Institutional Trust and Attitudes towards Public Welfare Provision

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1. **Introduction**

Why do some people have favorable attitudes toward public welfare provision while others do not? Provision of public welfare is of great importance for social scientists and policy makers since it is a key tool for a society to deal with income inequality. Therefore, it is crucial to understand public attitudes toward the provision of welfare service. Existing literature in various disciplines in social science shed light on various factors that determine individuals' preferences for public welfare provision. The most prevalent explanation focuses on the self-interest. The key argument in this stream of the literature is that individuals support the provision of welfare service or a particular type of welfare program when it is in their material interests (Alesina and La Ferrara, 2005; Mayda and Rodrik, 2005). Another wide-spread conventional wisdom focuses on ideology: left-leaning individuals are more in favor of redistribution and public welfare while rightist ideologies are associated with minimum governmental economic intervention.

In this paper, I focus on institutional trust. In line with Rothstein et al. (2012) and Svallfors (2013), I claim that support for public welfare service is heavily affected by people's trust in the public institutions that oversee and control welfare programs. The underlying logic is that the more one is confident in the impartiality and efficiency of political institutions in charge of the articulation and implementation of public welfare programs, the more likely they are to support public welfare provision. When people perceive these political institutions to be free of corruption and highly professional, they are more wiling to invest their political support and to pay tax for public welfare programs. When citizens are confident that their money, i.e. tax, is not misused, they are more likely to support for the public provision of welfare service.

My core argument is three-fold. First, I argue that the effect of institutional trust is more prominent when it is explicitly associated with paying tax than when it is not. The key logic behind this argument is based on people's concern about misuse of public funds. Thus, I expect that people with strong institutional distrust *can be in favor of* public provision of welfare per se but *will be skeptical of* increasing tax for public welfare. The second argument concerns different types of institutions: perception of tangible institutions matters more than that of intangible institutions. I propose that people's perception of lower-level political institutions have more prominent effects on their public welfare attitudes than higher-level political institutions. Third, I propose that this individual-level effect is mediated by the context that individuals are nested in. In this paper, I focus on local-level political polarization. Here, I expect that in areas with strong partisan leaning (being a particular political party's stronghold) people's trust in political institutions matters less because the local partisan context strongly encourages them to form attitudes for or against public provision of welfare service.

The empirical analysis in section 3 will be based on conventional statistical strategies that assume SRSWR (Simple Random Sampling With Replacement). In the subsequent sections, however, I employ four techniques designed for complexity of survey data in order to more properly test the above-mentioned arguments. First, I use a weight variable to correct for bias coming form misrepresentation of the population in the data. Second, I consider complex sampling design focusing on clustering. Third, I employ multiple imputation method to deal with missing observations. Last, as above-mentioned, I employ techniques to deal with contextual analysis.

I test my arguments using the 2016 KGSS (Korea General Social Survey) data. In general, the results of this paper suggest that institutional trust has strong effects on people's attitude towards provision of welfare service, even after taking major issues associated with survey data analysis into account. Specifically, the results support my claim that there is some nuance in the way that institutional trust influences welfare attitudes. First, institutional trust has far stronger effects on attitudes toward public welfare provision when it is explicated associated with tax increase. Second, it is tangible institutions, not intangible ones, that matter for attitudes toward public welfare provision. These results are fairly robust across model assuming SRSWR, models with weighting, and models that consider weighting and clustering. On the other hand, the interactive effect of local-level political polarization gets little support.

2. Theory and Hypotheses

As mentioned in the introduction, I distinguish between attitudes toward general idea of public welfare (is provision of public welfare desirable?) and attitude toward the need for tax increase for public welfare (will you pay tax for public welfare?). My expectation is that institutional trust will have strong effects on the latter but not as much on the former.

H1: Citizens with strong institutional trust will support for tax increase necessary for public welfare provision

H2: Citizens' institutional trust will have weak or no effects on their general attitude toward public welfare provision.

In addition, I will examine different institutions: tangible and intangible. My claim is that citizens form their attitudes toward public welfare provision based more on tangible institutions rather than intangible institutions. What citizens deal with in ordinary life is public officials or local governments rather than abstract entities such as national governments. Thus, I expect that citizens' perception of tangible institutions will have more visible effects on their attitudes toward public welfare provision.

H3: Citizens' attitude toward tangible institutions will have strong effects on their welfare attitudes

H4: Citizens' attitude toward intangible institutions will have weak or no effects on their welfare attitudes

Finally, I am going to examine the effect of local contexts. I claim that the level of partisan polarization at the local level can moderate the effect of institutional trust on attitudes toward public welfare provision. In the context where the locality is heavily skewed toward a political party, I expect that the effect of institutional trust will be weaker because the local political/partisan context strongly encourages people to form attitudes for or against public provision of welfare service.

H5: In localities with political polarization, the effect of institutional trust diminishes.

3. Statistical Analysis Assuming Simple Random Sample: Naive Approach

3.1. Data

In order to test the above-mentioned hypotheses, I use the 2016 KGSS data. Simply speaking, KGSS is a Korean version of GSS (General Social Survey) in the United States. The 2016 KGSS's target population is non-institutionalized residents in Korea who are 18 years of age or older and who can communicate in Korean. The total number of respondents is 1052 with the response rate of 47%. The sampling is conducted through five stages utilizing an area probability sampling method. The first four stages select the required number of households. The fifth stage selects an eligible person from each selected household (Survey Research Center, 2016).

In the first stage, the entire country was pre-stratified into 17 parts according to the highest-level administrative areas (Si or Do). Table 1 presents the 17 strata and its respective population size based on the census data. In the second stage, a total of 100 PSUs (Primary Sampling Unit: Dong, Eub, or Myon) were randomly selected from each of the 17 stratum. In the last two columns, we can see that the number of samples allocated to each stratum is proportionate to its actual population size.[1] In the third stage, SSUs (secondary Sampling Unit: Tong, Ban, or Ri) were also randomly selected again based on PPS. Using the household list in each SSU, the fourth stage randomly samples households. All of these stages of sampling are based on PPS (Probability Proportional to Size) and it is important to note that it makes the entire sample an EPSEM (Equal Probability of Selection Method) sample. Finally, the fifth stage selects from each household based on the last birthday method (Survey Research Center, 2016).

[1] The PSU will be used as the cluster variable in the later section.

