day, where the weights are the surface area of each canton. Replication code for this process is publicly available in a GitHub repository. The surface area of each canton is obtained the Ecuadorian statistics authority (INEC, for its initials in Spanish) geoportal, along with the map shapefiles and political administrative divisions to match the canton names and codes to the AB data (Instituto Nacional de Estadística y Censos, n.d.). I then merge this data with the AB data using interview dates and canton codes as join identifiers.

Figure 1 shows the distribution of respondents by interview date in the AmericasBarometer

[3] In Ecuador, the relevant institution is the Instituto Nacional de Meteorología e Hidrología.

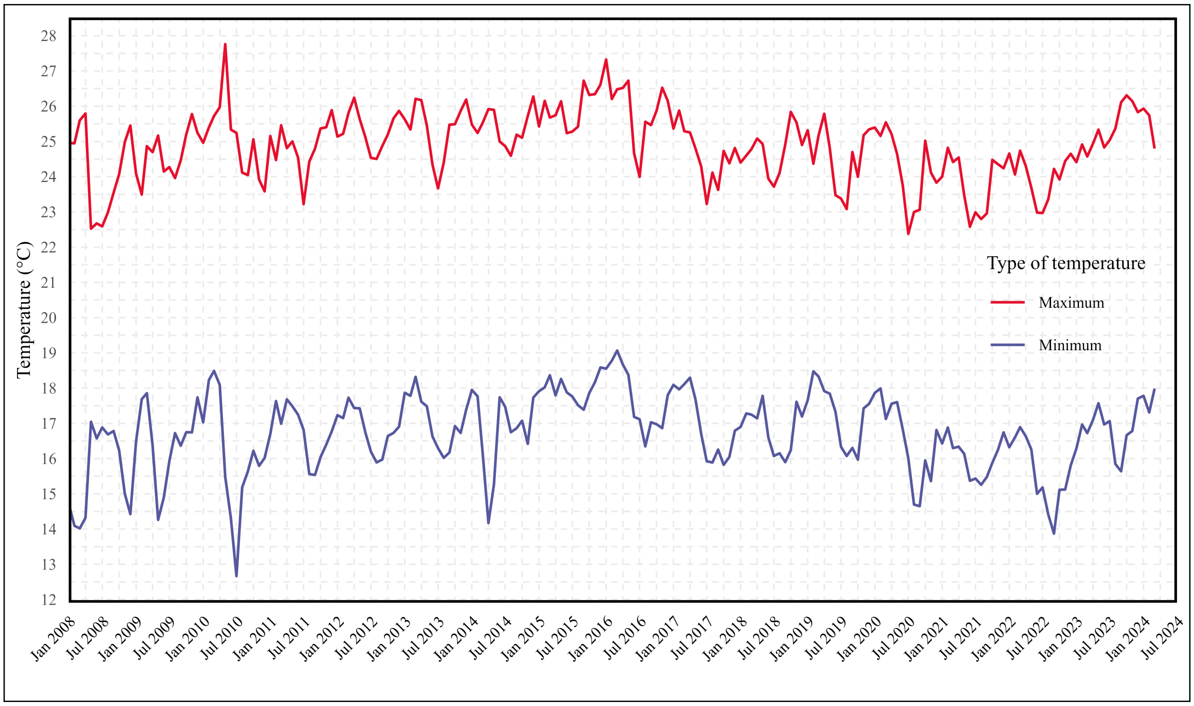
Figure 1: Survey dates of the Americas Barometer in Ecuador, 2008-2023



survey waves. As it can be seen, most stay in a relatively small time frame. The 2018 wave (sometimes referred as the 2018/19 wave) is the most spread out due to the survey being carried out between late 2018 and early 2019. Most waves are carried out January to April. These periods contain rich variation of temperature across cantons.

In Figure 2 above I show mean monthly minimum and maximum temperatures from 2008 to 2023. There are no notable upward or downward trends through time, with some periods showing higher temperatures. An important feature is that the spread between minimum and maximum temperatures is relatively stable, which will be important for the identification strategy, which I describe below.

