Estimating Voters’ Taste for Risk: 
Candidate Choice under Uncertainty

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1 Introduction

When citizens enter the voting booth on election day, they do so in an environment where the stakes are often unclear. Over the last 40 years, political scientists have been interested in the choice dynamics at work in such situations. Voters may be uncertain of the competence of the candidates, the likelihood that a given candidate will win the election, and even of their own policy positions. But a central concern to political scientists has been uncertainty about the positions taken by candidates on the controversies of the day, and the effect of such uncertainty on the attractiveness of candidates to voters.

Recent work in political science has taken up the question of issue voting under conditions of uncertainty—situations in which voters have imperfect information about the policy positions of candidates. Models that recognize this principle are certainly realistic portrayals of the campaign environment. But these studies may be limited in important respects. Specifically, to date, the study of vote choice under uncertainty has made a common assumption of quadratic preferences implying that citizens behave in a very risk-averse manner when casting votes (see Davis, Hinich, and Ordeshook 1970; Enelow and Hinich 1981; Bartels 1986; Alvarez 1997, Hinich and Munger 1994, though see Shepsle 1972). But this is simply a modelling choice. Many other utility functions consistent with “proximity” voting could be chosen, including functions that imply risk neutral and risk acceptant behavior in the sense developed below.\footnote{In what follows, we develop a non-standard, but, we believe, more accurate definition of risk preference in the context of spatial modelling. While no single-peaked utility function can be globally risk acceptant under the standard mathematical formalization of risk aversion, globally risk acceptant spatial preference are possible using the formalization developed below.}

The assumption of risk-aversion is not simply a technical choice: it has important implications for how we view the process of citizen choice in elections and campaigns. If voters are risk-averse, candidates can benefit by making clear their positions on issues that they know will appeal to the electorate. Risk-averse voters therefore improve the quality of campaign discourse because candidates are punished for taking vague positions. But this scenario is only one among several possibilities. If voters are risk-neutral or risk-acceptant, candidates may have incentive to muddle the details of their policy plans and send ambiguous signals.
about their positions (Shepsle 1972). Such a story of the campaign process may be less normatively appealing than one in which voters are risk-averse, but it might also more accurate portray the dynamics of political campaigns. We believe that the nature of risk preferences among the electorate should, therefore, be subject to greater scrutiny.

There is a long research tradition to draw upon in such an undertaking. Understanding choice under uncertainty is a enduring topic in economics and psychology (for example, Pratt 1957, Arrow 1964, Stiglitz 1969, Keeney & Raiffa 1979, Kahneman & Tversky 1979, Wolf & Polman 1983, Hey & Orme 1994, Camerer 1995). Tastes for risk preferences have been studied in the context of gambling (Weitzman 1965, Ali 1970, Quandt 1986, Woodland & Woodland 1991, Jullien & Salanie 2000), insurance (Viscusi & Evans 1990, Cicchetti & Dubin 1994), and duration of unemployment (Feinberg 1977) to name a few. In the main, two questions have been posed. First, is observed behavior consistent with the expected utility hypothesis of Savage and Friedman (1954; see also Kahneman & Tversky 1979)? Second, to the extent that such behavior is consistent with the precepts of expected utility, what are individuals’ tastes for risk?

Economists interested in these questions have found that, on the whole, risk preferences are context dependent; risk-averse behavior is observed in insurance and durable goods markets, while risk-acceptant behavior is observed in gambling markets. Horse races and consumer marketing are common analogies for political campaigns. It is appropriate to ask, then, whether the voting booth is more similar to the betting window or the appliance store. The answer contributes to the understanding of choice under uncertainty in general and the understanding of voting behavior and democratic politics in particular. In this paper, we do just this. Specifically, we move beyond the assumption of a particular spatial utility function and estimate voter’s preferences for risk. We find that, contrary to the literature, voters are less risk averse than the quadratic model implies. Indeed, by the definition of risk preference developed below, we find voters to be generally (nearly) risk-neutral and, in some cases, risk-acceptant.

The paper proceeds as follows. Section 2 develops the notion of tastes for risk in the context of spatial voting models. Section 3 presents a method for the estimation of risk preference. Section 4 describes the data to which the method is applied. Section 5 presents
results of the estimation. Section 6 concludes.

2 Risk Preferences in Spatial Models

As Lipshitz and Strauss (1997) note, the lack of a fixed definition of uncertainty often results in confusion in the study of such uncertainty. It is therefore important for us to spend some time describing our definition of uncertainty and our understanding of preferences over risk. The canonical model of choice under uncertainty is the expected utility hypotheses (Savage and Freidman 1954, Pratt 1957, Arrow 1964), developed in the context of preferences over lotteries. We begin by briefly reviewing the foundations of this theory. The expected utility of a given lottery is characterized by a set of monetary endowments $W$ that an individual would obtain under each outcome of the lottery and a probability distribution, $P$, over those outcomes. The expected value of the lottery is simply the expected or long-run average utility that the lottery would provide the individual,

$$EU(W, P) = \sum_i p_i U(w_i)$$

where $i$ indexes the outcomes of the lottery and $U$ is a Von Neumann-Morganstern utility function that assigns a utility value to every possible level of wealth. By assumption, the utility function is increasing in wealth; more wealth is always preferred to less.

The expected monetary payoff of the lottery $(W, P), E(W)$, is $\sum_i w_i p_i$. $E(W)$ represents the actuarially “fair” value of the lottery in the sense that, in the long run, an individual who repeatedly faces the lottery would have, on average, the same wealth as an individual who repeatedly receives $E(W)$ with certainty. Note that the sure payoff of $E(W)$ is itself a (degenerate) lottery in which only outcome can occur. Thus, expected utility can be used to establish preferences over the choice between playing a particular lottery and receiving its actuarially fair value with certainty. This choice is often cast in terms of the willingness to pay the actuarially fair value of a lottery in order to play. Individuals are said to be “risk-averse” with respect to a lottery if, in order to play, they would be unwilling pay its actuarially fair value. That is, if they prefer the certain wealth of $E(W)$ they achieve by not
playing, to the risky lottery. Similarly, individuals are “risk-acceptant” or “risk seeking” if they would pay the actuarially fair price and “risk-neutral” if they are indifferent between lottery and its fair price.

Expected utility theory implies the so called “sure thing” principle. The principle states that regardless of taste for risk, no individual may prefer a lottery that pays at most \( m \) dollars to one that pays at least \( m \) dollars. For example, no individual would refuse to pay one dollar to play a lottery that pays at least two dollars to every entrant. This in turn implies that no individuals receive utility or disutility simply from engaging in risky lotteries per se.

