Measuring Public Opinion toward Social Welfare in Taiwan*

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Abstract

Policy representation has been one of the foremost topics in political science. The pre-condition is the stability of policy preferences. While individual opinions may be influenced by many sources, scholars have found the macro level of opinion to be stable. The disaggregation of survey data may lead to the problem of a large standard deviation being encountered due to the small number of observations in some counties. Therefore, multilevel regression with post-stratification (MRP) is used to estimate public opinion toward budget spending on social welfare between 2007 and 2013. These MRP estimates are validated. However, this data analysis shows mixed results regarding the stability of public opinion in Taiwan.

* I thank seminar participants at the Center for Survey Research, Academia Sinica, and the discussant at the annual conference of Taiwan Political Science Association, National Sun-Yat-Sen University, Kaohsiung City, November 30-December 1, 2013. Thanks also to the National Science Council, which provides support for collecting all of the telephone and internet survey data used in this study. I am very grateful to Teppei Yamamoto's reading of the draft and Eric Yu's instruction in MRP.

Keywords: Public Opinion, Social Welfare, Multilevel Regression with Poststratification

I. Preferences toward Public Policies

The health of a democracy depends on policy representation and policy responsiveness, and therefore many scholars have examined the relationship between preferences and policies. Most scholars adopt the notion of "dynamic representation." Soroka and Wlezien (2009) have contended that the general public responds to policy while politicians are controlled by elections. The dynamic relationship is that opinion has a positive effect on policy and that policy negatively influences the next year's preferences (p.38).

There are numerous studies on national and sub-national public opinion. In addition to Page and Shapiro (1992), Wlezien (1995) and Erikson, MacKuen, and Stimson (2002) have explored the dynamic relationship between mass preferences and policy. Wlezien proposed the thermostatic model, in which the policy input is intended to reflect the general public's responses to spending. Erikson, MacKuen, and Stimson (2002) evaluated the extent to which the electorate and government interreact with each other through presidential elections, approval rates, and partisanship. Rationality in terms of retrospection and expectation determines perceptions of governance.

Estimating sub-national public opinion has become a popular topic (Tausanovitch and Warshaw 2013). Erikson, Wright, and McIver (1993) used national survey data across various years to measure state ideology and provided evidence of democratic governance in the American states. Pacheco (2010) measured the longitudinal variation in state public opinion in different policy areas and linked these measures to various policy outputs at the state level. Specifically, she applied multilevel regression with post-stratification (MRP) to a small sample of data with a pooled time frame. She found that opinions in response to policy changes depend on the issue. Lax and Philips (2009) also used MRP to estimate state-level public opinion regarding gay rights. They found that state-support for gay rights is congruent with the adoption of policies. Warshaw and Rodden (2012) applied MRP to Congressional district-level opinion and showed that MRP estimates provide very good predictions of referenda results. Tausanovitch and Warshaw (2013) also probed into citizens' policy preferences at the Congressional district-level.

Thanks to a cross-national study, the International Social Survey Programme (ISSP), policy opinion linkages across countries have been examined and have inspired further research (e.g., Soroka and Wlezien 2004; 2005). Regarding social welfare in Taiwan, Hsieh and Niou (1996) measured the individual's position on a 0-10 scale of economic equity and economic growth in the 1993 local election. The median position for the respondents was five. Tsai and Yu (2011) examined data for 2006 and 2007, and found evidence of the responsiveness of local governments to public opinion, especially on environmental protection. They asked respondents whether the government should allocate more money to social welfare, environmental protection, education, and transportation given that the government budget was limited. Although their study explored dynamic representation, their disaggregated approach, while easy to implement, may have been less accurate for small administrative units. Moreover, there could be temporal instability in disaggregated public opinion (Kastellec, Lax, and Phillips 2014). MRP has been proved to yield more precise estimates by incorporating information regarding respondents' demographics and geography.

II. Stability of Public Opinion

One of the major beliefs regarding democracy is that people are aware of public policies and that their opinions are represented in politics. The underlying premise is that public opinion is stable and discernible. Otherwise, policies may reflect badly on public opinion. Instead, only those involved have opportunities to mediate policies. Therefore, a sound connection between public policies and the general will of the people is the prerequisite of democracy.