Figure 2: Mean monthly temperatures, 2008-2023



3.2 Identification strategy

I exploit variation produced by a natural experiment: the transitory nature of daily temperature changes. I assume these changes are random and exogenous to variables related to political mechanisms or other variables that can affect the performance of political leaders. By making this assumption, I can define a presidential popularity function as follows:

$$\text{approval}_{it} = \alpha + \tau_d + \theta_j + \beta \text{temp}_{jd} + \mathbb{X}'_{it}\gamma + u_{it} \tag{1}$$

where approval_{it} is presidential approval, τ_d and θ_j are vectors of interview date and canton fixed effects, temp_{jd} is daily temperature, $\mathbb{X}'_{it}$ a vector of survey-wave and individual varying controls, γ the vector of associated control coefficients and u_{it} an error term. The parameter β is the coefficient of interest, which measures the effect of temperature on presidential approval. The assumption of randomness in daily temperature changes implies that

$$\mathrm{E}[\text{temp}_{jt} \times u_{it}] = 0 \tag{2}$$

which allows me to estimate β consistently.

A potential wory is that temperature, as measured by the CPC Global Unified Temperature data, suffers from measurement error, $\hat{\beta}$ can suffer from attenuation bias, which leads to underestimation of the true effect of temperature on presidential approval. Attenuation bias will exist if measurement error is more likely to be present in days with higher or lower temperatures, or for certain cantons. There is no reason to assume this is the case, but I address this possibility in the conclusion. If measurement error is present but not correlated with the error term, then $\hat{\beta}$ will still be consistently estimated, but with less precision.

Further, given that I only observe presidential approval in an ordinal or binary scale, I cannot directly estimate Equation 1. While it is possible to use a linear probability model, I choose to follow the literature and use logistic regression to estimate a variant of Equation 1, as follows:

$$P(\text{approval}_{it} = 1) = G(\lambda \mathbf{R'}) = G(\alpha + \tau_d + \theta_j + \beta \text{temp}_{jd} + \mathbb{X}'_{it}\gamma + u_{it}) \quad (3)$$

where $P(\text{approval}_{it} = 1)$ is the probability of approving the incumbent president, G is the link function, $\mathbf{R}$ is a vector of explanatory variables, which includes all variables in Equation 1, and λ is the associated vector of coefficients. I estimate Equation 2 using the logistic function as G. I cluster all standard errors at the canton level, to allow for spatially clustered correlation in the error term.

4 Results

4.1 Baseline specifications

Table 3 shows baseline results of the logit fixed effects estimation of Equation 3, which are the baseline empirical models of the paper. These only include weather variables and canton and interview date fixed effects. The results from these specifications serve as a benchmark for the subsequent models that include additional control variables, as suggested by my review of the Theory in Section 2. Further, models without any type of political behaviour controls leverage a large sample size, as I do not lose any observations due to missing values. I later estimate models with controls to examine the robustness of the baseline results and the existence of omitted variable bias.

Specification (1) considers only daily minimum temperature as a weather variable, which shows a positive logit coefficient which is not statistically distinguishable from zero at any conventional significance level. Specification (2) only includes maximum daily temperature, which shows a negative logit coefficient that is statistically significant at the 0.01 level. Specification (3) includes my measure of average temperature, again showing no statistically significant relationship between temperature and presidential approval.

Specification (4) considers the relationship between both minimum and maximum daily temperature variables, to account for possible interconnected relationships between these two variables. I also include a daily precipitation variable, to account for the possibility that a more humid rain may have an additional effect on approval ratings. It is shown that maximum temperature keeps its significance at the 0.01 level, while the other weather variables remain statistically insignificant at any conventional significance level. It is valuable to note that standard errors for all of my coefficients in this table are not notably large, which suggests that the lack of statistical significance may not be due to a lack of precision. The sign of the coefficients is evidence which supports the hypothesis that voters may commit attribution errors when evaluating politician’s performance, and tend to evaluate the president worse in days with higher temperatures, as per my hypothesis of mood misattribution.