Under the assumption that utility is increasing in wealth, risk preferences are reflected in the shape of the utility function in the following way. Concave utility functions imply risk aversion, convex functions imply risk acceptance, and linear utility functions imply risk-neutrality. Figure 2 illustrates this result. The figure considers a simple lottery over two outcomes \( w_l \) and \( w_h \) which occur with probability \( p \) and \( 1 - p \) respectively. When the utility function, is concave, as in the left-hand panel. Utility obtained from the certain payoff of \( E(W) \) is greater then the expected utility (\( EU(W,P) \)) of the lottery. When the utility function is convex, as in the right-hand panel. The expected value of the lottery lies above the utility that comes from obtaining the actuarially fair monetary payoff.

The definition of risk preferences in terms of the concavity or convexity of the utility function breaks down if the outcomes of the lottery are not expressed in terms of monetary endowments (or, more generally, some quantity in which utility is increasing). For example, consider a vastly simplified version of the casino game craps in which a single die is rolled. Suppose that the player receives a dollar payoff equal to the absolute difference between the outcome of the roll and 3.5. For example, if the die yields a 1 or a 6, the player receives $2.50. A simple calculation reveals that the expected monetary payoff of this game is about $1.83. We might then say that anyone unwilling to pay $1.83 to play the game is risk averse and anyone willing pay more than $1.83 is risk acceptant. By the sure thing principle we would expect all potential players to pay $0.50 (the minimum payoff) and no one to pay more than $2.50 the maximum payoff.

Now suppose that rather than defining utility over the monetary value of the outcomes,
Utility, Risk, and the Expected Utility Hypothesis

Figure 1: The panels show typical monotonically increasing utility functions. The left panel shows a risk-averse utility profile. Notice that the utility curve is concave, $U(E(w)) > EU(W, P)$, and $C(W, P) < E(w)$. The right-hand panel shows a risk seeking utility profile. Here the utility curve is convex, $U(E(w)) < EU(W, P)$, and $C(W, P) > E(w)$.
we define utility over the outcome of the roll, $x$. In this case,

$$U(x) = |x - 3.5|$$

Defining the utilities in this way presents no problem for analysis. The utility function defined over roll outcomes or monetary outcomes are identical in terms of their prediction about expected utility and, thus, choice behavior. However, with the utility function defined over the die roll, the definition of risk preference does not carry through. The average outcome of the roll, $E(X) = 3.5$, is the value that minimizes utility. Thus, by the sure thing principle, the lottery (roll of the die) must be preferred to the expected roll. The standard definition of risk preferences given above would therefore label all players risk acceptant with respect to this game because they all choose to roll the die rather than accept the zero payoff associated with the expected roll. Risk acceptance has been inferred from a choice involving no risk at all; every possible outcome of the game is preferable to the utility of zero that is associated with the expected outcome of the game. While none of our predictions about preferences are altered when we consider payoffs in terms of die outcomes rather than monetary payoffs, the attribution of risk aversion and acceptance is dramatically changed. If the same choice behavior does not imply the same risk preferences in these two cases, something in the definition of risk preferences must have broken down.

Put simply, the non-monotonicity of utility in the outcome of the die roll renders meaningless the comparison of the expected utility of the roll to the utility of the expected outcome. Indeed all roll outcome are preferred to expected outcome and there is no sense in which taste of risk taking bears on the choice to play the game lottery rather than accept its expected value. Regardless of risk preferences over dollar payoffs, *every* individual prefers to roll the die rather than receive the fixed payoff associated with average outcome of the roll. Only when utility is monotonically increasing in the measured outcome or payoff of the game is it reasonable to equate taste for risk with the choice between the expected outcome of a lottery and the lottery itself. Yet, this comparison is routinely and conventionally employed when analyzing uncertainty and risk in the context of spatial voting models which by definition involve non-monotonic (single-peaked) preferences.
2.1 The Spatial Model of Vote Choice under uncertainty

This logic has important implications for the characterization of voters’ risk preferences in the context of the spatial voting model of policy voting. We assume voters have single-peaked symmetric preferences over a policy outcome \( \theta \in \mathbb{R}^1 \) and have a most preferred or ideal point at \( \theta^* \). For the moment, we will assume there is only a single policy dimension. Thus preferences over the policy outcome have the form.

\[
U(\theta) = -g(|\theta - \theta^*|)
\]  

(1)

where \( g \) is a (strictly) monotonically increasing function. When deciding over two alternative policy outcomes, \( \theta \) and \( \theta' \), the specific form of \( g \) need not be specified. All that matters is which alternative is closer to \( \theta^* \). However, if voters must choose between lotteries over policy outcomes then specific functional form is central. In many respects, an election represents choice between lotteries. It is reasonable to assume that voters lack complete information about the positions each candidate will implement if elected. Thus, the choice of which candidate to vote for is, in essence, a choice among lotteries with names like Bush, Clinton, Gore, or Perot. If we assume voters vote sincerely, a vote reveals an individual’s most preferred policy lottery (candidate).

Each candidate can thus be described by the set of policies \( \Theta \), she might implement and a probability density \( f \) over those alternatives. For convenience, let \( \Theta = \mathbb{R}^1 \) for all candidates and let the density \( f(\theta) = 0 \) for all \( \theta \) which it is known with certainty that a given candidate will not implement. Thus, each candidate \( c \) is fully characterized by their probability distribution \( f_c \). The expected utility that a voter with ideal point \( \theta^* \) receives from a given candidate is

\[
EU(f, \theta^*) = -\int g(|\theta - \theta^*|) f(\theta) d\theta.
\]

(2)

Equation 2 is sufficient to fully describe voter choice under uncertainty in the spatial model. Often (Bartels 1986, Alvarez 1997; though see Jackson 1991, Westholm 1997) it is assumed \( g(t) = t^2 \) yielding the “quadratic” preferences model. In this case, Equation 2 can be
compactly expressed as,

\[ EU(f; \theta^*) = - (E(\theta) - \theta^*)^2 - V(\theta) \]

(see Enelow & Hinich 1981). Under these circumstances, \( EU \) is a function of only the mean and variance of the distribution of \( \theta \) and not its complete density, \( f \). Since, \( EU \) is decreasing in \( V(\theta) \), it seems reasonable to conclude that quadratic preferences are “risk-averse;” the more uncertainty (variance) there is in a candidate’s potential position, the less a voter with quadratic preferences likes that candidate. The quadratic utility function,

\[ U(\theta) = -(\theta - \theta^*)^2, \]

is concave in \( \theta \), which is one of indicators of risk aversion described above. Taken together these two facts might suggest that a good definition of risk preference in the spatial setting is simply the one used in the general economic setting described above. Risk-averse voters would be those with \( U \) concave in \( \theta \) and risk-acceptant voters are those with \( U \) convex in \( \theta \). This definition is commonly employed in the literature (Shepsle 1972). Further simplifying, some have identified risk-aversion as the situation where \( EU \) is decreasing in \( V(\theta) \).

