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ABSTRACT

Confidence in Public Institutions and the Run up to the October 2019 Uprising in Lebanon*

This paper uses the 2013 World Value Survey, as well as the 2016 and 2018 waves of the Arab Barometer, to analyze the dynamics of trust in public institutions in Lebanon. It finds strong evidence that confidence in most public institutions has decreased between 2013 and 2016. The evidence of this decrease is robust to the numerical scale assigned to the different ordinal categories of trust and to assumptions on the missing values generating process. This finding highlights the importance for policymakers in developing countries to survey the perceptions and political attitude of their constituents in order to improve the performance of public institutions.

JEL Classification: D72, O53, P16, P40

Keywords: confidence, institutions, uprising, ordinal variable

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1 Introduction

We are currently witnessing a worldwide decrease in election turnout coupled with an increase in distrust in governments and elites. Three recent well-known manifestations of this phenomenon are: American Trump supporters (2016), the Gilets Jaunes movement that began in France (2018), and the democratic forces in Hong Kong (2019). In these three instances, the increasing distrust was conveyed through voting outcomes. However, what happens if a political system does not offer the space for the expression of such a distrust? It is in such a context that the 2011 Arab Spring started in the Middle East and North Africa region. It began with multiple social protests against authoritarian governments and a desire for democratization and justice in Tunisia, Egypt, Libya, Syria, Yemen, Sudan, and Algeria.[1] In 2019, Lebanon was similarly struck by an unprecedented massive uprising across all its regions and political allegiances.

Lebanon was described by The Economist as "almost a caricature of poor governance".[2] Although elections are held and the Lebanese constitution guarantees power transfer after an election, the sectarian political structure, *consociationalism*[3], limits the democratic expression of the electorate.[4] In addition, by requiring consensual decisions, consociationalism leads to paralysis in policy making. It is in these circumstances that on October 17, 2019, the Lebanese government proposed to impose a six dollars monthly tax on WhatsApp that led to a historic uprising in the entire country. This uprising turned into multiple social protests demanding social justice, the replacement of the corrupted political elite, and the

[1]For more information on the Arab Spring, the reader can refer to Campante & Chor (2012) and Acemoglu, Hassan & Tahoun (2018).

[2]The Economist, October 24th, 2019.

[3]For more details see Weiss (2009), Fakhoury (2019), and Geha (2019).

[4]It is worth noting that according to an opinion poll conducted by the Lebanese Center for Policy Studies, 35% of surveyed individuals from the low income group report having received a bribe for their vote. Significant proportion of votes in other income groups have also been bought (see Lebanon Public Opinion Survey, Lebanese Center for Policy Studies 2018). Coupled with a voter turnout of 49.7%, it is reasonable to assume that election results do not reflect the preferences of the population. For election turnout statistics, the reader may refer to UNDP (2018), *2018 Lebanese Parliamentary Elections: Results & Figures.*

end to the sectarian political system that shaped the last three decades of the post 1975-1990 civil war era. Caught by surprise, many politicians have argued that this uprising does not reflect a real desire for change since, very recently (in May 2018), a general election was held and the Lebanese voted the same political class back into power.[5] Considering the conflicting perceptions between the political elite and protesters, and given that the voter turnout was very low, it is essential to explore whether the electoral outcome genuinely reflects the population's views.

Motivated by the worldwide decrease in election turnout and the associated distrust in governments and elites, we exploit the unprecedented circumstances in Lebanon where the lack of space to express distrust is significant. Our objective is to assess whether the desire for a complete overhaul of the political elite observed in 2019 is substantiated by facts or just a constructed artefact. In doing so, we use the 2013 World Value Survey as well as the 2016 and 2018 waves of the Arab Barometer and focus on change in the "qualitative average" trust (or confidence)[6] in Lebanese public institutions between 2013 and 2016 and between 2016 and 2018. Given that trust is an ordinal variable, any increasing numerical scale can be assigned to the ordered categories. Thus, using these ordinal variables raises empirical challenges as ranking distributions based on computed averages may lead to arbitrary results. Consequently, policymakers may have valid reasons to dismiss any analysis based on the "average" level of trust since these results are contingent on an arbitrary choice of numerical scale applied to ordinal data. To overcome these challenges, we adopt the approach of Alison and Foster (2004) (hereinafter AF) for such comparisons, but adapt it for comparisons using bounds based on Horowitz and Manski (1995).

This paper has three contributions. First, it provides evidence on the change in salience

[5] See Baalbaki (2018).

[6] Although there is a subtle difference between the words "trust" and "confidence" in English, both words are translated to "thiqa" in the Arabic questionnaire of both surveys. For our purpose, we use the words "trust" and "confidence" interchangeably.

of trust in political institutions in a context where political elites are dismissive of the narratives of the popular uprising. Thus, it points to the instrumental role of analyzing information on people's perceptions (e.g., trust, confidence and satisfaction) of public policy in developing countries where such information is discounted and, in some cases, outright rejected. Second, to the best of our knowledge, we are the first to exploit ordinal information from trust variables to carry out comparisons of "average" trust in authorities while maintaining minimal assumptions on the numerical scale, using AF's framework. The third contribution is a statistical test for first-order stochastic dominance to assess the change in the "average" level of trust for survey data with missingness problems. To that end, we adapt the statistical procedure of Davidson and Duclos (2013) to the context of survey sampling with missing data. The proposed test is robust to the nature of the missingness-generating process. To obtain this robustness property, the comparisons use the worst-case upper and lower bounds of the cumulative distribution functions (e.g. Tamer, 2010, Section 3.1 and Manski, 2003).

Empirical evidence shows that the trajectory of the perceptions conveyed in the surveys is consistent with the messages expressed in the streets in 2019. Had policy makers paid attention to the available surveys, they would have been able to extract information on how their citizens perceive the existing public institutions and, thus, avert the uprisings three years in advance. The policy recommendation is quite straightforward. Conducting and analyzing surveys on perceptions and political attitudes of the population is essential in less democratic developing countries; accounting for the evidence they provide is instrumental for stability.