Figure 3: Marginal Effects of Max. Temperature on Presidential Approval

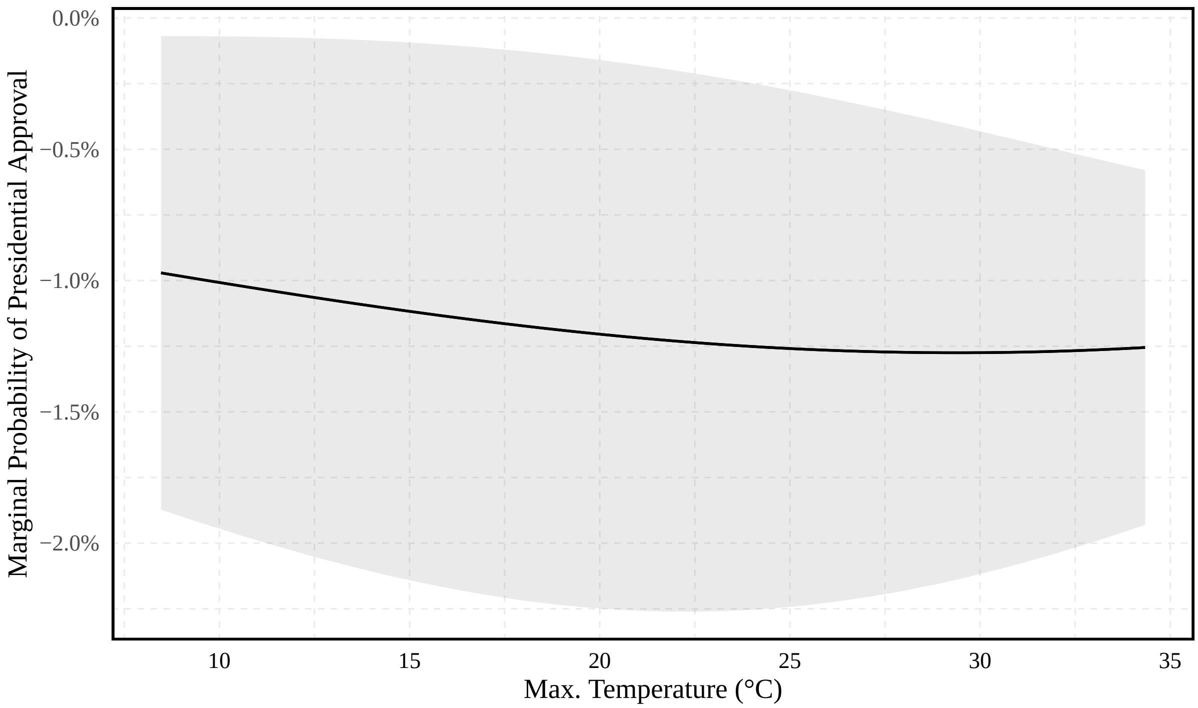


Figure 3 shows the marginal effects plot of maximum temperature on presidential approval from Specification (4). The plot shows that the marginal probability of presidential approval decreases as maximum temperature increases. At about 10°C of maximum daily temperatures, an additional degree makes survey respondents one percent point less likely to approve of the president. At the highest maximum temperature, which is about 34°C, an additional degree (a warmer day) makes survey respondents about 1.3 percent points less likely to approve of the president. These translate to an average marginal effect of -1.1%, as it can be seen in the Appendix, which presents average marginal effects for all the tables in the paper.

4.2 Controlling for political behaviour

Table 2: Logit coefficients for specifications with controls

	(1)	(2)	(3)	(4)
Min. temperature (°C)	0.013			0.014
	(0.059)			(0.054)
Max. temperature (°C)		−0.107***		−0.112***
		(0.031)		(0.029)
Avg. temperature (°C)			−0.110*	
			(0.060)	
Precipitation (mm)				−0.008
				(0.006)
Female	−0.126***	−0.128***	−0.130***	−0.127***
	(0.053)	(0.053)	(0.053)	(0.053)
Age	0.004*	0.003*	0.003*	0.003*
	(0.002)	(0.002)	(0.002)	(0.002)
Rural area	−0.044	−0.057	−0.049	−0.053
	(0.112)	(0.114)	(0.113)	(0.116)
Primary education (ref. No education)	0.114	0.112	0.120	0.109
	(0.339)	(0.334)	(0.334)	(0.335)
Secondary education	0.134	0.135	0.140	0.130
	(0.341)	(0.336)	(0.336)	(0.337)
Higher education	0.065	0.064	0.071	0.059
	(0.347)	(0.342)	(0.342)	(0.343)
Not in Labour Force	−0.068	−0.063	−0.061	−0.066
	(0.060)	(0.061)	(0.060)	(0.060)
Unemployed	−0.172	−0.179	−0.174	−0.180
	(0.114)	(0.115)	(0.114)	(0.115)
Perceived worse personal economy	−0.404***	−0.406***	−0.402***	−0.407***
	(0.087)	(0.087)	(0.088)	(0.087)
Perceived worse country economy	−0.731***	−0.729***	−0.730***	−0.728***
	(0.087)	(0.087)	(0.087)	(0.087)
Ideology score (0-10)	−0.053***	−0.052***	−0.053***	−0.052***
	(0.016)	(0.016)	(0.016)	(0.016)
Supports democracy	0.405***	0.408***	0.407***	0.407***
	(0.089)	(0.090)	(0.090)	(0.090)
Political pride score (0-7)	0.219***	0.218***	0.217***	0.218***
	(0.022)	(0.022)	(0.022)	(0.022)
Perceives corruption	0.272***	0.278***	0.277***	0.277***