Stratum	Number of household	%	Number of PSU
1	4,194,176	20.23	20
2	1,416,648	6.83	7
3	970,618	4.68	5
4	1,136,280	5.48	5
5	573,043	2.76	3
6	592,508	2.86	3
7	442,250	2.13	2
8	62,807	0.3	1
9	4,786,718	23.08	23
10	673,978	3.25	3
11	656,321	3.17	3
12	871,459	4.2	4
13	774,562	3.74	4
14	840,864	4.06	4
15	1,153,559	5.56	6
16	1,343,984	6.48	6
17	246,516	1.19	1
Total	20,736,291	100	100

Table 1. Stratum and PSU Allocation (Survey Research Center, 2016)

3.2. Variables

Table 2 provides information on major variables included in the analysis. First, I have two dependent variables. *Public Welfare* measures respondents' general attitude towards public provision of welfare service. On the other hand, *Tax Welfare* incorporates an important dimension: willingness to make financial contribution to public welfare service, i.e. tax payment. As previously mentioned, I aim to tease out the difference between attitudes with and without implication for financial transaction. Figure 1 provides the distribution of the two dependent variables.

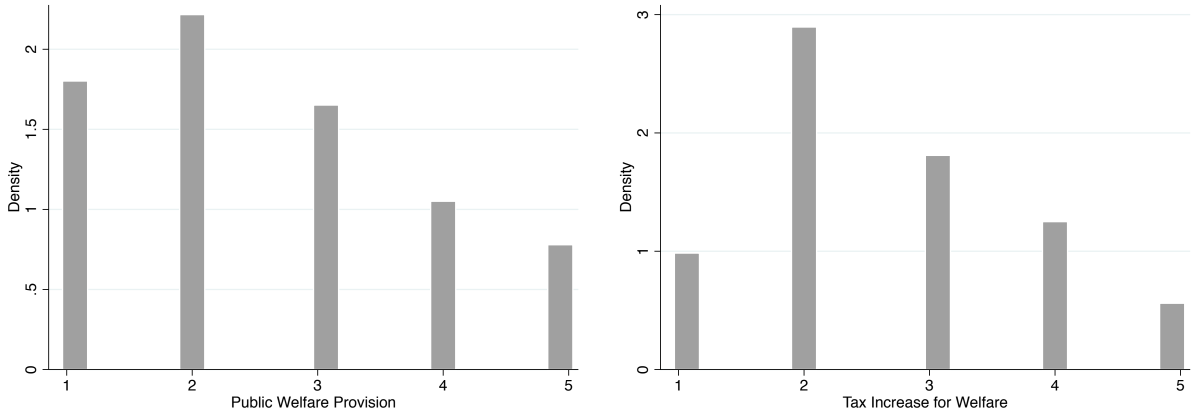

Figure 1. Dependent Variables

Second, in order to capture citizens' perception of different institutions, I included three independent variables: *National Trust*, *Local Trust*, and *Official Trust*. The first two measures respondents' trust in the national government and the local government, respectively. I expect that the first variable, *National Trust*, captures citizens' trust in intangible institutions. On the other hand, I design the second and third independent variables, *Local Trust* and *Official Trust*, to capture citizens' trust in more tangible institutions. *Local Trust* measures citizens' trust in their local governments and *Official Corruption* measures the perception of public official's corruption level.

Alongside with standard demographic variables including *Age, Sex*, and *Education*, I also include two additional control variables to deal with potential omitted variable bias: *Ideology* and *Satisfaction Government*. *Ideology* measures respondents' self-reported position on the liberal-conservative continuum. It is important to control for political ideology because it can both affect attitudes toward public welfare and perception of political institutions. Similarly, satisfaction with the current government can affect both one's perception of political institutions (more satisfied more likely to trust) and government welfare/tax policies. The descriptive statistics for all the variables used for my test is reported in Table 3.

Variable	Question	Answer
Tax Welfare	How much do you agree or disagree with the following statement? More tax should be collected to expand social welfare.	Strongly agree (1) ~ Strongly disagree (5), Don't know (8)
Public Welfare	To pursue one's happy life, how much do you agree with the following statement?	The government should provide welfare at the maximum level (0) ~ The government should provide minimum assistance as needed (5)
National Trust	Would you say you have a great deal of confidence, only some confidence, or hardly any confidence in the national government?	A great deal of confidence (1) ~ Hardly any confidence at all (3), Don't know (8)

Local Trust	Would you say you have a great deal of confidence, only some confidence, or hardly any confidence in the local government	A great deal of confidence (1) ~ Hardly any confidence at all (3), Don't know (8)
Official Corruption	In your opinion, about how many public officials in Korea are involved in corruption?	Almost none (1) ~ Almost all (5), Can't choose (8)
Ideology	To what degree do you think yourself politically liberal or conservative?	Very liberal (1) ~ Very conservative (5), Don't Know (8)
Satisfaction Government	On the whole, how good do you think the current government is in administering state affairs?	Very good (1) ~ Very poor (5), Can't choose (8)
Education	The education level of the respondent	Low (0) ~ High (10)
Sex	The sex of the respondent	Male (1), Female (2)
Age	The age of the respondent	Actual age
Income	The income level of the respondent	Low (1) ~ High (21)

Table 2. Variable Summary

Variable	N	Mean	S.D.	Min	Max
Tax Welfare	1044	2.668	1.126	1	5
Public Welfare	1049	2.572	1.277	1	5
National Trust	1019	2.402	.602	1	3
Local Trust	1015	2.35	.618	1	3
Official Corruption	1041	3.31	.984	1	5
Education	1051	3.545	1.706	0	8
Sex	1051	1.548	.498	1	2
Age	1051	49.586	18.609	18	99
Income	963	8.883	5.995	0	21
Ideology	1016	3.001	.936	1	5
Satisfaction Government	1033	3.61	1.079	1	5

Table 3. Descriptive Statistics

3. 3. Estimation and Results

Treating the two dependent variable as continuous, I fit OLS regression model. First, I regressed *Tax Welfare* on three independent variables, respectively, along with controls. As seen in Table 4, all the independent variables behave as expected. Citizens' trust in local governments and public officials are strongly associated with their support for tax increase for public welfare. The coefficients for *Local Trust* and *Official Corruption* are statistically significant at 0.01 level. Not only do they show statistical significance, they also have substantial influence. On average, people with the lowest level of trust in their local government score 0.5 point higher on the five-point scale measure of tax increase for public welfare provision than those with the highest level of trust in their local government. *Official Corruption* also have a slightly weaker but still strong effect on people's propensity to support for tax increase for public welfare service. In contrast, the coefficient of *National Trust*, people's trust in their national government, is statistically indistinguishable from 0. That is, no matter how much trust people have in the national government, it is little of importance in terms of their attitude towards tax increase for public welfare. Altogether, the results in Table support Hypotheses 1, 3, and 4.