The stability of public opinion reflects stable underlying attitudes. Citizens should have consistent views on politics if their attitudes are to be governed by principles of political abstraction. If people's responses to questions vary from one survey to another without predicable patterns, it is idiosyncratic views and not ideology that configure attitudes (Converse 1964).

According to Converse, public opinion is not as stable as we might believe because the general public lack the ideology to constrain their opinions. Only a few citizens are able to convey abstract ideology, whether liberal or conservative, to political objects. Those who actively use the liberal-conservative dimension to attach significance to policies make voting decisions based on candidates' positions on issues, but other people make choices based on group interests, the "nature of time," and for various other reasons. Converse's longitudinal data analysis reveals the low stability of policy items; random changes in responses suggest weak ideological constraints. Converse concluded that most people are unable to use contextual information and ideology to assess policy implications.

Converse's theory posits that an individual's level of ideology is correlated with that respondent's level of education and the amount of information he possesses. Another doubt regarding the theory of democracy stems from empirical evidence that reveals that most citizens are not fully informed about politics, including the operation of the political system, party stances, political issues and other political facts (Delli Carpini and Keeter 1996; Delli Carpini 2005). It is because the general public lacks the interest, time, or other resources. However, it is found that uninformed voters may take cues from elite discourses or their affiliated groups, or they just make a guess when responding to survey questions (Lupia 1994). In other words, people who have no preferences may hold noticeable objective positions as their preferences. Because people indeed emulate others who possess information, we often observe public opinion to be well informed.

Scholars suggest that the variability of political attitudes arises due to measurement error (Achen 1975; Ansolabehere, Rodden, and Snyder 2008). Achen derived the variance of measurement error in which the independent assumption of respondents' changes in opinion are taken account. After largely correcting Converse's correlation coefficients with the independence assumption, Achen concluded that measurement error due to the vagueness of questions attenuates the stability of responses. Ansolabehere, Rodden, and

Snyder confirmed Achen's findings by averaging multiple survey items in the same policy area to reduce measurement error. They even found issue voting to prevail in cases where individual items are combined to construct issue scales.

While Achen and other scholars greatly revised the long-term image of voter ignorance, scholars turned to study aggregate public opinion. Page and Shapiro (1992) argued that public opinion is stable because the random changes in individual attitudes that result in the instability of public opinion cancel each other out after they are aggregated. Moreover, they argued that people are able to learn new information as news coverage piles up. At the aggregate level, collective public opinion is arguably rational and changes in a meaningful way (Enns and Kellstadt 2008; Page and Shapiro 1992).

A. Generalizability of Social Welfare Preferences in Taiwan

In Taiwan, social welfare refers to the welfare of senior citizens, child welfare, disabled persons' welfare, general social assistance, and other emergency assistance. The Ministry of Interior determines the budget for social welfare, while local governments are responsible for its allocation. Local governments can have their own welfare policies. For example, parents can receive monthly subsidies or pensions for every newborn baby.

Like other government spending, social welfare has been a controversial issue. While political parties and most voters have rarely balked at budgetary expansion, especially in relation to social welfare, more recently the absurdity of spending on events has become an issue (Tsai 2014). This might be because the major social cleavage has been national identity but not socio-economic issues;

class-less politics has characterized political development (Rigger 2001). Both major parties and the general public therefore embrace the value of economic growth and treat social welfare as an election checkbook at the same time.[1] However, social welfare may have a social desirability problem in mass surveys. Compared to other policies, such as transportation, environmental protection, education and law enforcement, according to Tsai and Yu (2011) the proportion of respondents demanding social welfare is becoming larger. A testable hypothesis is that people tend to hold their preferences toward social welfare due to social desirability. The peculiarities of social welfare should be noted when we contemplate verifying this research in other situations of interest.

Little is known about Taiwan's micro- or macro-level preferences toward public policies. According to Tsai and Yu (2011, 95), the distributions of social welfare, transportation and environmental protection between 2006 and 2007 are similar. Therefore, it is expected that people will have stable preferences over a period of time.

Previous research suggests stable aggregate public opinion and policy responsiveness. This study intends to provide more empirical evidence by using Bayesian inference. In brief, there are three motivations of this study:

1. To estimate public opinion for each city/county when there

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1 Fell (2005) found that the Democratic Progressive Party (DPP)'s emphasis on the welfare issue has expanded into all these groups except for Mainlanders, while the Kuomintang (KMT) cannot decide whether the government should distribute more welfare to state employees and retirees, or to laborers, farmers, and fishermen.

is only a small number of observations for the national sample.