Table 2: Logit coefficients for specifications with controls *(continued)*

	(1)	(2)	(3)	(4)
	(0.090)	(0.089)	(0.090)	(0.089)
Tolerates bribes	−0.243***	−0.252***	−0.251***	−0.249***
	(0.092)	(0.091)	(0.091)	(0.091)
Trust in police score (0-7)	0.116***	0.118***	0.117***	0.117***
	(0.021)	(0.021)	(0.021)	(0.021)
Trust in local gov. (0-7)	0.058	0.058	0.059	0.059
	(0.044)	(0.044)	(0.044)	(0.043)
N	5855	5855	5855	5855
AIC	7194	7183	7189	7185
RMSE	0.443	0.442	0.443	0.442
Canton fixed effects	X	X	X	X
Interview date fixed effects	X	X	X	X

Note: Models explaining presidential approval through daily weather variables and controls. Standard errors shown in parentheses are clustered by canton. ***p<0.01, **p<0.05, *p<0.1.

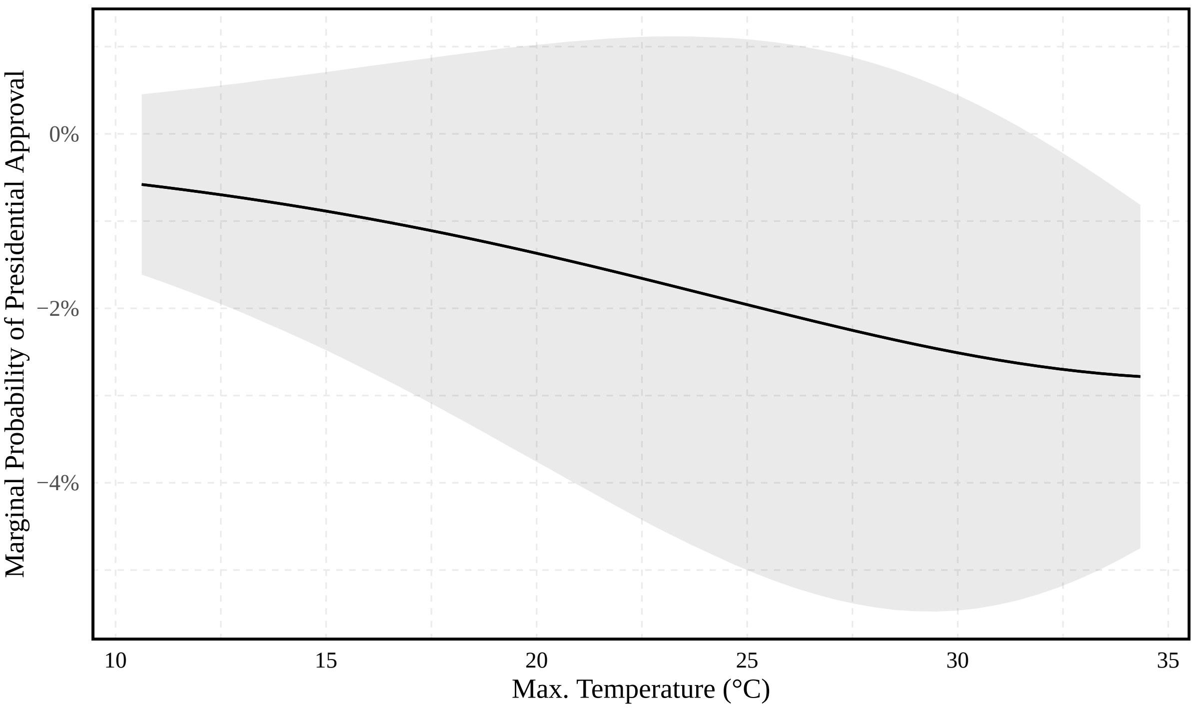
Table 4 shows the results of the logit fixed effects estimation of Equation 1 with additional political behaviour controls. I control for regular demographic and socioeconomic variables, as well as political ideology and behaviour. Further, I control for sex, age and rural status (vs. an urban status reference level). I also compare the effect of different levels of education, where my reference level is no reported education level (0 years of education). For labour market status, I consider four categories, where the reference level is being employed and binary variables for not being the labour force (retired, not working, student, and homemakers.) and being unemployed (looking actively for a job). Personal perceptions of both personal and country economic situations are included too. The country's economic situation is particularly informative, given that it partials out the relationship of economic voting from the weather variables, as I pointed out in the theory section.