This formulation is not, however, so simple. Such definitions suffer from the same problems found in the die roll example presented above. \( U \) is not monotonic in \( \theta \). Thus, the comparison of \( U(E(\theta)) \) to \( EU(\Theta, f) \) that undergirds the definition of risk preference—the willingness to pay more or less than a lottery’s actuarial value to play—fails. Because it is this undergirding that gives rise to definitions based on the convexity or concavity of the utility function, these definitions also fail in the case of the voter. To see this, consider a voter with ideal point \( \theta^* \) and a candidate who the voter believes will implement either \( \theta^* + a \) or \( \theta^* - a \) with probabilities \( p \) and \( 1 - p \) respectively. In this case, \( U(E(\theta)) = U(\theta^*) = g(0) \)

while

\[ EU(\Theta, P) = pg(a) + (1 - p)g(a) = g(a) \]

Thus regardless of her taste for risk, the voter prefers to have \( E(\theta) \) with certainty to the lottery between \( \theta^* + a \) and \( \theta^* - a \). Indeed while the lottery involves uncertainty over which
policy is implemented it involves no risk with respect to the voter’s utility. The voter receives $g(a)$ regardless of which policy is implemented. In this case, policy uncertainty did not result in any utility uncertainty and thus involved no risk. However, under the standard definitions developed above, preferring of $E(\theta)$ to the lottery $(\Theta, P)$ implies that the voter is risk-averse.²

In order to characterize the risk preferences of voters, we need to transform the outcome space from one that is non-monotonic in utility to one that is monotonic in utility; that is, we need a spatial analog to money. Issue distance is just such an analog. An alternative function defined over issue distances is isomorphic to one defined over policy outcomes and utility is strictly monotonic function of the distance between the outcome and the voter’s ideal point. Given this transformation, the standard definitions of risk preference can be applied.

Rather than characterizing risk preferences in terms of the curvature of $U$, risk preferences in the spatial model are characterized by the curvature of $g$, the function that maps distance into utility. If $-g$ is concave a voter is risk-averse. That is, she would prefer a candidate who will implement a policy $d$ units away from $\theta^*$ to a candidate who will implement a policy that is on average $d$ units away. Similarly, if $-g$ is convex, a voter is risk seeking. If $-g$ is linear, a voter is risk neutral. Figure 2.1 shows examples of utility functions defined over $\theta$ for each of these risk preference types. Note that while each of these types has regions around $\theta^*$ that are concave, they are concave, linear, and convex respectively in the distance between the outcome ($\theta$) and the voter’s ideal point ($\theta^*$). The quadratic preferences described above have $g(t) = t^2$ and thus are risk-averse preferences by this definition. However, equating

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²To place the argument in a more explicitly political context, consider an idealized case of a voter whose ideal point lies at a moderately liberal position on a seven-point liberal-conservative dimension. Let us say that this voter’s bliss point is 3. He is offered a choice between two candidates who also appear to be moderately liberal. The first candidate is a prominent incumbent who is well known by his constituents. So the voter is certain that the first candidate is also a 3 on the liberal-conservative scale. The second candidate, however, is somewhat of an enigma. He appears to be a moderately liberal candidate, but he has made some statements indicating that he might be a little more liberal or a little more conservative than our voter’s preferred position. So our voter knows that the second candidate lies somewhere in the range of 2 to 4. The second candidate could, therefore, be a 2, a 3, or a 4, with equal probability. So, while the expected placement of candidate 2 is 3—our voter’s ideal point—the variance of that placement is greater than candidate 1. So here, the voter will prefer candidate 1 to candidate 2, no matter their risk profile. If they pick the first candidate, they get their preferred position for certain. If they pick the second candidate, there is only a 1/3 probability they will get their ideal policy position, and a 2/3 chance they will get a policy that is different than their ideal position. Here, then, is a case where voters will penalize candidates for the uncertainty of their position, even if the voters are risk-acceptant.
Three Spatial Utility Functions

Figure 2: Shapes of spatial utility functions consistent with various forms of risk preference for voter with ideal point at $\theta^*$.

$EU$ in increasing $V(\theta)$ with risk seeking, or $EU$ independent of $V(\theta)$ as risk-neutrality is not correct.

In the spatial setting, uncertainty in the policy outcome has two distinct effects on expected utility. First, increasing uncertainty in how far the policy outcome will be from the voter’s ideal point while holding the expected distance constant will increase the expected utility of the risk seeking and reduce the expected utility of the risk-averse. The second effect is that increasing the uncertainty in $\theta$ increases the expected distance between the policy outcome and the voter’s ideal point, even if the candidates expected position remains unchanged. This result is proved in the appendix. Thus increased uncertainty in a candidate’s location both increases a voter’s uncertainty about how far she is from the candidate, but also leads the voter to believe she is farther from the candidate in expectation. Thus, candidates may be penalized for increasingly uncertain positions, even if voters are not averse to risk.

These two effects work in unison in the case of risk-averse preferences, such as the quadratic preferences often used in the issue voting literature. Under these circumstances, increasing the variance of candidate position will reduce the voter’s expected utility for the candidate, both because the candidate’s expected distance from the voter is greater and because the voter prefers less uncertainty ceteris paribus. In the case of a risk seeking voter, however, the two effects work in opposition. While a risk seeking voter prefers less certain
candidates to more certain candidates, holding expected distance fixed, increasing uncertainty also increases expected distance, thereby lowering expected utility. As in the example that began this discussion, there are cases in which the expected distance effect dominates the uncertainty in distance effect and \( EU \) declines as uncertainty is increased regardless of taste for risk. Because of these competing effects it is not possible to characterize risk preference in terms of increasing, decreasing, or constant \( EU \) in \( V(\theta) \). We must instead consider the shape of the spatial utility function.

These definitions of risk preference are easily carried over to multiple dimensions. In this case, the expected utility is written as

\[
EU(f, \theta^*, W) = -\int g \left( \left( (\theta - \theta^*)^T W (\theta - \theta^*) \right)^{1/2} \right) f(\theta) d\theta
\]

where \( \theta \) and \( \theta^* \) are \( K \times 1 \) vectors representing candidate positions and voter ideal points on each of \( K \) issues, \( W \) is a \( K \times K \) weighting matrix allowing for a generalized distance measure in which issues vary in salience or preferences are nonseparable. The same feature of the curvature of \(-g\) describes the risk preferences of the voter in this case.