	Model 1	Model 2	Model 3
National Trust	0.015		
	(0.068)		
Local Trust		0.164***	
		(0.062)	
Official Trust			0.134***
			(0.038)
Education	-0.031	-0.036	-0.031
	(0.030)	(0.030)	(0.030)
Sex	0.167**	0.164**	0.165**
	(0.074)	(0.074)	(0.073)
Age	-0.006**	-0.006**	-0.007**
	(0.003)	(0.003)	(0.003)
Income	0.004	0.004	0.005
	(0.007)	(0.007)	(0.007)
Ideology	0.174***	0.170***	0.178***
	(0.040)	(0.040)	(0.040)
Satisfaction Government	-0.044	-0.072*	-0.061
	(0.041)	(0.039)	(0.037)
Constant	2.359***	2.151***	2.022***
	(0.333)	(0.332)	(0.327)
N	907	903	921
R-squared	0.032	0.041	0.047

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 4. OLS Regression: Tax Increase for Public Welfare

Table 5 reports the results for people's general attitude toward public welfare. Here, it is important to note that the question of interest is about the general idea of public welfare provision. The results provide partial support for Hypothesis 2. The coefficient of *Official Trust* is now insignificant. Compared to its effect on the support for tax increase for welfare, it is irrelevant for the general attitude toward the idea of public welfare provision (Model 6). However, Model 5 shows that the coefficient of *Local Government* is still statistically significant. It suggests that institutional trust can also affect people's attitude toward the general idea of public provision of welfare service. Nevertheless, we can see that the coefficient of Local Government in Model 5 is smaller than in Model 2. The coefficient on *National Trust* is again statistically indistinguishable from 0. This provides addition support for Hypothesis 3 and 4.

	Model 4	Model 5	Model 6
National Trust	-0.113		
	(0.078)		
Local Trust		0.121*	
		(0.071)	
Official Trust			0.063
			(0.043)
Education	0.075**	0.074**	0.079**
	(0.035)	(0.035)	(0.034)
Sex	-0.153*	-0.174**	-0.181**
	(0.084)	(0.085)	(0.083)
Age	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)
Income	0.020**	0.020**	0.022***
	(0.008)	(0.008)	(0.008)
Ideology	0.204***	0.197***	0.203***
	(0.046)	(0.046)	(0.045)
Satisfaction Government	-0.028	-0.074*	-0.070
	(0.047)	(0.044)	(0.043)
Constant	1.682***	1.366***	1.376***
	(0.379)	(0.380)	(0.376)
N	912	907	925
R-squared	0.053	0.053	0.055

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 5. OLS Regression: Public Welfare Provision

4. Weighting

So far, I have estimated the mean of the key variables (Table 3) and the regression coefficients of the independent and control variables (Table 4 and 5). However, how much confidence do we have in our estimates? When certain subsections of the population are over- or under-represented, it can potentially bias our estimation of descriptive statistics, such as mean or median, and of regression coefficients in bivariate analysis. This section thus reexamines the univariate and bivariate analysis in the previous sections focusing on weighting.

4. 1. Weighting Method

Most of all, it is important to note that the 2016 KGSS is an EPSEM. In the context of multiple-stage sampling method like the 2016 KGSS, being an EPSEM sample means that every unit that is finally included in the sample has the same probability of being selected in advance of sampling (by *design*). Thus, the *design weight* is effectively 1. Second, another way of weighting, *model-based weight*, is unavailable for two reasons. One is that the 2016 KGSS is not a panel study so it is impossible to model attrition using logistic regression or hazard model. The other is the 2016 KGSS sample is not drawn from a comprehensive sampling frame. Even though it was the case, it would be difficult to acquire frame variable that are highly predictive of non-response.

Therefore, the 2016 KGSS provides a post-stratification weight variable based on raking. For post-stratification adjustment, it uses four variables: sex, age, region, and urban-rural divide. [2] It would be feasible to use ratio method if there were enough units in each cell for the 4-way. However, it is not the case for the 2016 KGSS. That is why the 2016 KGSS uses raking weighting or iterative proportional weighting. Table 6 presents its descriptive statistics and Figure 2 presents the histogram for the post-stratification weight variable. We can see that there are a small number of units that are heavily under-represented in the sample and thus have extremely high values with the maximum of 3.436 (also note that the mean is designed to be 1).

Variable	N	Mean	S.D.	Min	Max
Weightd	1051	1	.48	.252	3.436

Table 6. OLS Regression: Public Welfare Provision

[2] Sex (Male, Female), Age (18-29, 30-39, 40-49, 50-59, 60 and over), Region (Seoul, Kyunggi, Kangwon, Chungchong, Kyungsang, Cholla, Jeju), and Urban-rural divide (Urban, Rural).

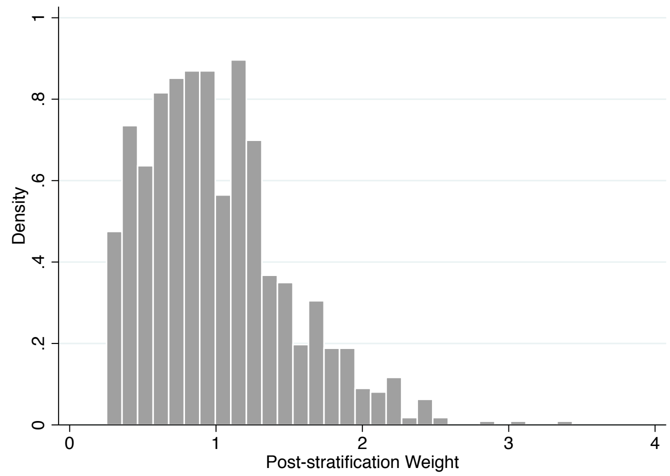

Figure 2. Post-stratification Weight

4. 2. Descriptive Statistics

Where there are differential probabilities of selection into the sample, descriptive statistics such as means, medians, and proportions are always potentially biased estimates of the population parameters. No matter whether differential probabilities of selection stem from the the sample design or the process of implementation, weighted analysis is necessary to correct for bias that comes from under- and over-representation for the population.