I also control for political ideology. Finally, I include variables for democracy support, political pride, corruption perceptions, corruption tolerance (bribes) and trust scores for police and local government. By including these controls, I aim to address any potential omitted variable bias that could bias estimates in Table 1. A disadvantage to these models is that lose a large amount of observations, since not all questions are asked consistently across survey rounds. Further, I completely lose the 2021 wave due to a lack of the most fundamental controls, which were not asked due to the restricted survey design which was adopted to the COVID-19 pandemic.

Specifications (1) through (4) are the same as in Table 3, but with the addition of the political behaviour controls. These results show that the sign and statistical significance of daily maximum temperature remain unchanged, showing that the relationship between temperature and presidential approval is robust to the inclusion of these controls. Further, I also find a negative and statistically significant relationship between presidential approval and my measure of average temperature in specification (3), which was not present in the baseline models.

With regard to the political behaviour controls, I find that the relationship between presidential approval and my controls is consistent with the literature. Those who perceive the country's economic situation as worse are less likely to approve of the president, as are those who perceive the country as more corrupt and those more tolerant to bribes. The former result is consistent with most of the literature on economic voting. Further, I find that support for democracy, police, and political pride are positively related to presidential approval, while the opposite is true for those who are more right-wing and those who are unemployed. No demographic or socioeconomic variables are statistically significant at any conventional significance level other than sex (female).

Figure 4: Marginal Effects of Max. Temperature on Presidential Approval with Controls



Above, Figure 2 the marginal effects plot of maximum temperature on presidential approval from Specification (4) with controls is shown. Comparing to Figure 1, it is shown that the inclusion of controls does not change the decreasing marginal probability of presidential approval across maximum temperature. The relationship is in fact increased after controls are included, suggest a downward bias in the baseline models. The average marginal effect of maximum temperature on presidential approval is -2.2%, as it can be seen in the Appendix.

4.3 Heterogenous effects of temperature on presidential approval

In this subsection I allow for heterogeneity in the effect of temperature on presidential approval by including an interaction term. Table 3 below follows the general model below.

$$y_{it} = \alpha + \tau_t + \theta_j + \beta \,\text{temp}_{it} + \mathbb{X}'_{it}\gamma + \delta \,\text{temp}_{it} \times g_{it} + u_{it} \tag{4}$$

All variables are defined as in Equation 1, but I include an interaction term between temperature and any explanatory variable g_{it}, which before used to be included in the vector of controls $\mathbb{X}'_{it}$. In this subsection, I explore important covariates that can interact with temperature to affect presidential approval, which are region[4], perceived economic situations for both the country and the respondent, and political ideology. If the interaction term is statistically significant, it would suggest that the effect of temperature on presidential approval is not constant across the population, and that the relationship between temperature and presidential approval is conditional on the value of the covariate. The controls on vector $\mathbb{X}'_{it}$ are the same as in Table 2 for this subsection, but are not shown in the table for brevity.

[4] I did not include region as a explanatory variable in other models since it would induce perfect collinearity.