2. To assess the stability of aggregate public opinion across certain periods of time. In this study, stability is operationalized as the association between aggregate attitudes at two time points. If attitudes at two time points are independent of each other, i.e., there is no association, then there is no stability of attitudes.

3. To examine the stability of public opinion across different survey instruments.

Using four waves of cross-section survey data, I show that MRP generates better estimates of public opinion at the sub-national level. However, this data analysis reveals mixed results regarding the stability of public opinion in Taiwan.

III. Data

This research uses data from five sources with slightly different wording and survey modes. In doing so, the stability of aggregate public opinion is tested not just across time, but also across different approaches.

1. In 2007, a national telephone survey asked respondents whether the government should allocate more money, less money, or the same amount of money to social welfare. The sample size was 3,035.

2. A nationwide series of telephone interviews was administered in 2009 and 2010, respectively, where respondents were asked whether the budget on social welfare should be increased a lot, increased somewhat, remain the same, be decreased somewhat, or be decreased a lot.

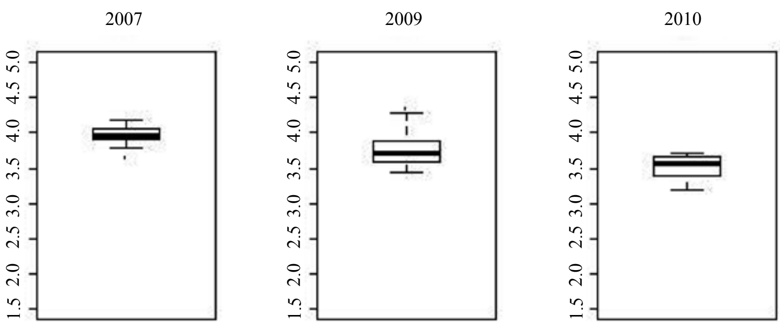
3. In 2012, another telephone survey asked respondents if they agreed that the local government had spent a lot on social welfare or if they agreed that it had not spent much on social welfare. The measurement of opinion toward social welfare was different from in the previous three surveys, and thus we can observe whether public opinion remains stable across 2007, 2009, 2010, and 2012. Moreover, Taichung, Tainan and Kaohsiung counties were merged with their neighboring cities and were elevated to municipal cities like Taipei and Kaohsiung City in 2010. Therefore, we can assess the stability of public opinion based on different measurements and different government structures.

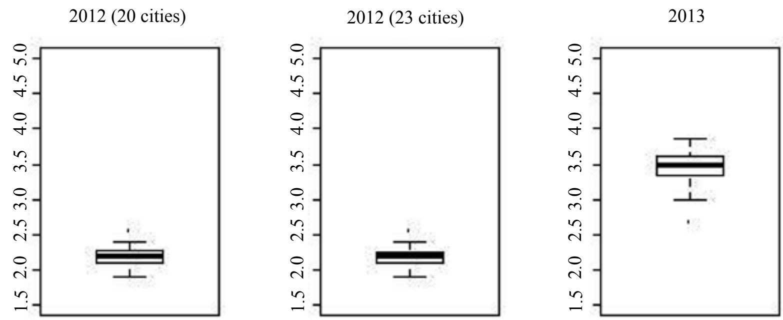
4. In 2013, I conducted two internet surveys and merged them to form one dataset. I asked respondents whether we should increase the amount of budget allocated to social welfare a lot, increase it somewhat, let it remain the same, decrease it somewhat, or decrease it a lot. In terms of the wording of questions, the surveys in 2009, 2010, and 2013 have the same format, but the 2007 and 2012 polls use different wording. Furthermore, the small sample size of this internet survey, i.e., 683, posits a challenge for estimation. The demographic backgrounds of the respondents in the internet surveys could be biased toward those more highly educated and the younger generation.

With the five datasets referred to above, this research intends to analyze the stability of aggregate public opinion. Before introducing the estimation method, I shall note the small number of observations for some cities/counties. This problem, which is inherent in a national sample, causes great uncertainty among the disaggregated estimates for some cities/counties, even though they may be unbiased. We should also notice that some of the five datasets have medium-sized samples, which creates difficulties when estimating policy preferences, even for cities like Taipei. As Kastellec, Lax, and Phillips (2014) and other studies on estimating public opinion suggest, MRP has the advantage of fitting a hierarchical model with a small number of observations to both national and subnational samples.