Equally important is that weighting increases the standard errors for our descriptive statistics. This is because outliers in under-represented groups (those with the weight over 1) have even more influence after weighting. Typically, the inflation of sampling variance (standard error) by weighting is measured by coefficient of variation and it is calculated by dividing the standard deviation of the weight with its mean. The mean is 1 in our case and the coefficient of variation is simply the standard deviation of the weight: 0.48. Alternatively, we can also approximate the inflation by squaring the coefficient of variation and adding 1: $\mathrm{Inflation} \approx 1 + \mathrm{CV}_{\mathrm{weight}}^{2}$ (here, it lead to 1.23).

Table 7 compares the mean of the variables included in the analysis when they are weighted and not. First of all, we can see that the unweighted means are different from the weighted means. The differences can be either substantial or unsubstantial depending on the context. For the purpose this paper, estimation of the population mean is not of substantial interest. Nevertheless, it is important to note that weighting corrects for bias and thus makes a difference. In addition, we can confirm that standard errors inflate after weighting. Unweighted standard errors in the second column tend to be smaller than weighted ones in the fourth column.

Variable	Unweighted		Weighted	
	Mean	S.E.	Mean	S.E.
Tax Welfare	2.668	0.035	2.651	0.038
Public Welfare	2.572	0.039	2.590	0.043
National Trust	2.402	0.019	2.398	0.021
Local Trust	2.350	0.019	2.348	0.021
Official Corruption	3.310	0.030	3.288	0.031
Education	3.545	0.052	3.790	0.051
Sex	1.548	0.015	1.504	0.017
Age	49.586	0.574	46.972	0.545
Income	8.883	0.193	10.083	0.216
Ideology	3.001	0.029	2.960	0.032
Satisfaction Government	3.610	0.034	3.683	0.036

Table 7. Descriptive Statistics:
Comparison between Unweighted and Weighted Models

4. 3. Regression Analysis

First of all, unweightd analysis is appropriate if our independent variable is the only variable impacted by differential response. In addition, even if our independent variable is complicated by another variable (e.g. our independent variable is trust in government and younger people both have lower trust in government and have low response-rate), we can the variable (e.g. age) as a control variable. By doing so, we can treat bias stemming from sampling as an omitted variable.

For our analysis, it is obvious that our independent variables, ones about citizen's trust, are potentially complicated by numerous variables, including age in the above-mentioned example. Furthermore, it is hard to know what variables cause non-response in our independent variables. Even if we knew them, measuring them without error would be extremely difficult. Simply speaking, it is virtually impossible to model non-response. Therefore, it is much safer and prudent to conduct weighted analysis in our case.

Table 8 and Table 9 compare the regression analyses before and after weighting for *Tax Increase* and *Public Welfare*, respectively. Above all, the results after weighting do not alter the major finding in the unweighted analyses in the naive models. In fact, it provides additional support for the hypothesis 2 that institutional trust has little effect on general attitudes toward public welfare provision: the coefficient on *Local Trust* became statistically indistinguishable from 0 after weighting (Model 5 in Table 9). However, it can be driven by the inflation of the standard error due to weighting (from 0.071 to 0.084) and, the size of the regression coefficient has, in fact, increased. Although weighting does not alter the major findings, it should also be emphasized that the estimate of the slope and the standard error do differ. In particular, we can see that weighting increases standard errors.

	Model 1		Model 2		Model 3	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
National Trust	0.015	0.051				
	(0.068)	(0.072)				
Local Trust			0.164***	0.192***		
			(0.062)	(0.067)		
Official Trust					0.134***	0.142***
					(0.038)	(0.04)
Education	-0.031	-0.047	-0.036	-0.053	-0.031	-0.047
	(0.03)	(0.032)	(0.03)	(0.032)	(0.03)	(0.032)
Sex	0.167**	0.186**	0.164**	0.180**	0.165**	0.190**
	(0.074)	(0.078)	(0.074)	(0.078)	(0.073)	(0.077)
Age	-0.006**	-0.007***	-0.006**	-0.007***	-0.007**	-0.008***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
Income	0.004	0.004	0.004	0.004	0.005	0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ideology	0.174***	0.200***	0.170***	0.197***	0.178***	0.209***
	(0.04)	(0.043)	(0.04)	(0.043)	(0.04)	(0.043)
Satisfaction	-0.044	-0.045	-0.072*	-0.066	-0.061	-0.053
	(0.041)	(0.047)	(0.039)	(0.044)	(0.037)	(0.042)
Constant	2.359***	2.264***	2.151***	2.066***	2.022***	1.955***
	(0.333)	(0.335)	(0.332)	(0.333)	(0.327)	(0.34)
N	907	907	903	903	921	921
R-squared	0.032	0.043	0.041	0.055	0.047	0.061

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Unweighted and Weighted Regression Analysis: Tax Increase for Public Welfare

	Model 4		Model 5		Model 6	
	Unweighted	Weighted	Unweighted	Weighted	Unweighted	Weighted
National Trust	-0.113	-0.070				
	(0.078)	(0.094)				
Local Trust			0.121*	0.123		
			(0.071)	(0.084)		
Official Trust					0.063	0.067
					(0.043)	(0.048)
Education	0.075**	0.043	0.074**	0.042	0.079**	0.049
	(0.035)	(0.041)	(0.035)	(0.041)	(0.034)	(0.041)
Sex	-0.153*	-0.143	-0.174**	-0.170*	-0.181**	-0.186**
	(0.084)	(0.090)	(0.085)	(0.090)	(0.083)	(0.089)
Age	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.020**	0.022**	0.020**	0.023***	0.022***	0.025***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Ideology	0.204***	0.254***	0.197***	0.243***	0.203***	0.246***
	(0.046)	(0.054)	(0.046)	(0.054)	(0.045)	(0.054)
Satisfaction	-0.028	-0.051	-0.074*	-0.079	-0.070	-0.078
	(0.047)	(0.057)	(0.044)	(0.053)	(0.043)	(0.052)
Constant	1.682***	1.616***	1.366***	1.363***	1.376***	1.372***
	(0.379)	(0.427)	(0.380)	(0.422)	(0.376)	(0.412)
N	912	912	907	907	925	925
R-squared	0.053	0.064	0.053	0.063	0.055	0.065

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 9. Unweighted and Weighted Regression Analysis: Public Welfare Provision

5. Clustering

In the previous section, I have attempted to adjust for unrepresentativeness using weighted analyses. Now, we have some increased confidence in our estimates from the univariate and bivariate analyses. However, we have ignored that our data is not based on SRSWR. In this section, I deal with the issue of increased sampling variance that stems from clustering and present the corrected results for the descriptive statistics and the regression analyses. [3]

5. 1. Clustering and Statistical Analysis

Clustering refers to the identification of groups that contain units. For practical reasons (logistical and financial), survey researchers often choose to sample intensively in a group of clusters while leaving other clusters unselected at all. If our unit of analysis is senior college student and our cluster is college, then we select a group of colleges while leaving other colleges unselected at all.