### 2.2 Risk Preferences and Voting Under Uncertainty

The nature of the risk preferences of the electorate has important political implications. By the logic of the previous section, we know that all voters—regardless of their risk preference—will support a candidate who espouses their most preferred position over one who espouses that position with a degree of uncertainty. Understanding the risk profile of the electorate therefore has important implications for the meaning of uncertainty in the electoral environment. The risk profiles we assign to voters have implications for the kinds of strategies that candidates should adopt in campaigns. If voters are risk-averse, candidates will best serve their cause by adopting clear, unambiguous positions. On the other hand, an electorate that is risk-acceptant is willing to tolerate uncertainty. In this world, it makes sense for candidates to try to be all things to all people.
In order to estimate risk preferences in the mass public we begin by restricting the set of possible functions, \( g \), and densities over candidate location, \( f \). Beginning with a single issue dimension, we assume that \( f \) is a normal density with mean \( \mu_c \) and variance \( \sigma_c^2 \). Thus, a voter’s information about a candidate’s positions can be fully summarized by \((\mu_c, \sigma_c)\). Further \( g \) is assumed to be of the form,

\[
g(t) = t^{2\alpha}
\]

with \( \alpha > 0 \). Note that \( \alpha > 1/2 \) implies risk aversion, \((-g \text{ concave})\). \( \alpha < 1/2 \) implies risk acceptance, \((-g \text{ convex})\). and \( \alpha = 1/2 \) implies risk neutrality, \((-g \text{ linear})\). Given these restrictions, we can write the expected utility of a candidate for a given voter with an ideal point \( \theta^* \)

\[
EU(\theta^*, \mu_c, \sigma_c, \alpha) = - \int ((\theta - \theta^*)^2)^\alpha f(\theta; \mu_c, \sigma_c) d\theta.
\]

Though somewhat restrictive, this formation has as a special case the quadratic preferences that are most commonly encountered in the literature \((\alpha = 1)\) and does allow for a wide variety of risk profiles. Most importantly for our purposes, because the quadratic model is nested within this specification, we are able to directly test that model against this more general alternative.

In the case of multiple dimensions, we assume the density of candidate locations is multivariate normal with mean vector \( \mu_c \) and variance matrix \( \Sigma_c \). We assume that uncertainty is uncorrelated across issues (that \( \Sigma \) is diagonal). As before, \( \theta^* \) is the vector of voter ideal points and \( W \) is a diagonal matrix of issue weights.\footnote{This implies that preferences are separable.}

The overall expected utility is thus,

\[
EU(\theta^*, \mu_c, \Sigma_c, \alpha) = - \int ((\theta - \theta^*)^\top W(\theta - \theta^*))^\alpha f(\mu_c, \Sigma_c) d\theta.
\]

In the analysis that follow, we will model the risk preferences of voters using two types

\footnote{See Figure 2.1.}
of dependent variables. First, we use the respondent’s reported vote choice. Second, we use the “feeling thermometer” difference between the two major-party candidates. While the two dependent variables are highly correlated, they are each useful for our purposes for different reasons. The vote choice variable is advantageous because it is a direct measure of individual voting behavior. The feeling thermometer, on the other hand, allows us to measure differences in the intensity of preferences between voters—we can gauge just how strongly each respondent supported a given candidate. In addition, the feeling thermometer difference measure allows us to examine the preferences over the major party candidates for those citizens who voted for third party candidates or chose not to vote.

3.1 Modelling vote choices

We begin by deriving the estimation routine for vote choice in a two candidate election. Here we assume that the decision to vote for candidate 1 over candidate 2 is a function of a difference in expected utility and a shock $s_c$. The shock contains both a random component and a systematic component capturing non-policy determinants of vote choice (for example, gender, race, or partisan identification). The voter is assumed to vote for candidate 1 if

$$\beta EU(\theta^*, \mu_1, \Sigma_1, \alpha) + s_1 > \beta EU(\theta^*, \mu_2, \Sigma_2, \alpha) + s_2$$

or

$$\beta [EU(\theta^*, \mu_2, \Sigma_2, \alpha) - EU(\theta^*, \mu_1, \Sigma_1, \alpha)] < s_1 - s_2$$

where $\beta > 0$ weights the relative importance of the policy positions relative to the shocks. Letting $\Delta s = s_1 - s_2$, we can write

$$\Delta s = -\lambda_0 - Z\lambda + \epsilon$$

Feeling thermometers are measures that gauge respondents affect towards prominent political groups and figures. Respondents are told: “Now, I’d like to get your feelings toward some of our political leaders and other people who are in the news these days. I’ll read the name of a person and I’d like you to rate that person using something we call the feeling thermometer. Ratings between 50 degrees and 100 degrees mean that you feel favorable and warm toward the person. Ratings between 0 degrees and 50 degrees mean that you don’t feel favorable toward the person and that you don’t care too much for that person. You would rate the person at the 50 degree mark if you don’t feel particularly warm or cold toward the person.”
where $\lambda_0$ represents some baseline advantage of candidate 2 over candidate 1, $\lambda$ is a vector of coefficients associated with voter specific systematic components of the shock, $Z$ and $\epsilon$ is a random disturbance. Substituting $\Delta$s into the previous inequality, we find that a voter chooses candidate 1 over candidate 2 if

$$\lambda_0 + \beta [EU(\theta^*, \mu_2, \sigma_2, \alpha) - EU(\theta^*, \mu_1, \sigma_1, \alpha)] + \lambda Z < \epsilon$$

If we assume $\epsilon$ is distributed standard normal, we have a probit model in which the probability of voting for candidate 1 is

$$\Pr(V = 1) = \Phi(\lambda_0 + \beta [EU(\theta^*, \mu_2, \Sigma_2, \alpha) - EU(\theta^*, \mu_1, \Sigma_1, \alpha)] + \lambda Z)$$

where $\Phi$ is the standard normal cumulative distribution function. Assuming the votes are cast independently across voters (indexed by $i = 1, \ldots, N$), a full likelihood can be formed as,

$$L(\alpha, \beta, \lambda_0, \lambda, W) = \prod_i \Phi(\lambda_0 + \beta [EU(\theta^*_i, \mu_{i2}, \Sigma_{i2}, \alpha) - EU(\theta^*_i, \mu_{i1}, \Sigma_{i1}, \alpha)] + \lambda Z_i)^{V_i} \times (1 - \Phi(\lambda_0 + \beta [EU(\theta^*_i, \mu_{i2}, \Sigma_{i2}, \alpha) - EU(\theta^*_i, \mu_{i1}, \Sigma_{i1}, \alpha)] + \lambda Z_i)^{1-V_i}$$

(4)