Before moving to the multilevel regression analysis, I construct a simple boxplot to summarize the average support for more social welfare spending across cities/counties from 2006 to 2013. Notice that respondents are asked whether they think the government should spend more, less, or the same amount of money in 2012 (i.e., there are only three categories and the middle point is "2"). Figure 1 shows that the median of the responses is a little bit above the middle category, which is "3" except in 2012. In order to have a consistent measure of the outcome variable, the 3-point or 5-point scales will be reduced to the dichotomous outcome variable.

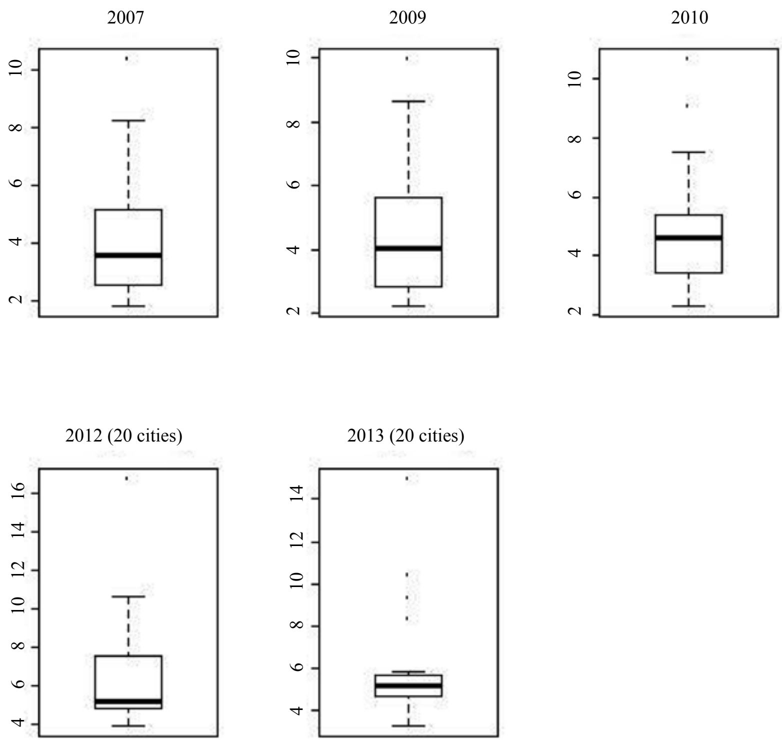
Figure 1. Boxplots of Support for Social Welfare, 2007-2013





Data sources: Tsai (2006), Tsai (2009), Tsai (2012).

Figure 2. Boxplots of Spending for Social Welfare Per Capita, 2007-2013



Data sources: Tsai (2006), Tsai (2009), Tsai (2012).

In Figure 2, five boxplots depict the spending on social welfare per capita for each city/county. The range of the data is remarkable, especially in 2012 and 2013. In 2007, 2009, and 2010, it is Penghu County that has the highest social welfare spending per capita for its small population. Although most cities and counties allocate less than 10 billion dollars to social welfare, after Taichung, Tainan and Kaohsiung became metropolitan cities in 2010, Taipei City had more than 40 billion dollars for social welfare and it spent more than 14,000 dollars on each resident.

Because Tsai and Yu (2011) used welfare spending per capita to predict the disaggregated public opinion in 2006 and 2007, I follow suit in 2007, 2009, 2010, 2012, and 2013. Table 1 presents the ordinary least squares (OLS) regression results. It is apparent that there is a very weak relationship between social welfare spending and public opinion toward welfare.

Table 1. OLS Regression of Support for Social Welfare by Welfare Spending Per Capita

	2007	2009	2010	2012	2013
Intercept	4.004**	3.611***	3.709***	2.173***	2.197***
	(0.054)	(0.115)	(0.067)	(0.086)	(0.333)
Spending per capita	-0.009				
in 2007	(0.011)				
Spending per capita		0.034			
in 2009		(0.023)			
Spending per capita			-0.035*		
in 2010			(0.012)		
Spending per capita				0.003	

	2007	2009	2010	2012	2013
in 2012				(0.012)	
Spending per capita					-0.013
in 2013					(0.050)
R^2	0.029	0.094	0.266	0.005	0.004
Adjusted R^2	-0.016	0.051	0.231	-0.050	-0.051
N	23	23	23	20	20

Data sources: Tsai (2006), Tsai (2009), Tsai (2012).