The remainder of this paper is organized as follows. Section 2 establishes the measurement and statistical inference framework. Section 3 reports the results of our empirical analysis of the recent evolution of trust in public institutions in Lebanon and Section 4 concludes.

2 Measurement and statistical inference approach

Our methodological approach is motivated by our desire to present the facts while maintaining minimal assumptions since the "credibility of inference decreases with the strength of the assumptions maintained" (Manski, 2003). To this end, we adopt a dominance approach that allows for orderings of trust over time that are robust to any change in the numerical scale. We also develop a statistical test that is robust to the nature of the missing values generating process.

2.1 Measurement issues and dominance framework

We aim to perform a simple comparison of the "average" level of confidence between 2013 and 2016 and between 2016 and 2018 to assess whether people's confidence in authority has been decreasing prior to October 2019 uprising. Given that we have information on different dimensions of confidence in authority (i.e., courts, government, parliament, political party, and police force), this task should be in principle quite simple. Unfortunately, the implementation of this comparison is more complex as the information available on confidence in authority is ordinal and thus provides qualitative information on confidence levels. More specifically, there are four categories of responses regarding people's trust in authority: *"not at all"*, *"not very much"*, *"a lot"*, and *"a great deal"* to which a numerical scale $\nu(\cdot)$ is applied such that the variable takes values from 1 to 4. Any other monotonically non-decreasing numerical scale $\nu(\cdot)$ can assign different numerical values to the categories and still represent the same ordering conveyed by the qualitative information.

Let x_i be a confidence variable for N individuals, we want to compare a simple average level of confidence

$$C = \frac{1}{N} \sum_{i=1}^{N} \nu(x_i), \tag{1}$$

where $\nu(\cdot)$ is a numerical scale applied to the different confidence categories. To illustrate the potential issue in computing the "average" level of confidence, consider the two hypothetical distributions of probabilities over the four categories of confidence: $A := (0.2, 0.4, 0.2, 0.2)$ and $B := (0.3, 0.2, 0.2, 0.3)$. For each of these distributions, the ordinal content of the confidence variable can be cardinalized using two different numerical scales: $\nu_1(\cdot) = (1, 2, 3, 4)$, $\nu_2(\cdot) = (1, 8, 9, 10)$. If one computes the value of the "average" confidence for these two non-decreasing scales, the results indicate that, for numerical scale $\nu_1(\cdot)$, there is a higher "average" confidence in distribution B (=2.5) than in distribution A (=2.4). However, if one uses the numerical scale $\nu_2(\cdot)$, the results are reversed; "average" confidence in distribution B(=6.7) is lower than in distribution A (=7.2). This simple example illustrates how the "average" confidence may arbitrarily rank distributions when applied to an ordinal confidence indicator.

Despite this disappointing result, it is possible that in some situations, a ranking remains consistent for any choice of numerical scale. AF show that it is possible to characterize robust rankings of distributions of ordinal variables with respect to their "average" using first-order stochastic dominance. To understand the intuition behind their result, note that simple algebraic manipulation of equation (1) for K categories yields

$$I = \nu(K) - \sum_{x=1}^{K-1} \Delta\nu(x)F(x), \tag{2}$$

where $\Delta\nu(x) = \nu(x+1) - \nu(x)$ and $F(x) = \Pr[X \leq x]$ is the cumulative distribution function (CDF) of X. Since we consider all non-decreasing numerical scales, we know that $\Delta\nu(x) \geq 0$ for all $x \in \{1, .., K-1\}$. For two distributions F_A and F_B, AF use these inequalities to show that $C_A \geq C_B$ for all numerical scales $\nu(\cdot)$ such that $\Delta\nu(x) \geq 0$ for all $x \in \{1, ..., K-1\}$ if and only if

$$F_A(x) \leq F_B(x), \quad \forall x \in \{1, .., K-1\}. \tag{3}$$

This result is simple yet powerful. It implies that even if we have purely ordinal data, we can, in some circumstances identify a situation for which the ranking of two distributions in terms of "average" would remain consistent for any non-decreasing numerical scale one could impose on the categories.

2.2 Statistical inference

Using survey samples on confidence levels of the Lebanese population, one can thus compare the "average" level of trust over time by assessing the stochastic dominance condition in (3) using a statistical test for first-order stochastic dominance. Let X_{18}, X_{16} and X_{13} be three independent discrete random variables representing the individuals' confidence level in 2018, 2016, and 2013, respectively. These random variables have $K = 4$ categories with common support $\mathcal{S} = \{1, 2, 3, 4\}$, and CDFs F_{18}, F_{16} and F_{13}, respectively. For ease of exposition, let $\mathcal{S}^{\circ} = \mathcal{S} - \{4\} = \{1, 2, 3\}$. The testing problem is

$$H_0 : \max_{x \in \mathcal{S}} (F_{13}(x) - F_{16}(x)) \geq 0 \quad \text{or} \quad \max_{x \in \mathcal{S}} (F_{16}(x) - F_{18}(x)) \geq 0 \quad \text{Vs.} \tag{4}$$

$$H_1 : F_{13}(x) < F_{16}(x) < F_{18}(x) \quad \forall x \in \mathcal{S}^{\circ} \tag{5}$$

We formulate the null and alternative hypotheses as in (4) and (5), respectively, since we would like to use the data to provide strong evidence that confidence in Lebanon's institutions has decreased between 2013 and 2016 and between 2016 and 2018 (i.e., the alternative hypothesis).[7] The null hypothesis states that X_{13} does not strictly dominate X_{16} or, X_{16} does not strictly dominate X_{18} both stochastically, at first-order. We exclude the support point $\{4\}$ in H_1 since $F_{13}(4) = F_{16}(4) = F_{18}(4) = 1$. The alternative hypothesis is the negation of the null, and states that there is a chain of strict stochastic dominance: X_{13} dominating X_{16} and X_{16} dominating X_{18}, stochastically, at first-order.