The parameters $\alpha$, $\beta$, $\lambda_0$, $\lambda$, and $W$ are fixed across individuals. $\Sigma_{ic}$, $\mu_{ic}$, $\theta_i$, and $Z$ are data.\(^6\) Exactly how each voter’s perceptions of each candidate’s mean positions ($\mu_{ic}$) and the variances of those positions ($\Sigma_{ic}$) are estimated is described in the next section. As it turns out, data on the diagonal elements of $\Sigma_{ic}$ can only be imputed up to a constant of proportionality $\gamma > 0$. This constant is estimated as an additional parameter yielding the

\(^6\)We allow both the candidate placement mean and variance to vary across individuals. This strategy differs from that of other authors, such as Alvarez (1997), who fix the candidate positions at the mean of the sample. We choose this strategy because it is the voter’s perception of the candidate stand that is critical for the calculation of utility.
following full likelihood

\[
L(\alpha, \beta, \lambda_0, \lambda, W, \gamma) = \prod_i \Phi(\lambda_0 + \beta [EU(\theta^*_i, \mu_{i2}, \gamma \Sigma_{i2}, \alpha) - EU(\theta^*_i, \mu_{i1}, \gamma \Sigma_{i1}, \alpha)] + \lambda Z_i) V_i \times \\
(1 - \Phi(\lambda_0 + \beta [EU(\theta^*_i, \mu_{i2}, \gamma \Sigma_{i2}, \alpha) - EU(\theta^*_i, \mu_{i1}, \gamma \Sigma_{i1}, \alpha)] + \lambda Z_i))^{1-V_i}
\]

(5)

One further identifying restriction must be made. In order to uniquely identify $\beta$, one of the issue weights (diagonal elements of $W$) is fixed to unity. This restriction results in no loss of generality except in the case where the true value of the normalized weight is zero—that is, where the issue had no effect on utility. In practice, we do not expect this result to occur.\(^7\) With the exception of the parameters $\alpha$ and $\gamma$ the likelihood is standard probit. The presence of these parameters greatly complicates estimation. The multidimensional integral in Equation 5 cannot be solved analytically and must be approximated. We achieve this approximation by Monte Carlo methods. The overall likelihood is maximized directly by using numerical methods. The procedure is computationally intensive because the multidimensional integral must be calculated for each observation several times in each iteration. Programs to implements to the estimator are available from the authors. Typical runs required several hours.

3.2 Modelling feeling thermometer differences

The second dependent variable we considered was the difference in feeling thermometer scores between two candidates. In this case, each feeling thermometer score was taken to be a direct measure of a voter’s expected utility plus a shock of the sort described above. Thus the difference in feeling thermometer score given to candidate 1 and candidate 2 is

\[
\Delta FT = \beta [EU(\theta^*_i, \mu_{i2}, \gamma \Sigma_{i2}, \alpha) - EU(\theta^*_i, \mu_{i1}, \gamma \Sigma_{i1}, \alpha)] + (s_1 - s_2).
\]

Substituting for $\Delta s$ and rearranging, we have

\[
\Delta FT = \lambda_0 + \beta [EU(\theta^*_i, \mu_{i2}, \gamma \Sigma_{i2}, \alpha) - EU(\theta^*_i, \mu_{i1}, \gamma \Sigma_{i1}, \alpha)] + \lambda Z + \epsilon.
\]

\(^7\)In our analysis, we use as the fixed issue, the general liberal/conservative ideology dimension. If the issue voting literature is clear on one point, it is that this dimension matters in candidate selection.
If we assume that $\epsilon$ is in this case distributed normally with mean 0 and variance $\sigma_\epsilon^2$, the full likelihood can be written as,

$$ L(\alpha, \beta, \lambda_0, \lambda, W, \gamma) = \prod_i f(\Delta FT_i \mid m, \sigma_\epsilon) $$

where

$$ m_i = \lambda_0 + \beta [EU(\theta_i^*, \mu_{i2}, \gamma \Sigma_{i2}, \alpha) - EU(\theta_i^*, \mu_{i1}, \gamma \Sigma_{i1}, \alpha)] + \lambda Z_i. $$

Excepting $\alpha$ and $\gamma$ this likelihood could be estimated by OLS. Including $\alpha$ and $\gamma$ the likelihood is estimated using numerical methods and involves the same numerical approximations and computational burden described in the vote choice case.\(^8\)

### 4 Estimating the Model

Having derived the estimation techniques, we next moved to analyzing the risk preferences of the electorate. But there are several issues we need to consider before we begin our analysis. First, we need to specify the variables to include in $Z$— the non-policy determinants of an individual’s candidate preference. To follow convention, we include measures of the race, gender, and partisanship of the respondents.

Second, we need to consider how to measure the distance between a particular candidate’s issue position and an individual’s bliss point. Constructing such a measure is not necessarily a straightforward task; different researchers have developed different metrics for issue distance. Here, we allow the effects of distance to vary by issue type, but we constrain the effects of a particular issue to be same for each candidate in an election. This setup is advantageous, because it allows for additive utility functions and allows us to account for shifts in the salience of different issues on the political scene over different elections.

In addition to gauging issue distance, we need to measure the perceptual uncertainty of

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\(^8\)If $\Delta FT$ is a reasonable proxy for difference in voters’ expected utilities then this variable is preferable to vote choices on efficiency grounds. This continuous dependent variable reveals much more information about voter utility functions and thus allows more precise parameter estimates. If, however, $\Delta FT$ is not a good proxy for expected utility then vote choice is the preferable variable to model. Interestingly, the results presented below estimates generated using each variable (appropriately scaled) are quite similar suggesting that perhaps $\Delta FT$ is a reasonable measure of expected utility.
voters over those distances. As noted in Section 3, candidate placements are not necessarily fixed points. Instead, voters view candidates as holding a range of possible issue positions, each with a different probability. These are given by the densities over candidate location, \( f \). These densities may vary from voter to voter, both with respect to the central tendency of their issue position (\( \mu_c \)) and with respect to their uncertainty concerning that position (\( \sigma_c \)). To estimate our model, we therefore need measures of five quantities for each individual per issue dimension (indexed by \( k = 1, \ldots, K \)) that we wish to analyze: the voter’s ideal point on the issue (\( \theta_{ik}^* \)), the perceived placement of the two major party candidates on that issue (\( \mu_{i1k}, \mu_{i2k} \)), and the uncertainty surrounding each candidate’s position on the issue (\( \sigma_{i1k}, \sigma_{i2k} \)).