What are the consequences of cluster in terms of estimation? First of all, we should note that each cluster will almost always be *not* a microcosm of the entire population. Suppose two extreme cases. In one extreme case, each cluster is a microcosm of society. That is, each cluster is like a miniature of the entire population. In this case, clustering has no effect on our statistical analysis. In the other extreme case, each cluster has no variance in the variable of our interest. In this type of extreme case, we get effectively no information from additional respondent within the cluster. Since there is no variation in the variable of our interest, the effective sample size will simply equal the number of clusters. The point here is that the more homogenous our cluster becomes (the closer to the latter scenario), the less confidence we have in our estimation.

When clusters are homogeneous, the conventional method assuming SRSWR leads to incorrect estimation of the uncertainty. As above-mentioned, when clusters are homogenous, the effective sample size is smaller than the simple N because each additional respondent provides little new information. When the effective sample size is smaller than simple N, the sampling variance of our estimate (such as mean or median) is larger along with increased standard errors, p-values, and confidence intervals.

5. 2. Descriptive Statistics

First of all, I calculated ICC (Intra-class Correlation): a measure of within-cluster homogeneity with 0 each cluster being a microcosm and 1 each cluster being perfectly homogeneous. I calculated

[3] I personally corresponded with the KGSS manager in Survey Research Center (http://kgss.skku.edu) about the availability of the variable that identifies the 17 strata. However, Survey Research stopped providing the most of geocoded data for privacy concerns. The only available geographic variable was “region” which stratifies the whole country into seven top-level administrative areas. However, it is not a proper “strata” in that random sampling did not take place at the “region” level but at the 17-subregion level. Nevertheless, I tried using “region” as the strata variable but it was unavailable because there was a stratum (Jeju Island) with only one PSU.

ICC for all the variables included in our analysis. As seen in Table 10, ICC varies from the minimum of 0.044 (*Sex*) to the maximum of 0.317 (*Education*). It means that, on average, *Education* is distributed most homogenously within the cluster while *Sex* is the variable that is closest to the microcosm of the society.

Also, in the fourth column, I calculated DEFF as a measure of uncertainty inflation caused by design effects (i.e. clustering). DEFT is simply the square root of DEFF (the fifth column). Also, DEFF is the function of the cluster size and ICC. Since the number of observations differ across variables, I reported the sample size and, accordingly, the cluster size for each variable. We can see that DEFF (and DEFT) widely varies across variables. Since the cluster size does not deviate much from the mean cluster size (10.51 = 1051/100), DEFF is mostly a function of ICC. We can see that *Education* is the variable whose estimation uncertainty is most heavily inflated while *Sex* is the one whose estimation uncertainty is least affected by clustering. Finally, we can see that the effective sample size for each variable. Since the effective sample size is N divided by DEFF, the patterns across the variables are similar to DEFF.

Variables	ICC	N	Cluster Size	DEFF	DEFT	Effective N
Tax Welfare	0.048	1044	10.44	1.453	1.205	723
Public Welfare	0.083	1049	10.47	1.782	1.335	590
National Trust	0.076	1019	10.22	1.699	1.304	619
Local Trust	0.068	1015	10.21	1.622	1.273	648
Official Corruption	0.049	1041	10.43	1.464	1.210	718
Education	0.317	1051	10.49	4.006	2.001	262
Sex	0.044	1051	10.49	1.419	1.191	741
Age	0.222	1051	10.49	3.105	1.762	338
Income	0.243	963	9.54	3.076	1.754	342
Ideology	0.057	1016	10.21	1.526	1.235	689
Satisfaction Government	0.118	1033	10.37	2.109	1.452	498

Table 10. ICC, DEFF, and DEFT

In Table 11, we can confirm that the standard errors have increased without exception when we reflect clustering in our estimation. Here, again, the standard error of *Education* has increased radically from (0.051 to 0.103) while that of *Sex* remains almost the same. As a general pattern, we can also see that the standard errors increase from the naive model to the model reflecting only weighting to the model reflecting both weighting and clustering. Finally, we can see that clustering does not affect our estimation of the mean: the means reported in column 3 are exactly the same as the means reported in column 5.

Variable	Unweighted		Weighted		Weighted + Clustering	
	Mean	S.E.	Mean	S.E.	Mean	S.E.
Tax Welfare	2.668	0.035	2.651	0.038	2.651	0.042
Public Welfare	2.572	0.039	2.590	0.043	2.590	0.055
National Trust	2.402	0.019	2.398	0.021	2.398	0.026
Local Trust	2.350	0.019	2.348	0.021	2.348	0.025
Official Corruption	3.310	0.03	3.288	0.031	3.288	0.038
Education	3.545	0.052	3.790	0.051	3.790	0.103
Sex	1.548	0.015	1.504	0.017	1.504	0.018
Age	49.586	0.574	46.972	0.545	46.972	0.967
Income	8.883	0.193	10.083	0.216	10.083	0.348
Ideology	3.001	0.029	2.960	0.032	2.960	0.036
Satisfaction Government	3.610	0.034	3.683	0.036	3.683	0.050

Table 11. Descriptive Statistics:
Comparison between Unweighted, Weighted, Weighted Clustered Models

5. 3. Regression Analysis

Table 12 and Table 13 compare the regression analyses assuming SRSWR and reflecting weighting and clustering. Above all, the results reflecting both weighing and clustering do not alter the major findings from the naive models or the models that only reflect weighting (the only visible difference across model is the effect of *Local Trust* on *Public Welfare*). Also, it should be noted that the regression coefficients stay the same between the weighted models and the weighted and clustered models. This is unsurprising because clustering only affect sampling variance.