Table 3: Logit coefficients for models with interaction terms

	(1)	(2)	(3)	(4)
Min. temp. (°C)	0.000	0.025	0.010	−0.050
	(0.057)	(0.057)	(0.059)	(0.070)
Max. temp. (°C)	−0.082***	−0.117***	−0.092***	−0.020
	(0.037)	(0.034)	(0.033)	(0.045)
Coastal × Min. temp. (°C)	0.061			
	(0.043)			
Amazon × Min. temp. (°C)	0.037			
	(0.056)			
Coastal × Max. temp. (°C)	−0.026			
	(0.054)			
Amazon × Max. temp. (°C)	−0.065*			
	(0.033)			
Worse country econ. × Min. temp. (°C)		−0.031		
		(0.022)		
Worse country econ. × Max. temp. (°C)		0.018		
		(0.030)		
Worse personal econ. × Min. temp. (°C)			−0.019	
			(0.023)	
Worse personal econ. × Max. temp. (°C)			0.005	
			(0.032)	
Ideology score × Min. temp. (°C)				0.011***
				(0.005)
Ideology score × Max. temp. (°C)				−0.014***
				(0.006)
N	5855	5855	5205	5205
AIC	7182	7185	6375	6368
RMSE	0.442	0.442	0.444	0.444
Canton fixed effects	X	X	X	X
Interview date fixed effects	X	X	X	X

Note: Models allowing for heterogeneous effects of temperature on presidential approval. Regional categories hold the Highlands region as the reference level. Standard errors shown in parentheses are clustered by canton. ***p<0.01, **p<0.05, *p<0.1.

These results show that heterogeneity exists in the effect of the temperature on presidential approval between different regions in the country. Survey respondents from the Amazon region are less likely to approve of the president at higher values of maximum temperature compared to those in the Highlands region. As pointed out in the background section, the Amazon region is the most humid and warm region in the country, which could explain this result if weather truly affects presidential approval. However, the AmericasBarometer surveys very little respondents in Amazon cantons, which is why this result is very preliminary. Survey respondents from the Coastal region do not show a statistically significant difference between temperature and presidential approval compared to those in the Highlands region. Given the large difference in temperatures between the Highlands and the Coastal region, this result is surprising and could point to biases in the estimation process.

I find no heterogeneity between personal and country economic situations, which suggests that economic voting may be unrelated to mood misattribution. Ideology does interact with temperature to affect presidential approval, but results are unclear. Citizens who identify closer to the political right are more likely to approve of the president at higher values of minimum temperature, but at the same time are likely to disapprove of the president at higher values of maximum temperature. In the Appendix, it is shown that the average marginal effect of minimum temperature is still statistically insignificant, while the average marginal effect of maximum temperature is -1.9%.

5 Conclusion

This paper has shown that daily temperature has a significant negative effect on presidential approval in Ecuador. Survey respondents are about 1.9 to 2.2 percentage points less likely to approve of the president when maximum daily temperatures increase by one degree. This result is robust to the inclusion of socioeconomic and political behaviour controls, including variables which control for partisanship, trust in the police, democracy, personal ideology identification, evaluations of the economy, among others. These results are consistent with some literature on retrospective voting and voter errors, which suggests that voters may commit attribution errors when evaluating politician's performance. I validate findings from Barrington-Leigh & Behzadnejad (2017), Lignier et al. (2023) and Quijano-Ruiz (2023), who find that weather impacts behaviour.

I argue that the weather affects the mood of individuals negatively, and in turn individuals search externally for factors to validate their mood. This leads to a misattribution of mood to the president's performance, which results in lower approval ratings. The causal mechanism which explains these empirical findings rests on psychological theories of mood misattribution. These describe that individuals in a bad mood are more likely to report feelings of life dissatisfaction, and that they are more likely to attribute their mood to external factors (Bower, 1981; Schwarz & Clore, 1983). I argue that warmer weather in Ecuador may lead to a negative moods, which in turn makes citizens direct their emotions towards the president's performance. This is consistent with the literature on the impact of weather across a range of outcomes, which finds that weather can have a significant impact on behaviour (Barrington-Leigh & Behzadnejad, 2017; Deller & Michels, 2022; Keller et al., 2005; Lignier et al., 2023; Quijano-Ruiz, 2023).

The results also show that the effect of temperature on presidential approval is not constant across the population. Women are more sensitive to higher temperatures than men, also found by Quijano-Ruiz (2023) using CPC weather data in Ecuador and by Barrington-Leigh & Behzadnejad (2017) in Canada. I find that the effect of temperature on presidential approval is conditional on the region of the country and the political ideology of the survey respondent. The result of heterogeneity across ideological groups produces conflicting results, suggesting that minimum and maximum temperatures have different effects on survey respondents identifying closer to the political right. I find no difference of the effect of temperature between those that negatively evaluate the economy compared to those who evaluate it positively or equal relative to last year. Results for regional heterogeneity, while understandable given that the Amazon region is the most humid and warm region in the country, are preliminary and should be taken with caution, because of the small sample size of the Amazon region in the AmericasBarometer surveys.