We have straightforward measures of the first three quantities. We use the respondent’s reported self-placement on the seven-point issue scale as their ideal point, (\( \mu_{ik}^\circ \)). We also use each voter’s reported placement of the candidates as their position on that issue, (\( \mu_{i1k}, \mu_{i2k} \)). But we still need a measure of the voter’s uncertainty around the perceived candidate placement, (\( \sigma_{i1k}, \sigma_{i2k} \)). This is not a straightforward task. The variances of issue perception are, after all, not directly observable. We must, therefore, indirectly estimate those from the available data. To do this, we follow the method used by Bartels (1986).

Bartels assumes that respondents will place candidates on a particular issue dimension if they are sufficiently certain of the candidate’s position on that issue, but they will refuse to place the candidate if their uncertainty concerning that position exceeds some threshold value. While we can not directly observe this uncertainty, if we assume that the uncertainty is systematically related to the observable characteristics of the respondents, we can measure the relative impact of these characteristics on uncertainty by modelling the decision to place a candidate in a probit framework. We can then use the coefficients from these models and our knowledge of the respondents’ characteristics to construct estimates of (\( \sigma_{i1k}, \sigma_{i2k} \)) for individual respondents (up to some arbitrary positive scale factor, \( \gamma \)).

---

9 Following Bartels (1986) to generate our measures of uncertainty, we used as predictors in our probit equations: Levels of political information (see Zaller 1992), how closely the respondent followed politics, interest in the presidential campaign, the number of campaign acts undertaken by the respondent (donating money, volunteering time, wearing a campaign button, attempting to convince someone else to vote for the candidate), age, race, education, gender, and party identification (entered as a series of six dummy variables).

10 This is an inferential method of measuring uncertainty. Other methods have been proposed. Alvarez
For our analysis, we use 3 issue dimensions: General liberal/conservative ideology, whether the government should provide jobs and a good standard of living, and whether the government should provide aid to minority groups. Together these dimensions capture a broad scope of issues relating to vote choice. Equally important, these questions are asked in every year of the survey (except 1992, where the candidate placements for the minority aid question were not asked). We can, therefore, compare our results across years.

Taken together, we have measures of all the quantities we need. We can therefore move to directly investigating the risk preferences of the electorate. To estimate our models, we used NES data from each of the seven Presidential election between 1972 (the year the seven-point issue scales were first introduced) and 1996. Using the full series of election is advantageous because, as Alvarez (1997) has argued, these seven elections vary on a number of important dimensions. Most elections involved a sitting president, but the 1988 (and, by some reckoning the 1976) election lacked an incumbent. Some candidates involved little known challengers (1976); others involved better known challengers (1984, for example) and two elections involved former vice-presidents (1984 and 1988). In short, the series of elections allows us to measure the risk preferences of voters under conditions that vary in the contextual conditions that should affect both uncertainty concerning candidates and the effect of that uncertainty on the vote choice.

5 Results

We estimated voting under uncertainty using the two dependent variables described in Section 3: the reported vote choice and the feeling thermometer difference. For both dependent variables, we coded the Democratic candidate as the high category. Table 1 presents the average of the model estimates, for the years from 1972 to 1996. Table 2 presents the results from analysis which pooled the data from all the years (excepting 1992, where the minority aid question was not asked). Alvarez (1997), for example, directly estimates uncertainty by measuring the difference between a given respondents placement of the candidate, and the mean placement of that candidate among the sample—essentially Alvarez argues that uncertainty can be measured by how “wrong” a respondent is in their candidate placement, assuming that the mean placement of the candidate for the sample is “right.”. Given that we use the respondents reported placement of the candidate in the issue distance function, we do not think this is appropriate for our purposes.
aid question was not asked).

The central question of our work concerns the risk preferences of the electorate. The results here are clear. Turning first to the average model estimates (Table 1), the estimate of $\alpha$ indicates that voters are—on average—ever so slightly risk averse. For both the vote choice and feeling thermometer analysis, $\alpha$ is about 0.6, indicating that the power term on the loss function is 1.2.\footnote{Remember, we assumed $g$ to be of the form $g(t) = t^{2\alpha}$. To derive the power term on this function, we must therefore multiply $\alpha$ by 2.} But the assumption of strong risk aversion implied by the use of quadratic utility functions ($\alpha = 1$) can clearly be rejected in both the vote choice case. In fact a null of risk-neutrality ($\alpha = 0.5$) cannot be rejected at any conventional level of significance in the case of vote choice. The results from the pooled analysis (Table 2) yield extremely similar results, especially accounting for the fact that the 1992 data are not included in these analysis. In short, the assumption of quadratic loss functions can be soundly rejected.

The other estimates from the model are interesting as well. Looking at Table 1, the coefficient on $\bar{\beta}$ is large in the vote choice model, but has a large standard error. Given that we are asking quite a bit from the data —after all, we use parameters on the same quantity to estimate both the curvature of the loss function and the weight given to issue distance in vote choice—we believe that it is important to focus on our estimate of the vote choice parameter, rather than the precision of that parameter. It may reassure the skeptical reader to note that the $\bar{\beta}$ in the pooled vote-choice model is highly statistically significant (see Table 2). This result indicates that—as we expect—issues matter in the vote choice process. Turning to the $\Delta FT$ measure, we find that issues matter in a substantively and statistically significant manner in sets of analyses. The difficulty in separately estimating $\alpha$ and $\beta$ is highlighted in Figure 4 which shows the estimated 95 percent confidence regions for the estimated $\alpha$ and $\beta$ in each election. The steeply downward sloping confidence ellipses reflect the strong negative correlation between estimates of $\alpha$ and $\beta$. This same downward sloping pattern is also observed in the estimates themselves where large estimated $\alpha$s are associated with small estimated $\beta$s. The large degree of overlap in the confidence regions (particularly in the case of the feeling thermometer difference case) suggests that much of the election-to-election variation in the estimated risk and issue weight parameters is attributable to
### Table 1: Averages of model estimates from National Election Study data from each Presidential election between 1972 and 1996.