Notes:Standard errors are in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05, $p < 0.1.

IV. Multilevel Regression with Poststratification

Multilevel Regression with Poststratification (MRP) has consistently proved to be successful when using national survey data to estimate the influence of demographic and geographic predictors on the dependent variable (Kastellec, Lax and Phillips 2014; Lax and Phillips 2009; Park, Gelman, and Bafumi 2004; Warshaw and Rodden 2012). I assume that people belong to groups, cohorts, classes, or districts. Each of them represents a context that may shape people's attitudes. In this study, I use age, education, gender, and the interaction between age and education to predict individual opinion.[2] One of the advantages of these demographic background variables is that they are exogenous to opinion, which avoids the problem of endogeneity. Without a sound theory to explain the

2 An additional discussion on the advantages of covariate interaction in MRP can be found in Ghitza and Gelman (2011).

causality of social welfare support and other political attitudes, this study focuses on the individual's background.

The principal idea of MRP is to partially pool data based on cities/counties. If we completely pool the data, we ignore the geographical differences among other things. If we do not pool the data, i.e., we treat respondents differently for each city/county, we ignore the common characteristics shared by age, education, and other group characteristics. Partial pooling returns stronger estimates than either no pooling or complete pooling, because it takes all of the information into account. Even if partial pooling generates similar results as for the other two approaches, we do not lose anything (Gelman and Hill 2007).

Each individual's survey responses are modeled as a function of demographic and geographical predictors, with respondents being partially pooled across strata (subgroups) to an extent determined by the data. After the model is estimated, I use census data to weight responses as a function of estimates multiplied by data for each demographic and geographical stratum. In doing so, we can calculate the average responses for each stratum and pool them by, for example, cities.

There are two levels in this MRP set-up. The individual level has four parameters: gender, age, education, and the interaction term between age and education. The district effects are modeled as a function of the state into which the district falls. Without the inclusion of more parameters, however, it is possible to validate the MRP estimates.

$$
\begin{aligned}
Pr\,(y_i - 1) = \mathrm{logit}^{-1}(&\beta^0 + \beta^{female} \times female_i + \alpha_{k|i|}^{aducation} + \alpha_{l|i|}^{age} + \\
&\alpha_{k|i|,\,l|i|}^{education \times age} + \alpha_{j|i|}^{city}) \qquad (1)
\end{aligned}
$$

$$
\alpha_j^{city} = \beta^1 + \alpha^{area} \times area_{m|j|} \qquad (2)
$$

$$
for\ \mathrm{j} = 1, \ldots, 23
$$

Equation 1 is a binary logistic regression model in which the individual's response is a function of gender, education, age, and the interaction term of education and age plus the city/county. Equation 2 models the influence of the city/county in terms of regions.

Due to the fact that some cities and counties were merged into municipalities in 2009, the number of local governments changed, so that most local government statistics are not consistent after 2009. Therefore, the city/county effects are modeled as a function of the region into which they fall.

I apply Bayesian inference implemented by Gibbs sampling to MRP. Bayesian statistics generate estimates as random draws from a posterior distribution. Although we can use a likelihood function to estimate public opinion, Bayesian statistics add more information from prior distributions multiplied by a likelihood function. In analyzing contextual influence in different societies, Western (1998, 1234) has shown that the Bayesian approach "provides a way of pooling information from a set of countries to obtain optimal statistical estimates for any particular country." In order to implement Bayesian inference for the MRP, I set up a prior distribution for the parameters (Gelman 2006; Gelman and Hill 2007) as shown below:

$$\beta^0 \sim N(0, 0.0001)$$
$$\beta^{female} \sim N(0, 0.0001)$$
$$\beta^1 \sim N(0, 0.0001)$$
$$\alpha_{k|i|}^{aducation} \sim N(0, \sigma^2_{education}), for\ k = 1, ..., 5$$
$$\alpha_{l|i|}^{age} \sim N(0, \sigma^2_{age}), for\ k = 1, ..., 5$$
$$\alpha_{k|i|, l|i|}^{education \times age} \sim N(0, \sigma^2_{age \times edcuation}), for\ k = 1, ..., 5, l = 1, ..., 5$$
$$\alpha_m^{area} \sim N(0, \sigma^2_{area}), for\ m = 1, ..., 7 \tag{3}$$