In the same line as Quijano-Ruiz (2023), who pioneers the use of CPC weather data in health services research, I introduce the use of this data for political behaviour studies, with promising results. CPC temperature data, though of lesser quality than weather station data, is of invaluable use for countries where weather station data is not available. There is a possibility that my temperature variables are subject to measurement error, which could bias my results. If this is the case, then my results are likely to be downward biased, which would suggest that the true effect of temperature on presidential approval is larger than what I estimate in this paper. The fact that I am able to find statistically significant results in an observational setting suggests that the true effect of temperature on presidential approval is likely to be larger, and future research should aim to address this possibility by using more precise temperature data, and by using more sophisticated methods to address measurement error. Replicating this study in other countries where temperature data of higher quality is available would also be valuable, in order to validate these results and understand the precision of CPC weather data for political science research.

I model the effect of temperature on presidential approval in a linear manner, which may be innacurate, given the complex nature of weather and the behavioural responses that weather may cause. Weather likely has a nonlinear effect on mood, which should be modeled with more sophisticated methods in future research to more accurately understand the effect of weather on presidential approval. I am also limited in the way that the AmericasBarometer is collected, which is bienally, and does not allow me to observe the effect of temperature on presidential approval in more granular frequencies and lower levels of spatial aggregation such as parishes or neighbourhoods.

Understanding how temperature and other weather-related variables affect political behaviour is important for extending the literature on attribution errors and retrospective voting, but even more so for understanding the way that political behaviour works in Latin America, a region which has been severely understudied in the literature. This paper is a first step in understanding the effect of weather on political behaviour in the literature, which moves away from the focus on standard variables which have been proven to be influenced by factors not present in developed countries. Understanding these mechanisms is important for better research, but also to enact public policy for democratic accountability.

6 References

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Appendix: Average marginal effects

Table 4: Average partial effects for baseline models in Table 3

	(1)	(2)	(3)	(4)
Min. temperature (°C)	0.004			0.006
	(0.006)			(0.006)
Max. temperature (°C)		−0.010***		−0.011***
		(0.004)		(0.004)
Avg. temperature (°C)			−0.005	
			(0.008)	
Precipitation (mm)				−0.001
				(0.001)
N	14 118	14 118	14 118	14 118
AIC	18 302	18 297	18 302	18 297
RMSE	0.465	0.465	0.465	0.465

Note: Average partial effects for baseline models explaining presidential approval through daily weather variables and canton and interview date fixed effects. Standard errors shown in parentheses are clustered by canton. ***p<0.01, **p<0.05, *p<0.1.

Table 5: Average partial effects for models with controls in Table 4

	(1)	(2)	(3)	(4)
Min. temperature (°C)	0.002			0.003
	(0.011)			(0.010)
Max. temperature (°C)		−0.021***		−0.022***
		(0.008)		(0.007)
Avg. temperature (°C)			−0.021	
			(0.014)	
Precipitation (mm)				−0.001
				(0.001)
Female	−0.025***	−0.025***	−0.025***	−0.025***
	(0.011)	(0.011)	(0.011)	(0.011)
Age	0.001*	0.001*	0.001*	0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Rural area	−0.009	−0.011	−0.010	−0.010
	(0.022)	(0.023)	(0.022)	(0.023)
Primary education (ref. No education)	0.022	0.022	0.024	0.021
	(0.067)	(0.065)	(0.066)	(0.066)
Secondary education	0.026	0.027	0.028	0.026
	(0.067)	(0.066)	(0.066)	(0.066)
Higher education	0.013	0.013	0.014	0.012
	(0.068)	(0.067)	(0.068)	(0.068)
Not in Labour Force	−0.013	−0.012	−0.012	−0.013
	(0.012)	(0.012)	(0.012)	(0.012)
Unemployed	−0.034	−0.035	−0.034	−0.035
	(0.023)	(0.023)	(0.023)	(0.023)
Perceived worse personal economy	−0.081***	−0.081***	−0.081***	−0.082***
	(0.019)	(0.017)	(0.019)	(0.019)
Perceived worse country economy	−0.151***	−0.150***	−0.150***	−0.150***
	(0.019)	(0.018)	(0.018)	(0.018)
Ideology score (0-10)	−0.010***	−0.010***	−0.010***	−0.010***
	(0.003)	(0.004)	(0.004)	(0.003)
Supports democracy	0.081***	0.081***	0.081***	0.081***
	(0.019)	(0.016)	(0.020)	(0.019)
Political pride score (0-7)	0.043***	0.043***	0.043***	0.043***
	(0.005)	(0.005)	(0.005)	(0.005)
Perceives corruption	0.054***	0.055***	0.055***	0.055***
	(0.020)	(0.017)	(0.020)	(0.020)
Tolerates bribes	−0.048***	−0.050***	−0.050***	−0.049***