However, as in any survey dataset, non-response presents challenges for inference. For

[7]Other notable testing procedures that posit a null of non-dominance include Berger (1988) and Alvarez-Esteban et al. (2017).

each data point,

$$\text{the practitioner observes} \begin{cases} X_Y & \text{if } D_Y = 1, \\ \text{missing value code} & \text{if } D_Y = 0, \end{cases}$$

where $D_Y = \mathbb{1}[X_Y \text{ individual responds to the survey item}]$ is the response indicator of an individual in the reference population of year $Y \in \{13, 16, 18\}$. Consequently, the population CDFs are not necessarily point-identified unless we are prepared to make strong unverifiable assumptions about the missingness-generating process. We circumvent the imposition of such assumptions by using the worst-case bounds on these CDFs put forward by Horowitz and Manski (1995), as they are robust to the nature of the missingness-generating process. While these CDF bounds can be wide in practice, they may be useful for comparing CDFs. Our approach to testing H_0 compares the worst-case lower bound of F_{16} and F_{18} with the worst-case upper bound of F_{13} and F_{16} respectively. To obtain these bounds, the missing values for the confidence variables are replaced respectively with the highest or lowest confidence possible. Allocating the highest value of confidence to the missing values, shifts the CDF downwards to the lowest possible point given the current distribution of the observed responses. Allocating the lowest value of confidence to the missing values, shifts the CDF upwards to the highest possible point given the current distribution of the observed responses. These bounds are CDFs and depend only on observed values. Following Horowitz and Manski (1995), we can define the upper and lower worst-case bounds of F_Y by $\overline{F}_Y$ and $\underline{F}_Y$, respectively:

$$\overline{F}_Y(x) = \text{Prob}\left[D_Y = 1\right] \text{Prob}\left[X_Y \leq x \mid D_Y = 1\right] + \text{Prob}\left[D_Y = 0\right] \quad \forall x \in \mathcal{S},$$

$$\underline{F}_Y(x) = \begin{cases} \text{Prob}\left[D_Y = 1\right] \text{Prob}\left[X_Y \leq x \mid D_Y = 1\right] & \forall x \in \mathcal{S}^\circ \\ 1 & \text{for } x = 4 \end{cases}.$$

To understand why $\bar{F}_Y(x)$ is an upper bound (i.e., $\bar{F}_Y(x) \geq F_Y(x)$ for each $x \in \mathcal{S}$), one can use the Law of Total Probability to derive the following representation of $F_Y(x)$:

$$F_Y(x) = \text{Prob}\left[D_Y = 1\right] \text{Prob}\left[X_Y \leq x \mid D_Y = 1\right] + \text{Prob}\left[X_Y \leq x \mid D_Y = 0\right] \text{Prob}\left[D_Y = 0\right]$$
$$\leq \text{Prob}\left[D_Y = 1\right] \text{Prob}\left[X_Y \leq x \mid D_Y = 1\right] + \text{Prob}\left[D_Y = 0\right] = \overline{F}_Y(x).$$

Similarly, to see why $\underline{F}_Y(x) \leq F_Y(x)$, for $x \in \mathcal{S}^\circ$:

$$F_Y(x) = \text{Prob}\left[D_Y = 1\right] \text{Prob}\left[X_Y \leq x \mid D_Y = 1\right] + \text{Prob}\left[X_Y \leq x \mid D_Y = 0\right] \text{Prob}\left[D_Y = 0\right]$$
$$\geq \text{Prob}\left[D_Y = 1\right] \text{Prob}\left[X_Y \leq x \mid= D_Y = 1\right] = \underline{F}_Y(x),$$

and $\underline{F}_Y(4) = F_Y(4) = 1$.

Instead of the testing problem (4) and (5), we consider the following testing problem:

$$H_0^1 : \max_{x \in \mathcal{S}} \left(\overline{F}_{13}(x) - \underline{F}_{16}(x)\right) \geq 0 \text{ or } \max_{x \in \mathcal{S}} \left(\overline{F}_{16}(x) - \underline{F}_{18}(x)\right) \geq 0 \quad \text{Vs.} \tag{6}$$
$$H_1^1 : \overline{F}_{13}(x) < \underline{F}_{16}(x) < \overline{F}_{16}(x) < \underline{F}_{18}(x) \ \forall x \in \mathcal{S}^\circ. \tag{7}$$

Rejecting H_0^1 in (6) for H_1^1 in (7), implies rejection of H_0 in (4) for H_1 in (5), since $\overline{F}_{13}(x) \geq F_{13}(x)$, $\underline{F}_{16}(x) \leq F_{16}(x) \leq \overline{F}_{16}(x)$, and $\underline{F}_{18}(x) \leq F_{18}(x), \forall x \in \mathcal{S}$.[8]

We treat the null hypothesis (6) as the union of two sub-hypotheses

$$H_0^{1,1} : \max_{x \in \mathcal{S}} \left(\overline{F}_{13}(x) - \underline{F}_{16}(x)\right) \geq 0 \tag{8}$$
$$H_0^{1,2} : \max_{x \in \mathcal{S}} \left(\overline{F}_{16}(x) - \underline{F}_{18}(x)\right) \geq 0, \tag{9}$$

and develop an intersection-union testing procedure. For each sub-hypothesis, we extend the testing procedure of Davidson and Duclos (2013) for testing $H_0^{1,1}$ and $H_0^{1,2}$ to account for survey sampling. To that end, we use the method of pseudo-empirical likelihood put forward by Chen and Sitter (1999).[9] We have three independent survey-samples: $\{X_{Y,i}, D_{Y,i}, W_{Y,i}\}_{i=1}^{n_Y}$ for $Y \in \{13, 16, 18\}$, where the $W_{Y,i}$ are the survey weights which have

[8]Because $\overline{F}_{13}(x) \geq F_{13}(x)$ and $\underline{F}_{16}(x) \leq F_{16}(x)$, $\overline{F}_{13}(x) - \underline{F}_{16}(x) < 0$ implies $F_{13}(x) - F_{16}(x) < 0$, and $\overline{F}_{16} \geq F_{16}(x)$ and $\underline{F}_{18}(x) \leq F_{18}(x)$, $\overline{F}_{16}(x) - \underline{F}_{18}(x) < 0$ implies $F_{16}(x) - F_{18}(x) < 0$.