Equation 3 presents the noninformative prior information for each of the coefficients. The estimators β follow the noninformative normal distribution, where the mean is 0 and the variance is 10^ -4[3]. The group for α represents the coefficients of the sub-groups. I assume that they follow a normal distribution with a hyperparameter of variance. These varying intercepts follow a normal distribution with a mean of 0 and variance associated with the uniform distribution. In principle, this model allows the data to generate estimates with limited outside information.[4]

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3 Because I expect that the prior information provides very little information regarding the inference, the regression coefficients β are assigned normal prior distributions with mean 0 and standard deviation 100. Moreover, my multi-level model is essentially a logistic regression model, so that the coefficient should be in the multiplicative form of exp (β). Therefore, I constrain the coefficients in the range (-100, 100), which corresponds to (e^{-100}, e^{100}). In other words, I assume that there is no way I will see effects as extreme as e^{-100} or e^{100} under this setup. The intercepts (α) also have a mean of 0 and a standard deviation of 100. Thus, they also have inverse-variance $\tau = 1/\sigma^2 = 10^{-4}$, where σ is drawn from uniform distributions on the range (0, 100). For more details, please see Gelman and Hill (2007, 354-55).

4 Unlike classical linear regression, Bayesian statistics assume that the *unknown* parameter is not fixed, and that there can be a prior distribution to represent our belief about the important characteristic of the parameter. Prior distributions

Equation 3 also shows that the coefficients of age, education and their interaction are multiple; there are as many coefficients as the number of sub-groups. Unlike the conventional linear regression model that has to set up k-1 dummy variables for k sub-groups, the Bayesian multilevel regression model allows for as many intercepts as the number of sub-groups.

To estimate a multilevel regression model, we can consider a linear mixed-model, such as lme4, LMER or arm as R packages, or a program that uses Markov Chain Monte Carlo simulation to iteratively produce chains of computer-generated values, such as JAGS. lme4 and arm which can fit generalized linear models efficiently, but may not estimate the uncertainty as well as the full Bayesian model. Unlike classical linear regression, Bayesian statistics assume that the *unknown* parameter is not fixed, and that there is a prior distribution to represent our beliefs about the important characteristics of the parameter. We use noninformative prior information to estimate parameters when there is too much information beyond the data. Fitting the same model to the classical linear equation should produce very similar results, but the Bayesian MCMC model can properly estimate the uncertainty, thereby giving rise to more precise inferences and predictions (Gelman and Hill 2007, 304).

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represent uncertainty about the unknown parameters before data are observed, and noninformative prior distributions can be used to estimate parameters when there is too much information beyond the data. Fitting the same model with the classical linear equation should produce very similar estimates because of the noninformative prior distribution, but the Bayesian approach models the uncertainty at each stage of the analysis. For example, the unknown variance of the coefficients is drawn from the inverse gamma distribution.

JAGS stands for Just Another Gibbs Sampler. Because we seek the posterior distribution based on the likelihood function and prior distributions, we need to specify every data point, parameter and hyperparameter. JAGS is used to run an interactive algorithm in which several parallel Markov chains start with some initial values and wander through a distribution of parameters until the simulations converge to a common distribution. After estimating the coefficients of the multi-level regression model, I use Equation 1 as a linear combination of coefficients and demographics to generate the predicted values of the outcome. The influence of the city/county shown in Equation 2 also contributes to the predicted values in the process of post-stratification.

A. Post-stratification

Post-stratification allows us to include the information from the census data. Supposing that there are 2×5×5 cells of the demographic geographic type, we calculate the corresponding population frequencies using census data for 2000 and 2010.