	(0.019)	(0.018)	(0.019)	(0.019)
Trust in police score (0-7)	0.023***	0.023***	0.023***	0.023***
	(0.005)	(0.004)	(0.004)	(0.004)
Trust in local gov. (0-7)	0.011	0.011	0.012	0.011
	(0.009)	(0.009)	(0.009)	(0.009)
N	5855	5855	5855	5855
AIC	7194	7183	7189	7185
RMSE	0.443	0.442	0.443	0.442

Note: Average partial effects for models explaining presidential approval through daily weather variables, canton and interview date fixed effects, and political behaviour controls. Standard errors shown in parentheses are clustered by canton. ***p<0.01, **p<0.05, *p<0.1.

Table 6: Average partial effects for models with interaction terms in Table 5

	(1)	(2)	(3)	(4)
Min. temperature (°C)	0.006	0.003	0.001	0.002
	(0.009)	(0.010)	(0.011)	(0.011)
Max. temperature (°C)	−0.020***	−0.022***	−0.018***	−0.019***
	(0.008)	(0.008)	(0.009)	(0.009)
Precipitation (mm)	−0.002	−0.002	−0.002	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Female	−0.025***	−0.025***	−0.027***	−0.027***
	(0.011)	(0.011)	(0.013)	(0.013)
Age	0.001*	0.001*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Rural area	−0.006	−0.011	−0.012	−0.011
	(0.023)	(0.023)	(0.026)	(0.026)
Primary education (ref. No education)	0.022	0.020	−0.034	−0.030
	(0.066)	(0.066)	(0.073)	(0.073)
Secondary education	0.027	0.024	−0.039	−0.036
	(0.067)	(0.066)	(0.074)	(0.074)
Higher education	0.013	0.011	−0.053	−0.050
	(0.068)	(0.068)	(0.074)	(0.074)
Not in Labour Force	−0.013	−0.013	−0.019	−0.019
	(0.012)	(0.012)	(0.013)	(0.013)
Unemployed	−0.033	−0.035	−0.038	−0.039
	(0.023)	(0.023)	(0.024)	(0.024)
Perceived worse personal economy	−0.082***	−0.082***	−0.083***	−0.084***
	(0.019)	(0.019)	(0.021)	(0.022)
Perceived worse country economy	−0.148***	−0.150***	−0.161***	−0.158***
	(0.017)	(0.016)	(0.024)	(0.023)
Ideology score (0-10)	−0.010***	−0.010***	−0.013***	−0.013***
	(0.004)	(0.004)	(0.004)	(0.004)
Supports democracy	0.079***	0.081***	0.082***	0.081***
	(0.019)	(0.019)	(0.025)	(0.024)
Political pride score (0-7)	0.043***	0.043***	0.043***	0.044***
	(0.005)	(0.005)	(0.008)	(0.008)
Perceives corruption	0.054***	0.055***	0.064***	0.062***
	(0.020)	(0.020)	(0.027)	(0.026)
Tolerates bribes	−0.050***	−0.049***	−0.053***	−0.053***
	(0.020)	(0.019)	(0.020)	(0.021)
Trust in police score (0-7)	0.023***	0.023***		

	(0.004)	(0.004)		
Trust in local gov. (0-7)	0.011	0.012	0.014	0.014
	(0.009)	(0.009)	(0.010)	(0.010)
N	5855	5855	5205	5205
AIC	7182	7185	6375	6368
RMSE	0.442	0.442	0.444	0.444

Note: Average partial effects for models allowing for heterogeneous effects of temperature on presidential approval. Standard errors shown in parentheses are clustered by canton. ***p<0.01, **p<0.05, *p<0.1.