[9]The details of the testing procedure are described in the appendix.

no missing values and n_Y is the number of observations in year Y. The surveys are such that $\sum_i W_{Y,i} = n_Y$ for each $Y \in \{13, 16, 18\}$.

To obtain a sample from the upper bound CDF $\overline{F}_Y$ using the sample $\{X_{Y,i}\}_{i=1}^{n_Y}$, replace each missing value in it with the smallest value in $\mathcal{S}$, (i.e. 1):

$$\overline{X}_{Y,i} = \begin{cases} X_{Y,i} & \text{if } D_{Y,i} = 1, \\ 1 & \text{if } D_{Y,i} = 0, \end{cases} \quad \forall i = 1, \ldots, n_Y.$$

Similarly, modifying the sample $\{X_{Y,i}\}_{i=1}^{n_Y}$ by replacing each missing value in it with the with the largest value in $\mathcal{S}$, (i.e. 4):

$$\underline{X}_{Y,i} = \begin{cases} X_{Y,i} & \text{if } D_{Y,i} = 1, \\ 4 & \text{if } D_{Y,i} = 0, \end{cases} \quad \forall i = 1, \ldots, n_Y,$$

yields a sample from the lower bound CDF $\underline{F}_Y$.

The intersection-union testing procedure for H_0^1 compares the minimum of the two pseudo-empirical log-likelihood-ratio statistics for each sub-hypothesis to an appropriate critical value. Similar to Davidson and Duclos (2013), Theorem 1 in the Appendix establishes that a conservative fixed-asymptotic critical value drawn from χ_1^2 distribution yields a valid test. That is

$$\text{Reject } H_0^1 \iff ELR_n > c(\alpha), \tag{10}$$

where $c(\alpha)$ is the $1-\alpha$ quantile from the χ_1^2 distribution, and ELR_n is the minimum of the two pseudo-empirical log-likelihood-ratio statistics as detailed in the Appendix.[10] Hence, a rejection of H_0^1 based on the decision rule (10) using a small significance level constitutes very strong evidence in favor of H_1^1, and thus, presents very strong evidence in favor of H_1 defined in (5).

[10] ELR_n is defined in (21) of the Appendix.

3 Data and Results

3.1 Data

To compare the patterns in the "average" confidence in authority we use data from the World Value Survey (2013)[11] and the Arab Barometer Surveys (2016 and 2018). Both surveys are nationally representative and report the level of confidence in Courts, Government, Parliament, Political Parties and Police Force. The datasets' sample sizes are $n_{13} = n_{16} = 1,200$ and $n_{18} = 2,400$. However, the question on trust in political parties was only asked on a subsample of size 1,215 in 2018. The non-response frequency for trust in the Government is quite large (18%), while the rest are all less than 10%. While it is tempting to consider particular assumptions/models to explain these non-response frequencies, they are unverifiable in practice and may yield biased inferences. Using the worst-case bounds, as we propose, permits the entire spectrum of models for these frequencies in inference. This approach is especially useful when this frequency is large (e.g., trust in Government) as there can be a diversity of explanations for it including fear of retaliation from public authorities.

3.2 Results

Results in the first row of Table 1 are the realized values of the empirical likelihood-ratio statistics and the conclusion of the hypothesis tests of H_0^1. Unfortunately, there is no evidence at the 5% level to reject non-dominance defined by H_0^1. As the realized values of the test statistic are all equal to zero, it follows that this conclusion also holds for any significance level. Therefore, we cannot establish the desired chain that shows a steady decrease in confidence over time. This finding is mainly driven by the comparisons between $F_{16}(x)$ and $F_{18}(x)$. For example, the right panel of Figure 1 displays the upper bound distribution $\overline{F}_{16}(x)$ and the lower bound distribution $\underline{F}_{18}(x)$ for trust in the government.

[11]Earlier versions of the Arab Barometer do not include these questions on trust.

From the figure, it is clear that the null hypothesis $H_0^{1,2}$ holds in the sample, implying that $ELR_n = 0$. We obtain similar results for trust in the other public institutions, indicating that we cannot robustly rank the trust levels in any public institutions between 2016 and 2018.

Let us now consider the left panel of Figure 1 displaying the upper bounds distribution $\overline{F}_{13}(x)$ and the lower bound distribution $\underline{F}_{16}(x)$ for trust in the government. This figure indicates that $\overline{F}_{13}(x) < \underline{F}_{16}(x)\ \forall x \in \mathcal{S}^\circ$ holds in the sample. This implies that $F_{13}(x) < F_{16}(x)\ \forall x \in \mathcal{S}^\circ$ holds in the sample. We perform the pseudo-empirical likelihood ratio test. The realized values of the test are displayed in the second row of Table 1 together with the conclusion of the hypothesis testing of $H_0^{1,1}$. For trust in courts, governments, parliament and political parties, we reject the null hypothesis in favour of the alternative $\overline{F}_{13}(x) < \underline{F}_{16}(x)\ \forall x \in \mathcal{S}^\circ$. It is also worth noting that for these variables, $H_0^{1,1}$ is also rejected at the 1% level.[12] However, $H_0^{1,1}$ cannot be rejected for trust in the police.

These results provide very strong evidence that trust levels in the Lebanese courts, government, parliament and political parties have dropped between 2013 and 2016, as the dominance orderings are statistically significant at the 1% level for these variables. Given that the asymptotic version of the test employs a conservative critical value, these findings are quite powerful. Thus, our conclusions are robust to any assumptions an analyst could make on the numerical scale applied to the trust level categories, and to any assumption made on the missingness-generating process. Consequently, an analyst cannot obtain a different result using any set of reasonable assumptions.