As described in the text the coefficients in the “vote choice” model use reported vote choice as the dependent variable and are based on a probit link. The “feeling thermometer difference” model uses differences in the feeling thermometer scores between the two major party candidates as a dependent variable and employ a linear link. The “scaled” feeling thermometer model column normalizes by dividing the appropriate coefficients such that parameters are defined on the same scale as the vote choice parameters.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Vote choice</th>
<th>Feeling thermometer difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est. (SE)</td>
<td>Raw Est. (SE)</td>
</tr>
<tr>
<td>Risk ($\alpha$)</td>
<td>0.61 (0.09)</td>
<td>0.59 (0.03)</td>
</tr>
<tr>
<td>Uncertainty ($\gamma$)</td>
<td>2.97 (0.77)</td>
<td>4.22 (0.79)</td>
</tr>
<tr>
<td>Issues ($\beta$)</td>
<td>0.90 (1.00)</td>
<td>6.91 (0.73)</td>
</tr>
<tr>
<td>Ideology ($w_1$)</td>
<td>1.00 -</td>
<td>1.00 -</td>
</tr>
<tr>
<td>Jobs ($w_2$)</td>
<td>0.60 (0.09)</td>
<td>0.46 (0.04)</td>
</tr>
<tr>
<td>Minority Aid ($w_3$)</td>
<td>0.52 (0.10)</td>
<td>0.47 (0.05)</td>
</tr>
<tr>
<td>Male</td>
<td>-0.26 (0.09)</td>
<td>-1.80 (1.20)</td>
</tr>
<tr>
<td>White</td>
<td>-0.07 (0.08)</td>
<td>-1.17 (0.96)</td>
</tr>
<tr>
<td>Party ID</td>
<td>1.08 (0.05)</td>
<td>20.41 (0.67)</td>
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<tr>
<td>Constant</td>
<td>0.31 (0.11)</td>
<td>0.78 (1.41)</td>
</tr>
<tr>
<td><strong>SEE</strong></td>
<td>1.00</td>
<td>26.95</td>
</tr>
</tbody>
</table>
Estimated parameters of the spatial voting under uncertainty model, pooled 1972 to 1996 data

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Vote choice</th>
<th>Feeling thermometer difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Est. (SE)</td>
<td>Raw Est. (SE)</td>
</tr>
<tr>
<td>Risk ($\alpha$)</td>
<td>0.50 (0.06)</td>
<td>0.61 (0.03)</td>
</tr>
<tr>
<td>Uncertainty ($\gamma$)</td>
<td>2.31 (2.37)</td>
<td>4.05 (0.97)</td>
</tr>
<tr>
<td>Issues ($\beta$)</td>
<td>0.44 (0.11)</td>
<td>6.49 (0.72)</td>
</tr>
<tr>
<td>ideology ($w_1$)</td>
<td>1.00</td>
<td>-</td>
</tr>
<tr>
<td>Jobs ($w_2$)</td>
<td>0.60 (0.08)</td>
<td>0.47 (0.04)</td>
</tr>
<tr>
<td>Minority aid ($w_3$)</td>
<td>0.45 (0.08)</td>
<td>0.47 (0.05)</td>
</tr>
<tr>
<td>Male</td>
<td>-0.09 (0.08)</td>
<td>0.87 (0.92)</td>
</tr>
<tr>
<td>White</td>
<td>-0.08 (0.06)</td>
<td>-3.21 (0.80)</td>
</tr>
<tr>
<td>Party ID</td>
<td>0.97 (0.05)</td>
<td>19.46 (0.74)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.00 (0.08)</td>
<td>-1.03 (1.02)</td>
</tr>
<tr>
<td>$SEE$</td>
<td>1.00</td>
<td>27.85</td>
</tr>
</tbody>
</table>

Table 2: Model estimates pooling National Election Study data from each Presidential election between 1972 and 1996. As described in the text the coefficients in the “vote choice” model use reported vote choice as the dependent variable and are based on a probit link. The “feeling thermometer difference” model uses differences in the feeling thermometer scores between the two major party candidates as a dependent variable and employ a linear link. The “scaled” feeling thermometer model column normalizes by dividing the appropriate coefficients such that parameters are defined on the same scale as the vote choice parameters.
sampling variation.

We are also reassured by the performance of the other variables in the model. The control variables \((Z)\)—gender, race, and party identification—all have effects in the expected direction. Moreover, the effect of partisanship is very large in both Table 1 and Table 2.\(^{12}\) In short, the model estimates are reasonable, lending credence to the performance of our estimation technique.

The model estimates also vary over time, in sensible ways. In Figure 3, we graph the value of \(\alpha\) and \(\beta\) for the vote choice and feeling thermometer difference dependent variables. Clearly there are points where the estimates are problematic. In 1988, for example, the coefficient on the issue term is essentially zero. But in most cases, the results are quite sensible. Most important for our purposes, the parameter on the loss function (which is given as \(2 \times \alpha\)) is below one in every year except 1988 and 1996 in the vote choice analysis and at about one in every year except 1996 in the feeling thermometer analysis.

5.1 1972 Risk Proclivity Analysis

While the analyses presented above are important, they rely on the assumption that the \(\alpha\) term does indeed measure risk-taking proclivities. While this assumption is common, it is advantageous to see if additional analyses can give us purchase on the face validity of this assumption. For this we turn to a more detailed analysis of the 1972 election. In the 1972 survey, the NES asked a battery of questions concerning the gambling behavior of the respondents. The gambling battery consists of a series of questions that asked respondents if they engaged in 19 common betting activities, ranging from taking part in football pools to buying raffle tickets, to investing in the stock market. In addition, respondents were asked a series of hypothetical questions that made direct reference to the risk-taking element involved in gambling. These items are advantageous for the purposes of assessing attitudes towards

\(^{12}\)Some readers have raised the concern that our method, while controlling for the direct effect of partisanship on vote choice, might not control for the indirect effects of partisanship through the measures of uncertainty. Strong partisans, the argument goes, might not bother to learn the issue positions of the opposing party’s candidate because they know they will not vote for the candidate of the opposition party. We do, in fact, control for this possibility by including dummies for partisan categories in our uncertainty equation, as noted above. Contrary to the readers’ expectations, respondents with strong attachments to any party are more certain where the candidate stands (following Bartels 1986).
risk because the items directly tap the risk-taking behavior of the respondents. Though the gambling proclivities of respondents might not correlate perfectly with their general acceptance of risk, there is reason to believe that the gambling items tap more general attitudes towards risk. Studies in psychology have detected an empirical link between risk-taking behavior and gambling (Powell et al. 1999). In fact, within the sample, this scale predicts the propensity to take risky behaviors outside the realm of gambling (for further discussion of the scale, see Berinsky ND). We therefore used the scale to split the sample into two groups: high-risk-takers and low-risk-takers.\footnote{Specifically, we split the sample at the median of the scale.}

We employed a variant of the model used above, where the $\alpha$ term is parameterized as a function of an additional independent variable. By using a dummy variable for this independent variable, we can estimate two $\alpha$ parameters: one for respondents with high risk proclivities, and one for respondents with low risk tendencies. We expect that the $\alpha$ for the high-risk respondents will be smaller, indicating higher risk acceptance.