	Model 1		Model 2		Model 3	
	Unweighted	Weighted+ Cluster	Unweighted	Weighted+ Cluster	Unweighted	Weighted+ Cluster
National Trust	0.015	0.051				
	(0.068)	(0.068)				
Local Trust			0.164***	0.192***		
			(0.062)	(0.067)		
Official Trust					0.134***	0.142***
					(0.038)	(0.038)
Education	-0.031	-0.047	-0.036	-0.053	-0.031	-0.047
	(0.03)	(0.034)	(0.03)	(0.034)	(0.03)	(0.033)
Sex	0.167**	0.186**	0.164**	0.180**	0.165**	0.190**
	(0.074)	(0.080)	(0.074)	(0.082)	(0.073)	(0.083)
Age	-0.006**	-0.007***	-0.006**	-0.007***	-0.007**	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.004	0.004	0.004	0.004	0.005	0.004
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ideology	0.174***	0.200***	0.170***	0.197***	0.178***	0.209***
	(0.04)	(0.052)	(0.04)	(0.054)	(0.04)	(0.051)
Satisfaction	-0.044	-0.045	-0.072*	-0.066	-0.061	-0.053
	(0.041)	(0.052)	(0.039)	(0.049)	(0.037)	(0.047)
Constant	2.359***	2.264***	2.151***	2.066***	2.022***	1.955***
	(0.333)	(0.337)	(0.332)	(0.341)	(0.327)	(0.364)
N	907	907	903	903	921	921
R-squared	0.032	0.043	0.041	0.055	0.047	0.061

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 12. Unweighted and Weighted Clustered Regression Analysis:
Tax Increase for Public Welfare

	Model 4		Model 5		Model 6	
	Unweighted	Weighted+ Cluster	Unweighted	Weighted+ Cluster	Unweighted	Weighted+ Cluster
National Trust	-0.113	-0.070				
	(0.078)	(0.098)				
Local Trust			0.121*	0.123		
			(0.071)	(0.089)		
Official Trust					0.063	0.067
					(0.043)	(0.045)
Education	0.075**	0.043	0.074**	0.042	0.079**	0.049
	(0.035)	(0.041)	(0.035)	(0.041)	(0.034)	(0.041)
Sex	-0.153*	-0.143	-0.174**	-0.170*	-0.181**	-0.186**
	(0.084)	(0.090)	(0.085)	(0.089)	(0.083)	(0.087)
Age	0.009***	0.009***	0.009***	0.009**	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.020**	0.022**	0.020**	0.023**	0.022***	0.025***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Ideology	0.204***	0.254***	0.197***	0.243***	0.203***	0.246***
	(0.046)	(0.052)	(0.046)	(0.054)	(0.045)	(0.053)
Satisfaction	-0.028	-0.051	-0.074*	-0.079	-0.070	-0.078
	(0.047)	(0.056)	(0.044)	(0.052)	(0.043)	(0.048)
Constant	1.682***	1.616***	1.366***	1.363***	1.376***	1.372***
	(0.379)	(0.459)	(0.380)	(0.447)	(0.376)	(0.433)
N	912	912	907	907	925	925
R-squared	0.053	0.064	0.053	0.063	0.055	0.065

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 13. Unweighted and Weighted Clustered Regression Analysis: Public Welfare Provision

To sum up, we can say that the results from the weighted clustered models are much more trustworthy than the naive models or than the models that only reflect weighting. Although they provide similar evidence in terms of hypothesis testing (even identical for the weighted models and weighted clustered models), we should have more confidence in the weighted clustered models because the results from these models have already dealt with incorrect estimation of the sample statistics and their sampling variance.

6. Missing Data

So far, we have dealt with weighting and clustering to get unbiased estimates along with correct measures of uncertainty. In this process, we used list-wise deletion method where only cases with complete information on all variables are used. However, missing data can be another source of bias when the data is not MCAR (Missing Completely At Random: the probability of a variable being missing is uncorrelated with the true value of the variable itself, or with other variables). Using list-wise deletion when the data is not MCAR results in biased estimates.

In addition, we cannot make the most of the information (the data) when list-wise deletion is used. Although there is nothing that can be done for unit non-response where the respondent does not answer any questions at all, there is often considerable amount of information with item non-response. With item non-response, the respondent provides no answer to one or more questions but answers other questions. If we adopt list-wise deletion method to deal with item non-response, however, we simply throw out all the information for the respondents with any missing data on the variables selected for our analysis.

The analyses in the previous sections adopted list-wise deletion method. That is why the number of N in regression analysis barely exceed 900. However, our sample size is 1051 and the variable with the smallest N is 963 (*Income*). In this section, I adopt multiple imputation method to deal with missing data. Using multiple imputation not only enables us to make the most of the information at hand and to get unbiased estimates under a weaker assumption on missing data (MAR, Missing At Random) [4]

6. 1. Examining Missing Data

Before we proceed to multiple imputation, I briefly examine the pattern of missing data. Table 14 shows the number of cases according to the number of variables with at least one missing observation. We can see that there are only 897 complete cases. If we run a regression with all the variable included, we are going to use data on 897 respondents instead of 1051. Table 15 shows the number of valid observations across variables. Three demographic variables, *Education*, *Sex*, and *Age*, have full observations while *Income* has the smallest number of valid observations. Imputation for *Income* is particularly necessary given that it is included in all our regression models.

number of cases with varying number of variables with at least one missing observation						
0	1	2	3	4	5	total
897	108	28	9	8	1	1051

Table 14. Extent of Missing Data

[4] The probability of a variable being missing is uncorrelated to the value of the variable itself, conditional on other variables.

Variable	N
Education	1051
Sex	1051
Age	1051
Public Welfare	1049
Tax Welfare	1044
Official Corruption	1041
Satisfaction Government	1033
National Trust	1019
Ideology	1016
Local Trust	1015
Income	963

Table 15. Missing Data Across Variables

6. 2. Multiple Imputation

Multiple imputation creates multiple datasets. In each dataset, our imputation model imputes plausible values for missing observations. Specifically, these plausible values based on two parts: fitted values and random residuals ($\hat{y}$ + e). Using the imputation model, we produce multiple datasets. Finally, we average the results of our interest (e.g. mean) and calculate standard errors. In this subsection, I use multiple imputation based on MVN (multivariate normal) model. It imposes a rather strong assumption that all variables are jointly multivariate normal. And, it is very unlikely that the variables in my analysis are jointly multivariate normal. Nevertheless, this method is known to work fairly well despite the violation of MVN.

Table 16 and 17 compare the results for the regressions based on list-wise deletion and multiple imputation. Table 16 reports the results for *Tax Increase*. We can see that the results stay very similar in terms of hypothesis testing. Even though the results stay almost the same, it is important to note that the standard errors have decreased due to the increased number N (to 1051). Since multiple imputation fills up the empty observations, we have more information to use and thus standard errors decrease.