4 Conclusion

This paper presents evidence on erosion of trust in public institutions in Lebanon occurring prior to October 2019. In particular that there was a decrease in confidence in Lebanese

[12]The critical value in this case is approximately 6.63.

courts, government, parliament and political parties. This decrease is statistically significant despite the limited sample size, and minimal assumptions on (i) the numerical scale of the different ordinal categories of trust and (ii) missingness-generating process. The information conveyed by the perceptions reported in the surveys was mirrored on the streets in October 2019. If a policymaker would have looked into such information as they were made available, it would have allowed them to recognize the changing level of trust in public institutions and maybe forsee the uprisings three years in advance. The policy recommendation is quite straightforward. It is essential for policymakers in developing countries to closely monitor their constituents' perceptions and political attitudes and take them into account in policy making.

Future research should focus on the discrepancy between the generalized discontent expressed in the surveys and on the streets, and electoral outcomes. Also, it would be interesting to explore the causes of discontent and lack of trust. In this regard, there are many potential avenues to explore. One could study the complete mismatch between youth's education and employment opportunities as well as the mismanagement of public services. Examples of this mismanagement can easily be found in Lebanon: the incapacity of the government to offer a reliable supply of electricity (see Fakih and Marrouch, 2015) or the garbage crisis in 2015.[13]

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A Test Statistic and Asymptotic Distribution

A.1 Testing Procedure

The testing procedure follows Davidson and Duclos (2013) by focusing on the frontier of the null hypothesis of nondominance, H_0^1 in (6). In that direction, only one $x_1 \in \mathcal{S}^\circ$ such that $\overline{F}_{13}(x_1) = \underline{F}_{16}(x_1)$ for $H_0^{1,1}$ and only one $x_2 \in \mathcal{S}^\circ$ such that $\overline{F}_{16}(x_2) = \underline{F}_{18}(x_2)$ is required. Thus, to maximize the pseudo-empirical-likelihood function (PELF) under the constraint of the null, we begin by computing the maximum across each sub-hypothesis where, for given $x_1, x_2 \in \mathcal{S}^\circ$ we impose the conditions that $\overline{F}_{13}(x_1) = \underline{F}_{16}(x_1)$ and $\overline{F}_{16}(x_2) = \underline{F}_{18}(x_2)$. We then choose for the constrained maximum those values of x_1 an x_2 which give the greatest value of the constrained PELF in each sub-hypothesis. For given x_1 and x_2, the constraints we wish to impose for sub-hypotheses $H_0^{1,1}$ or $H_0^{1,2}$ can be written as

$$\sum_i \sum_j p_j^{16} p_i^{13} W_{13,i} W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x_1) = 0 \quad \text{and} \tag{11}$$

$$\sum_i \sum_j p_j^{18} p_i^{16} W_{16,i} W_{18,j} h(\overline{X}_{16,i}, \underline{X}_{18,j}, x_2) = 0, \tag{12}$$

respectively, where $h(Z_1, Z_2, z) = 1\,[Z_1 \leq z] - [Z_2 \leq z]$ and $\{p_1^Y, \ldots, p_{n_Y}^Y\}$ for $Y \in \{13, 16, 18\}$ are probability masses on the samples. The maximisation problem corresponding to $H_0^{1,1}$ is

$$\begin{aligned} \max_{p_1^Y, \ldots, p_{n_Y}^Y : Y \in \{13,16\}} \sum_{Y \in \{13,16\}} \sum_i W_{Y,i} \log p_i^Y \quad \text{subject to} \\ p_i^Y > 0 \; \forall (i, Y), \; \sum_i p_i^Y W_{Y,i} = 1 \text{ for } Y = 13, 16, \quad \text{and} \\ \sum_i \sum_j p_j^{16} p_i^{13} W_{13,i} W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x_1) = 0. \end{aligned} \tag{13}$$

Furthermore, the maximisation problem corresponding to $H_0^{1,2}$ is

$$\begin{aligned}
\max_{p_1^Y,\ldots,p_{n_Y}^Y:Y\in\{16,18\}} \sum_{Y\in\{16,18\}} \sum_i W_{Y,i} \log p_i^Y \quad \text{subject to} \\
p_i^Y > 0\ \forall (i,Y),\ \sum_i p_i^Y W_{Y,i} = 1 \text{ for } Y = 16, 18, \quad \text{and} \\
\sum_i \sum_j p_j^{18} p_i^{16} W_{16,i} W_{18,j} h(\overline{X}_{16,i}, \underline{X}_{18,j}, x_2) = 0.
\end{aligned} \tag{14}$$

Denote the maximal values of the above optimisation problems (13) and (14) by $L_{R,1}(x_1)$ and $L_{R,2}(x_2)$, respectively.

The unconstrained estimators of $\overline{F}_{13}, \underline{F}_{16}, \overline{F}_{16}$ and $\underline{F}_{18}$ are

$$\hat{\overline{F}}_{13}(x) = n_{13}^{-1} \sum_i W_{13,i} 1\left[\overline{X}_{13,i} \leq x\right] \tag{15}$$

$$\hat{\underline{F}}_{16}(x) = n_{16}^{-1} \sum_i W_{16,i} 1\left[\underline{X}_{16,i} \leq x\right] \tag{16}$$

$$\hat{\overline{F}}_{16}(x) = n_{16}^{-1} \sum_i W_{16,i} 1\left[\overline{X}_{16,i} \leq x\right] \text{ and} \tag{17}$$

$$\hat{\underline{F}}_{18}(x) = n_{18}^{-1} \sum_i W_{18,i} 1\left[\underline{X}_{18,i} \leq x\right], \tag{18}$$

respectively. The pseudo-empirical likelihood-ratio test statistics, ELR_n, for the sub-hypotheses $H_0^{1,1}$ and $H_0^{1,2}$ are defined as