When we use vote choice as the dependent variable, we find the expected results. The coefficient on the risk-proclivity variable ($\Delta$ Risk) is in the expected direction and statistically significant at the .05 level using a one-tailed test. When we use the feeling thermometer difference as the dependent variable, the risk variable is also in expected direction, but rather small and statistically insignificant. Taken together, these results, while not overwhelming, are reassuring. We find risk effects in the expected direction.\footnote{Moreover, we are probably giving our model a strict test by using data from 1972—an election that the incumbent president, Richard Nixon, won in a landslide over an extremist challenger with well-articulated policy positions. Perhaps in other years, we would find a greater effect.} The important thing for our argument is that the analyses give face validity to our use of $\alpha$ to estimate risk aversion.
### 1972 parameterizing risk

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Est.  (SE)</th>
<th>Est.  (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Risk ($\alpha$)</td>
<td>0.47 (0.14)</td>
<td>0.53 (0.05)</td>
</tr>
<tr>
<td>$\Delta$ Risk</td>
<td>-0.06 (0.04)</td>
<td>-0.01 (0.01)</td>
</tr>
<tr>
<td>Uncertainty ($\gamma$)</td>
<td>1.80 (1.37)</td>
<td>2.19 (1.42)</td>
</tr>
<tr>
<td>Issues ($\beta$)</td>
<td>0.71 (0.42)</td>
<td>10.85 (2.26)</td>
</tr>
<tr>
<td>Ideology ($w_1$)</td>
<td>1.00 -</td>
<td>1.00 -</td>
</tr>
<tr>
<td>Jobs ($w_2$)</td>
<td>0.59 (0.14)</td>
<td>0.36 (0.07)</td>
</tr>
<tr>
<td>Minority Aid ($w_3$)</td>
<td>0.36 (0.14)</td>
<td>0.51 (0.10)</td>
</tr>
<tr>
<td>Male</td>
<td>-0.07 (0.14)</td>
<td>-2.77 (1.86)</td>
</tr>
<tr>
<td>White</td>
<td>0.63 (0.28)</td>
<td>-4.77 (3.32)</td>
</tr>
<tr>
<td>Party ID</td>
<td>0.92 (0.13)</td>
<td>16.42 (1.64)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.34 (0.29)</td>
<td>-4.08 (3.21)</td>
</tr>
</tbody>
</table>

$SEE$ = 29.55

Table 3: Model estimates using data from 1972. Here we parameterize the Risk ($\alpha$) term as a function of $\Delta$ Risk. The Risk coefficient gives the $\alpha$ for the “low risk” group. The sum of the $\Delta$ Risk coefficient and the Risk coefficient is the $\alpha$ for the “high risk” group. As described in the text, the coefficients in the “vote choice” model use reported vote choice as the dependent variable and are based on a probit link. The “feeling thermometer difference” model uses differences in the feeling thermometer scores between the two major party candidates as a dependent variable and employ a linear link.
Risk ($\alpha$) and issue weight ($\beta$) parameter estimates from the spatial voting under uncertainty model

Figure 3: This Figure shows the point estimates and estimated 95 percent confidence intervals for $\alpha$ and $\beta$ in each presidential election between 1972 and 1996. The horizontal lines represent the average parameters estimate over the period. Notice that the 95 confidence regions generally contain the overall mean and that larger (smaller) estimated $\beta$s are generally associated with smaller (larger) estimated $\alpha$s.
Estimated confidence ellipses for risk (\(\alpha\)) and issue weight (\(\beta\)) parameters

Figure 4: This Figure shows the 95 percent confidence regions for the estimates of \(\alpha\) and \(\beta\).

6 Conclusion

The results in this paper are clear. The assumption of strict risk-aversion that characterizes models of candidate choice under uncertainty are not tenable. Using data from Presidential elections over the last quarter-century, we estimate the risk preferences of the electorate. We find that the risk profile of the electorate changes somewhat over time, in sensible ways. But contrary to the assumptions of most scholars, we find risk-aversion among voters is the exception, not the rule. We also verify our model of risk-taking using data from the 1972 NES. There, using measures of proclivity towards risk-taking, we find evidence that our measure of risk taking—the power term on the loss function—does indeed capture tolerance of risk.

Taken together, these results have important implications for both the empirical study of elections and the normative issues surrounding campaigns. The use of quadratic utility functions may be mathematically simple, but this simplicity comes at the expense of an accurate representation of reality. Thus, future work should more directly confront the nature of the risk proclivities of the electorate.

More importantly, the results in this paper can also inform the study of campaigns. The
communication of information between candidates and voters lies at the heart of democratic politics. If voters are risk averse, they will punish candidates who obfuscate their policy position. But our findings suggest a less rosy view of the electoral process. If voters are risk neutral or risk acceptant—as in some cases we find they are—candidates may have reason to muddle their positions on the campaign trail and try to be all things to all people. Given the findings in this paper, if campaigns are not the ideal context for debates over public policy, we should not fault candidates—they are simply playing by the rules of the game set by the preferences of the mass public.
A Proof that increasing the variance of the candidates location, increases the voter’s expected distance from the candidate

Proof: Let the location of the candidate be described by the random variable $\theta$ with mean $\mu$, variance $\sigma^2$, and density $f$. Without loss of generality, assume that the voter’s idea point is 0 and that the mean of the candidate’s (unknown) location $\mu \geq 0$. The expected distance between the candidate and the voter is

$$E(D) = \int_{-\infty}^{\infty} |0 - \theta| f(\theta) d\theta.$$ 

Let $z = \frac{\theta - \mu}{\sigma}$ and let $h(z) = \frac{1}{\sigma} f(\frac{\theta - \mu}{\sigma})$. Note that $z$ has mean 0 and variance of 1. We can then write

$$E(D) = \int_{-\infty}^{\infty} |0 - \mu - \sigma z| h(z) dz.$$ 

differentiating by $\sigma$,

$$\frac{\partial E(D)}{\partial \sigma} = \int_{-\infty}^{-\frac{\mu}{\sigma}} -1zh(z)dz + \int_{-\frac{\mu}{\sigma}}^{\infty} 1zh(z)dz.$$ 

Noting that by construction $E(Z) = 0$, we also have

$$0 = \int_{-\infty}^{-\frac{\mu}{\sigma}} 1zh(z)dz + \int_{-\frac{\mu}{\sigma}}^{\infty} 1zh(z)dz.$$ 

Subtracting this expression from the previous expression we find,

$$\frac{\partial E(D)}{\partial \sigma} = -2 \int_{-\infty}^{-\frac{\mu}{\sigma}} zh(z)dz.$$ 

Because, by the assumption that $\mu \geq 0$, $\int_{-\infty}^{-\frac{\mu}{\sigma}} zh(z)dz \leq 0$, we have established that $\frac{\partial E(D)}{\partial \sigma} \geq 0$ completing the proof.
References