Table 17 reports the results for *Public Welfare.* Here, we can see two changes. First, the coefficient on *National Trust* became statistically significant at 0.1 level. Also, its sign is negative. This contradicts our hypothesis. However, over the different models, the results for *National Trust*, trust in intangible institution, are far from robust. Second, for *Local Trust,* we also see that the coefficient is now statistically insignificant with multiple imputation. This provides us further evidence for the hypothesis 2 that institutional trust has little to do with general attitudes toward public welfare provision. [5]

[5] I also ran the same regression analyses based on ICE (Multiple Imputation by Chained Equations). Although ICE is based on different statistical theories than MVN, the results are very similar. For my three independent variables,

	Model 1		Model 2		Model 3	
	List-wise Deletion	Multiple Imputation	List-wise Deletion	Multiple Imputation	List-wise Deletion	Multiple Imputation
National Trust	0.015	0.035				
	(0.068)	(0.064)				
Local Trust			0.164***	0.197***		
			(0.062	(0.059)		
Official Trust					0.134***	0.092***
					(0.038)	(0.036)
Education	-0.031	-0.058**	-0.036	-0.057**	-0.031	-0.060**
	(0.03)	(0.029)	(0.03)	(0.029)	(-0.03)	(0.029)
Sex	0.167**	0.213***	0.164**	0.210**	0.165**	0.212***
	(0.074)	(0.070)	(0.074)	(0.069)	(-0.073)	(0.070)
Age	-0.006**	-0.006**	-0.006**	-0.006**	-0.007**	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.004	0.005	0.004	0.005	0.005	0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Ideology	0.174***	0.156***	0.170***	0.147***	0.178***	0.152***
	(0.04)	(0.038)	(0.04)	(0.038)	(0.04)	(0.038)
Satisfaction	-0.044	-0.037	-0.072*	-0.064*	-0.061	-0.046
	(0.041)	(0.038)	(0.039)	(0.036)	(0.037)	(0.035)
Constant	2.359***	2.386***	2.151***	2.128***	2.022***	2.218***
	(0.333)	(0.313)	(0.332)	0.310)	(0.327)	(0.309)
N	907	1051	903	1051	921	1051
R-squared	0.032	-	0.041	-	0.047	-

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 16. List-wise Deletion and MI regression Analysis: Tax Increase for Public Welfare

the size and sign of regression coefficients are very similar. Also, their statistical significance is also very similar. The Stata code for ICE can be found in the replication files.

	Model 4		Model 5		Model 6	
	List-wise Deletion	Multiple Imputation	List-wise Deletion	Multiple Imputation	List-wise Deletion	Multiple Imputation
National Trust	-0.113	-0.127*				
	(0.078)	(0.073)				
Local Trust			0.121*	0.089		
			(0.071)	0.066		
Official Trust					0.063	0.027
					(0.043)	(0.041)
Education	0.075**	0.086***	0.074**	0.088***	0.079**	0.087***
	(0.035)	(0.033)	(0.035)	(0.033)	(0.034)	(0.033)
Sex	-0.153*	-0.159**	-0.174**	-0.161**	-0.181**	-0.160**
	(0.084)	(0.078)	(0.085)	(0.079)	(0.083)	(0.079)
Age	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.020**	0.019**	0.020**	0.019**	0.022***	0.020**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Ideology	0.204***	0.200***	0.197***	0.195***	0.203***	0.198***
	(0.046)	(0.042)	(0.046)	(0.043)	(0.045)	(0.043)
Satisfaction Government	-0.028	-0.022	-0.074*	-0.072*	-0.070	-0.061
	(0.047)	(0.043)	(0.044)	(0.041)	(0.043)	(0.040)
Constant	1.682***	1.671***	1.366***	1.343***	1.376***	1.419***
	(0.379)	(0.351)	(0.380)	(0.350)	(0.376)	(0.349)
N	912	1051	907	1051	925	1051
R-squared	0.053	-	0.053	-	0.055	-

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 17. List-wise Deletion and MI regression Analysis: Public Welfare Provision

7. Contextual Analysis

Now, I am going to conduct a contextual analysis to test the fifth hypothesis. The hypothesis is that where local because the local partisan context encourages them to form attitudes for or against public provision of welfare service. The underlying logic is that, where political polarization is severe, institutional trust can only weakly affect one's attitudes toward public welfare provision. Instead. This is because partisan logic tends to dictate individuals' attitudes toward public welfare provision.

To construct a context variable that captures the local level of political polarization, I used a question in the original data that asks about the respondent's attachment to the Saenuri Party.[6] The original coding is as follows: 1 (very negative), 2 (somewhat negative), 3 (neutral), 4 (somewhat positive), and 5 (very positive). To generate my contextual variable, *Local Polarization*, I first generated an individual level variable, *Polarization*, by recoding the original item into 3-scale measure: 1 (neural), 2 (somewhat negative & somewhat positive), 3 (very negative & very positive). High scores on *Polarization* means stronger partisan affiliation (either very negative or very positive toward Saenuri Party). Second, I generated the contextual variable, Local *Polarization*, by calculating the mean of *Polarization* by each PSU (there are 100 PSUs). Figure 3 plots the distribution of *Local Polarization.*

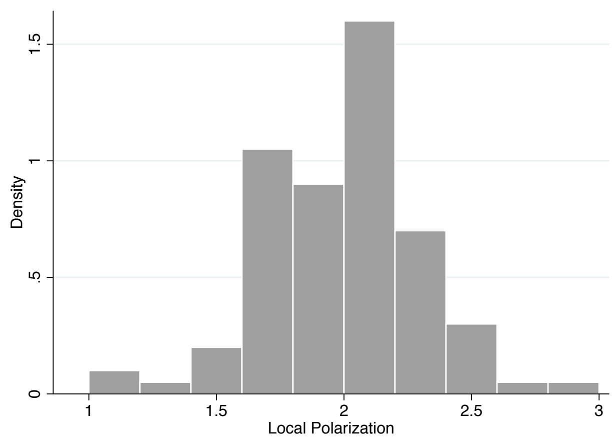

Figure 3. Distribution of *Local Polarization* over 100 PSUs

It is important to note that contextual variables based on aggregation, including *Local Polarization*, should be treated with caution. When the context (here, locality) is highly heterogeneous and the cluster size is small, the contextual variable is likely to be unreliable (highly subject to error). In order check the reliability of our contextual variable, I measured the level of reliability for my context measure using ANOVA. The test yields a reliability score 0.463. This suggests that the contextual variable is not very reliable and any statistical analyses based on this measure should be interpreted cautiously.