$$ELR_n^{(13,16)} = \begin{cases} \min_{x_1 \in \mathcal{S}^\circ} 2(L_{UR,1} - L_{R,1}(x_1)) & \text{if } \hat{\overline{F}}_{13}(x) < \hat{\underline{F}}_{16}(x)\ \forall x \in \mathcal{S}^\circ, \\ 0 & \text{otherwise,} \end{cases} \tag{19}$$

and

$$ELR_n^{(16,18)} = \begin{cases} \min_{x_2 \in \mathcal{S}^\circ} 2(L_{UR,2} - L_{R,2}(x_2)) & \text{if } \hat{\overline{F}}_{16}(x) < \hat{\underline{F}}_{18}(x)\ \forall x \in \mathcal{S}^\circ, \\ 0 & \text{otherwise,} \end{cases} \tag{20}$$

respectively, where

$$L_{UR,1} = \sum_{Y\in\{13,16\}} \sum_i W_{Y,i} \log(1/n_Y), \quad \text{and} \quad L_{UR,2} = \sum_{Y\in\{16,18\}} \sum_i W_{Y,i} \log(1/n_Y),$$

are the unconstrained maximum values of the PELF function under the different sub-hypotheses $H_0^{1,1}$ and $H_0^{1,2}$, respectively.

The pseudo-empirical likelihood-ratio statistic we employ for testing H_0^1 is defined as

$$ELR_n = \min\left\{ELR_n^{(13,16)}, ELR_n^{(16,18)}\right\}. \tag{21}$$

The formulation of ELR_n as in (21) implements the testing procedure if we observe the sample satisfies

$$\hat{\overline{F}}_{13}(x) < \hat{\underline{F}}_{16}(x) \quad \text{and} \quad \hat{\overline{F}}_{16}(x) < \hat{\underline{F}}_{18}(x) \quad \forall x \in \mathcal{S} - \{4\};$$

that is, dominance in the sample, holds, for each sub-hypothesis. Otherwise, $ELR_n = 0$ and we do not reject the null hypothesis. This formulation of the test statistic follows the prescription described in Section 6 of Davidson and Duclos (2013).

For a given $x \in \mathcal{S}^\circ$ such that $\overline{F}_{13}(x) - \underline{F}_{16}(x) = 0$ or $\overline{F}_{16}(x) - \underline{F}_{18}(x) = 0$, the next section develops conditions on the survey's design that yield

$$2(L_{UR,1} - L_{R,1}(x)) \xrightarrow{d} \chi_1^2, \quad \text{or} \tag{22}$$

$$2(L_{UR,2} - L_{R,2}(x)) \xrightarrow{d} \chi_1^2, \tag{23}$$

in design, as $\min\{n_{13}, n_{16}, n_{18}\} \to +\infty$. These are conditions that are common to many survey designs. Since $ELR_n \leq 2(L_{UR,1} - L_{R,1}(x))$ for a $x \in \mathcal{S}^\circ$, we can test H_0^1 using a conservative fixed-asymptotic critical value drawn from χ_1^2 distribution. That is

$$\text{Reject } H_0^1 \iff ELR_n > c(\alpha), \tag{24}$$

where $c(\alpha)$ is the $1 - \alpha$ quantile from the χ_1^2 distribution. Hence, a rejection of H_0^1 based on the decision rule (24) using a small significance level constitutes very strong evidence in favor of H_1^1, and hence, is very strong evidence in favor of H_1 defined in (4).

A.2 Asymptotic Null Distribution

This section develops the proof of the asymptotic distribution in (22), for brevity. The formal result is stated below as Theorem 1. It is without loss of generality as similar conditions would apply, with appropriate modifications, for establishing (23). The conditions of Theorem 1 are standard in many survey designs. The proof follows the derivations and arguments from Section 11.4 of Owen (2001), but with appropriate modifications, because we have two independent survey samples while that section's setup has two independent random samples.

Next, we state the conditions used in the proof of Theorem 1.

Condition 1 *For each $x \in \mathcal{S}^{\circ}$, the estimators of $\overline{F}_{13}(x)$ and $\underline{F}_{16}(x)$, given by $\hat{\overline{F}}_{13}(x)$ and $\hat{\underline{F}}_{16}(x)$,respectively, are design-consistent.*

This condition implies that

$$\hat{\overline{F}}_{13}(x_1) - \hat{\underline{F}}_{16}(x_1) = \sum_i \sum_j \frac{W_{13,i}}{n_{13}} \frac{W_{16,j}}{n_{16}} h(\overline{X}_{13,i}, \underline{X}_{16,i}, x_1) \tag{25}$$

is a design-consistent estimator of $\overline{F}_{13}(x_1) - \underline{F}_{16}(x_1)$.

Condition 2 *For each $x \in \mathcal{S}^{\circ}$, $VAR\left(\hat{\overline{F}}_{13}(x) - \hat{\underline{F}}_{16}(x)\right) > 0$. Additionally, define $H_{ij} = W_{13,i}W_{16,j}h(\overline{X}_{13,i}, \underline{X}_{16,j}, x)$ for each i and j. Let*

$$D = \frac{1}{n_{13}^2 n_{16}^2} \sum_i \sum_j H_{ij} \sum_\ell H_{i\ell} + \frac{1}{n_{13}^2 n_{16}^2} \sum_i \sum_j H_{ij} \sum_\ell H_{\ell j} \quad \textit{and}$$
$$K = \frac{1}{n_{13}} \sum_i W_{13,i} \bar{H}_{i\bullet}^2 + \frac{1}{n_{16}} \sum_j W_{16,j} \bar{H}_{\bullet j}^2,$$

for each i and j, where $\bar{H}_{i\bullet} = \frac{1}{n_{16}} \sum_j W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x)$ and $\bar{H}_{\bullet j} = \frac{1}{n_{13}} \sum_i W_{13,i} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x)$. Then for each $x \in \mathcal{S}^{\circ}$, $VAR\left(\hat{\overline{F}}_{13}(x) - \hat{\underline{F}}_{16}(x)\right)(4D^{-1} - 3KD^{-2}) \xrightarrow{P} 1$ in design, as $\min\{n_{13}, n_{16}\} \to +\infty$.

Condition 3 *For each $x \in \mathcal{S}^{\circ}$,*

$$\frac{\hat{\overline{F}}_{13}(x) - \hat{\underline{F}}_{16}(x) - \left(\overline{F}_{13}(x) - \underline{F}_{16}(x)\right)}{\sqrt{VAR\left(\hat{\overline{F}}_{13}(x) - \hat{\underline{F}}_{16}(x)\right)}} \xrightarrow{d} N(0,1)$$

in design, as $\min\{n_{13}, n_{16}\} \to +\infty$, where the variance computation is with respect to the design.

Next, we establish the asymptotic distribution theory in (22).

Theorem 1 *Suppose that $x \in \mathcal{S}^\circ$ has $\overline{F}_{13}(x) - \underline{F}_{16}(x) = 0$, and that Conditions 1 - 3, hold. Then* $2(L_{UR,1} - L_{R,1}(x)) \xrightarrow{d} \chi^2_1$ *in design, as* $\min\{n_{13}, n_{16}\} \to +\infty$.

Using Lagrange multipliers for deriving the solutions to the PELF problem (13), we find

$$p_i^{13} = \left[n_{13} + \lambda \sum_j p_j^{16} W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x) \right]^{-1}, \ i = 1, \ldots, n_{13}, \tag{26}$$

$$p_j^{16} = \left[n_{16} + \lambda \sum_i p_j^{13} W_{13,i} h(\overline{X}_{16,j}, \underline{X}_{16,j}, x) \right]^{-1}, \ j = 1, \ldots, n_{16}, \tag{27}$$

where λ is defined by $\sum_i \sum_j p_j^{16} p_i^{13} W_{13,i} W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x) = 0$.

We simplify our notation by matching it to that in Section 11.4 of Owen (2001) and follow his derivations. Introduce the terms

$$\bar{H}_{i\bullet} = \frac{1}{n_{16}} \sum_j W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x), \quad \tilde{H}_{i\bullet} = \sum_j p_j^{16} W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x) \tag{28}$$

$$\bar{H}_{\bullet j} = \frac{1}{n_{13}} \sum_i W_{13,i} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x), \quad \tilde{H}_{\bullet j} = \sum_i p_i^{13} W_{13,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x), \tag{29}$$

$H_{ij} = W_{13,i} W_{16,j} h(\overline{X}_{13,i}, \underline{X}_{16,j}, x)$, and $\bar{H}_{\bullet\bullet} = \hat{\overline{F}}_{13}(x) - \underline{\hat{F}}_{16}(x)$. Then,

$$p_i^{13} = \frac{1}{n_{13}} \left[1 - \left(\frac{\lambda \tilde{H}_{i\bullet}}{n_{13}} \right) + \left(\frac{\lambda \tilde{H}_{i\bullet}}{n_{13}} \right)^2 - \left(\frac{\lambda \tilde{H}_{i\bullet}}{n_{13}} \right)^3 + \cdots \right] \ \forall i$$

$$p_j^{16} = \frac{1}{n_{16}} \left[1 - \left(\frac{\lambda \tilde{H}_{\bullet j}}{n_{16}} \right) + \left(\frac{\lambda \tilde{H}_{\bullet j}}{n_{16}} \right)^2 - \left(\frac{\lambda \tilde{H}_{\bullet j}}{n_{16}} \right)^3 + \cdots \right] \ \forall j.$$

Substituting these values into $\sum_i \sum_j p_j^{16} p_i^{13} H_{ij} = 0$, we obtain

$$0 = \bar{H}_{\bullet\bullet} - \lambda \left[\frac{\sum_i \sum_j H_{ij} \tilde{H}_{i\bullet}}{n_{13}^2 n_{16}} + \frac{\sum_i \sum_j H_{ij} \tilde{H}_{\bullet j}}{n_{16}^2 n_{13}} \right] \tag{30}$$

$$+ \lambda^2 \left[\frac{\sum_i \sum_j H_{ij} \tilde{H}_{i\bullet}^2}{n_{13}^3 n_{16}} + \frac{\sum_i \sum_j H_{ij} \tilde{H}_{\bullet j}^2}{n_{16}^3 n_{13}} + \frac{\sum_i \sum_j H_{ij} \tilde{H}_{i\bullet} \tilde{H}_{\bullet j}}{n_{13}^2 n_{16}^2} \right] + \cdots \tag{31}$$

Under Condition 1 and $\overline{F}_{13}(x) - \underline{F}_{16}(x) = 0$, this equality is equivalent to a convergent power series in λ, with the modulus of the coefficients of λ^ℓ bounded by ℓ. Moreover, the limit of this series converges to zero in probability under the design. Hence, asymptotically, we can ignore higher-order terms in λ to find $\lambda \stackrel{a}{=} D^{-1}\bar{H}_{\bullet\bullet}$, where

$$D = \frac{1}{n_{13}^2 n_{16}^2} \sum_i \sum_j H_{ij} \sum_\ell H_{i\ell} + \frac{1}{n_{13}^2 n_{16}^2} \sum_i \sum_j H_{ij} \sum_\ell H_{\ell j}. \tag{32}$$

In finding this D, the term

$$\tilde{H}_{i\bullet} = \bar{H}_{i\bullet} - \frac{\lambda}{n_{16}^2} \sum_j H_{ij} \tilde{H}_{\bullet j} \tag{33}$$

has been replaced by $\bar{H}_{i\bullet}$ and $\tilde{H}_{\bullet j}$ has been replaced by $\bar{H}_{\bullet j}$, with the differences being absorbed into the coefficient of λ^2.