Table 18 and 19 report the results of regression analysis for the interactive effect between institutional trust and local level of political polarization. The results in Table 18 are from naive models that assume SRSWR while those in Table 19 are from models that consider both weighting and clustering. First of all, we can see that two interaction terms are statistically significant: 1) the interaction effect between trust in national government and local polarization for general

[6] The reason I considered Saenuri Party as the sole reference point is that it is the most long-last and institutionalized party in South Korea. Other parties are mostly weakly institutionalized and keep merging and splitting. For detailed discussion of party institutionalization in South Korea, see Hicken and Kuhonta (2015)

attitude toward public welfare provision and 2) the interaction between trust in local government and local polarization for general attitude toward public welfare provision (Model 4 and 5 in Table 18). However, the second of these two (*Local Trust* X *Local Polarization*) becomes statistically insignificant in the models that consider weighting and clustering (Model 5 in Table 19).

The only significant effect across the models is the interaction between institutional trust in national government (*National Trust*) and local polarization (*Local Polarization*) in predicting general welfare attitude (*Public Welfare*) in Model 4 (Table 19). The sign of the interaction terms appears to be in line with our expectation: more severe polarization attenuates the effect of institutional trust. However, this result contradicts the two fairly robust patterns identified in previous sections: 1) trust in intangible institutions (such as trust in national government) does not matter much and 2) institutional trust is more closely associated with attitudes toward tax increase for welfare than attitudes toward public provision of welfare per se. In addition, as mentioned above, the reliability of the contextual measure is not so strong. Therefore, the support for the hypothesis 5 should be considered weak.

	Tax Welfare			Public Welfare		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Local Polarization	-0.039	-0.003	0.071	1.305*	0.470	-0.692
	(0.598)	(0.484)	(0.438)	(0.675)	(0.550)	(0.500)
National Trust	0.125			1.307**		
	(0.471)			(0.530)		
Interaction (National Trust X Local Polarization)	-0.057 (0.235)			-0.723*** (0.265)		
Local Trust		0.283			0.910*	
		(0.397)			(0.450)	
Interaction (Local Trust X Local Polarization)		-0.060 (0.200)			-0.401* (0.227)	
Official Trust			0.253			-0.095
			(0.249)			(0.285)
Interaction (Official Trust X Local Polarization)			-0.062 (0.127)			0.079 (0.145)
Education	-0.031	-0.036	-0.030	0.069**	0.071**	0.081**
	(0.031)	(0.031)	(0.030)	(0.035)	(0.035)	(0.034)
Sex	0.168**	0.164**	0.166**	-0.149*	-0.174**	-0.182**
	(0.074)	(0.074)	(0.073)	(0.083)	(0.084)	(0.083)
Age	-0.006**	-0.006**	-0.006**	0.009***	0.009***	0.009***

	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.004	0.004	0.005	0.020**	0.020**	0.023***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Ideology	0.170***	0.167***	0.174***	0.194***	0.186***	0.194***
	(0.040)	(0.041)	(0.040)	(0.045)	(0.046)	(0.045)
Satisfaction Government	-0.037	-0.066*	-0.055	-0.004	-0.054	-0.055
	(0.041)	(0.039)	(0.038)	(0.047)	(0.044)	(0.043)
Constant	2.698	2.163	1.372	-10.053*	-2.898	7.548*
	(5.367)	(4.341)	(3.936)	(6.057)	(4.939)	(4.498)
N	907	903	921	912	907	925
R-squared	0.034	0.042	0.048	0.071	0.066	0.063

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 18. Contextual Analysis: Naive Models

	Tax Welfare			Public Welfare		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Local Polarization	0.348	-0.029	0.236	1.221	0.215	-0.777
	(0.548)	(0.531)	(0.478)	(0.805)	(0.670)	(0.477)
National Trust	0.524			1.351**		
	(0.452)			(0.614)		
Interaction (National Trust X Local Polarization)	-0.244 (0.226)			-0.729** (0.310)		
Local Trust		0.345			0.765	
		(0.444)			(0.581)	
Interaction (Local Trust X Local Polarization)		-0.079 (0.226)			-0.330 (0.297)	
Official Trust			0.387			-0.083
			(0.268)			(0.262)
Interaction (Official Trust X Local Polarization)			-0.127 (0.136)			0.070 (0.135)
Education	-0.050	-0.053	-0.047	0.035	0.038	0.050
	(0.034)	(0.034)	(0.033)	(0.041)	(0.041)	(0.040)

Sex	0.186**	0.179**	0.193**	-0.144	-0.173**	-0.190**
	(0.080)	(0.082)	(0.082)	(0.088)	(0.087)	(0.086)
Age	-0.007**	-0.007**	-0.007***	0.009***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Income	0.004	0.004	0.004	0.022**	0.023***	0.026***
	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.009)
Ideology	0.196***	0.192***	0.204***	0.245***	0.232***	0.236***
	(0.052)	(0.054)	(0.052)	(0.051)	(0.053)	(0.052)
Satisfaction Government	-0.032	-0.057	-0.044	-0.020	-0.055	-0.055
	(0.054)	(0.050)	(0.048)	(0.058)	(0.053)	(0.049)
Constant	1.570	2.108**	1.477	-0.804	0.910	2.872***
	(1.058)	(1.059)	(0.982)	(1.614)	(1.313)	(1.029)
N	907	903	921	912	907	925
R-squared	0.048	0.058	0.064	0.087	0.081	0.079

Standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 19. Contextual Analysis: Weighted Clustered Models

8. Conclusion

In this paper, I examined the effect of different types of institutional trust on attitudes toward public provision of welfare service. At the same time, I applied the most widely used survey analysis techniques to my empirical analyses. First of all, all three groups of approaches (naïve models, weighted models, and weighted clustered models) provide strong evidence that institutional trust matters for attitudes toward public welfare provision. Specifically, they commonly support my arguments that 1) institutional trust has far stronger effects on attitudes toward public welfare provision when it is explicated associated with tax increase 2) it is tangible institutions no intangible ones that matter for attitudes toward public welfare provision. Second, employing multiple imputation helped me make the most the available data and the results based on multiple imputation did not alter the major findings. Third, as opposed to my expectation, the contextual argument did not get robust empirical support.