Now keeping up to order λ^2 in the profile PELF and using a standard expansion of the logarithm function $\log(1+x)$ for $|x| < 1$, we find

$$\begin{aligned}
2(L_{UR,1} - L_{R,1}(x)) &= 2\sum_i W_{13,i} \log\left(1 + \frac{\lambda \tilde{H}_{i\bullet}}{n_{13}}\right) + 2\sum_j W_{16,i} \log\left(1 + \frac{\lambda \tilde{H}_{\bullet j}}{n_{16}}\right) \\
&\stackrel{a}{=} 2\sum_i W_{13,i} \left[\frac{\lambda \tilde{H}_{i\bullet}}{n_{13}} - \frac{1}{2}\left(\frac{\lambda \tilde{H}_{i\bullet}}{n_{13}}\right)^2\right] + 2\sum_j W_{16,i} \left[\frac{\lambda \tilde{H}_{\bullet j}}{n_{16}} - \frac{1}{2}\left(\frac{\lambda \tilde{H}_{\bullet j}}{n_{16}}\right)^2\right].
\end{aligned}$$

Replacing $\tilde{H}$'s by corresponding $\bar{H}$'s and keeping terms to order λ^2, we get

$$\begin{aligned}
2(L_{UR,1} - L_{R,1}(x)) &\stackrel{a}{=} 2\sum_i \frac{W_{13,i}\lambda \bar{H}_{i\bullet}}{n_{13}} - \frac{2\lambda^2}{n_{16}} \sum_j W_{16,j} \bar{H}_{\bullet j}^2 - \sum_i W_{13,i} \left(\frac{\lambda \bar{H}_{i\bullet}}{n_{13}}\right)^2 \\
&\quad + 2\sum_j \frac{W_{16,j}\lambda \bar{H}_{\bullet j}}{n_{16}} - \frac{2\lambda^2}{n_{13}} \sum_i W_{13,i} \bar{H}_{i\bullet}^2 - \sum_j W_{16,j} \left(\frac{\lambda \bar{H}_{\bullet j}}{n_{16}}\right)^2 \\
&= 4\lambda \bar{H}_{\bullet\bullet} - 3\lambda^2 \left(\frac{1}{n_{13}} \sum_i W_{13,i} \bar{H}_{i\bullet}^2 + \frac{1}{n_{16}} \sum_j W_{16,j} \bar{H}_{\bullet j}^2\right) \\
&\stackrel{a}{=} \bar{H}_{\bullet\bullet}^2 \,(4D^{-1} - 3KD^{-2}), \\
&= \left(\frac{\bar{H}_{\bullet\bullet}}{\sqrt{\mathrm{VAR}(\bar{H}_{\bullet\bullet})}}\right)^2 \mathrm{VAR}(\bar{H}_{\bullet\bullet})(4D^{-1} - 3KD^{-2})
\end{aligned}$$

where

$$K = \frac{1}{n_{13}} \sum_i W_{13,i} \bar{H}_{i\bullet}^2 + \frac{1}{n_{16}} \sum_j W_{16,j} \bar{H}_{\bullet j}^2.$$

To complete the argument, Conditions 2 and 3 imply

$$\mathrm{VAR}(\bar{H}_{\bullet\bullet})(4D^{-1} - 3KD^{-2}) \xrightarrow{P} 1,$$
$$\left(\frac{\bar{H}_{\bullet\bullet}}{\sqrt{\mathrm{VAR}(\bar{H}_{\bullet\bullet})}}\right)^2 \xrightarrow{d} \chi_1^2$$

in design, as $\min\{n_{13}, n_{16}\} \to +\infty$, respectively. ■

Table 1: Realised values of ELR_n and decision based on 5% significance level

	Courts	Government	Parliament	Political Party	Police Force
H_0^1	0 Do not Reject H_0^1	0 Do not Reject H_0^1	0 Do not Reject H_0^1	0 Do not Reject H_0^1	0 Do not Reject H_0^1
$H_0^{1,1}$	66.7 Reject $H_0^{1,1}$	21.66 Reject $H_0^{1,1}$	10.37 Reject $H_0^{1,1}$	17.22 Reject $H_0^{1,1}$	0 Do not Reject $H_0^{1,1}$

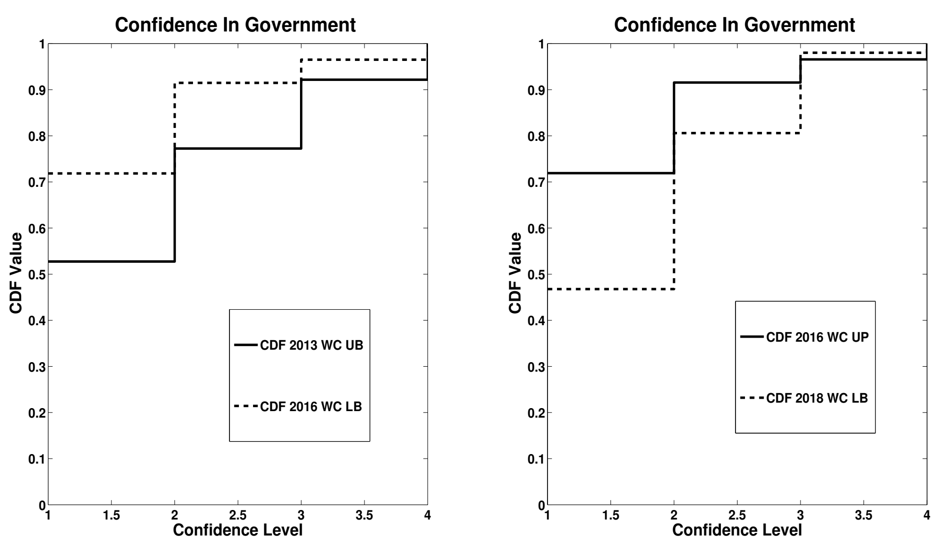

Figure 1: Trust in the government for the period 2013-2016 and 2016-2018