I sum up the predicted values from Equation 1 as the numerator. The denominator is the product between each category l representing city j and the probability of supporting an increase in the budget for each cell. In this study, I calculate the average responses over cities. In Equation 4, θ represents the post-stratified estimate, or average over cities in this study:

$$\theta_S = \frac{\Sigma_{j \in J_S} N_j \times \theta_j}{\Sigma_{j \in J_S} N_j} \tag{4}$$

where Nj refers to the population for category j, and j in J_S means that category j is a subset of city S. I use census data for 2000 and 2010 to obtain the population percentage for each cell N_j ; the 2007, 2009, and 2010 population percentages are post-stratified by the 2000 census, and the 2012 and 2013 population percentages are post-stratified by the 2010 census. θ_j is estimated from our multilevel model shown in Equation 5, where α represents the intercepts of the city/county and X denotes the vectors of demographic variables:

$$\theta_j = \log \mathrm{t}^{-1}(X_j\beta + \sum_S \alpha^S) \tag{5}$$

V. Findings

A. Disaggregated Policy Preferences and MRP Estimates

After modeling individual responses in a function of demographic/geographic variables using the MRP set-up, I array the estimated opinion and original data points to see how well the estimation performs. In order to prove the advantage of the multilevel regression model, I calculate the standard errors of the 95% confidence interval for the disaggregated public opinion and obtain the 2.5% and 97.5% MRP estimates.[5]

In Figure 3, most MRP estimates (solid dots) and disaggregated estimates (white dots) are close to each other except for small

5 Because every Bayesian statistic is a product of the likelihood function and the prior distribution, there are hundreds of estimates for each parameter. Therefore, all of the post-stratified opinions can be arrayed like a distribution and we take the median as the estimated opinion and the 2.5 and 97.5 percentiles as the two end points of a credible interval.

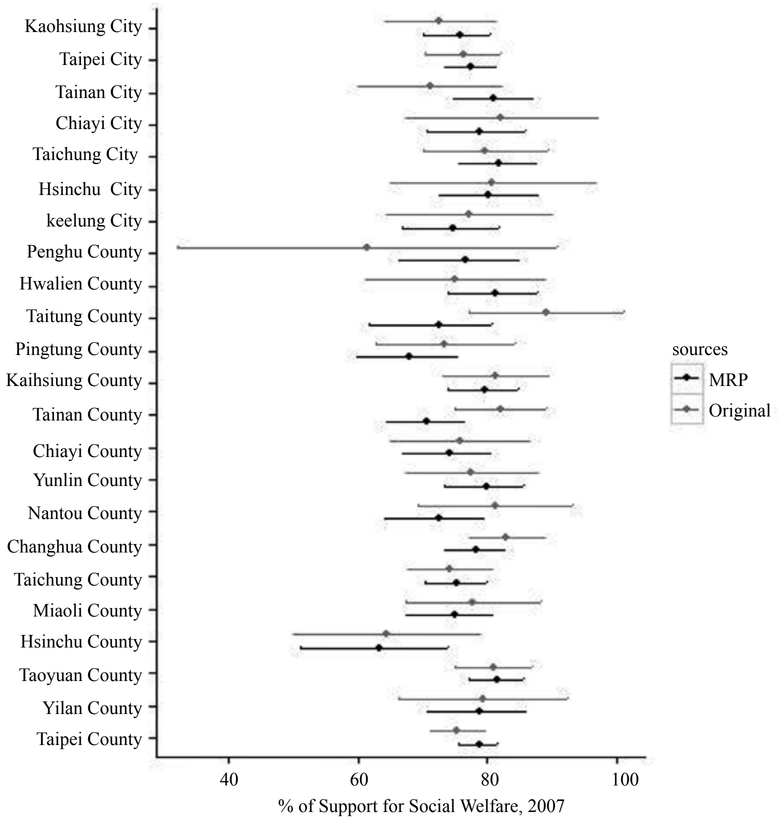
counties like Penghu and Taitung. Apparently, the MRP estimates have smaller credible intervals than the disaggregated estimates, especially for the cities/counties with smaller sample size. MRP estimates are located between 60 and 80 percent, while the credible intervals may go beyond the range. However, original data points are scattered between 40 and 100 percent.

Regarding the individual city/county, it is obvious that the MRP estimate for Taitung County is pulled away from the original data point. So is the MRP estimate for Penghu County. The distance between the MRP estimates and disaggregated estimates of Tainan City and County are a bit puzzling, but their credible intervals and confidence intervals overlap.

To be sure, both disaggregated and MRP-based estimation results show that most cities/counties embrace the idea of more social welfare. Will the public's mood change or remain the same in 2009?

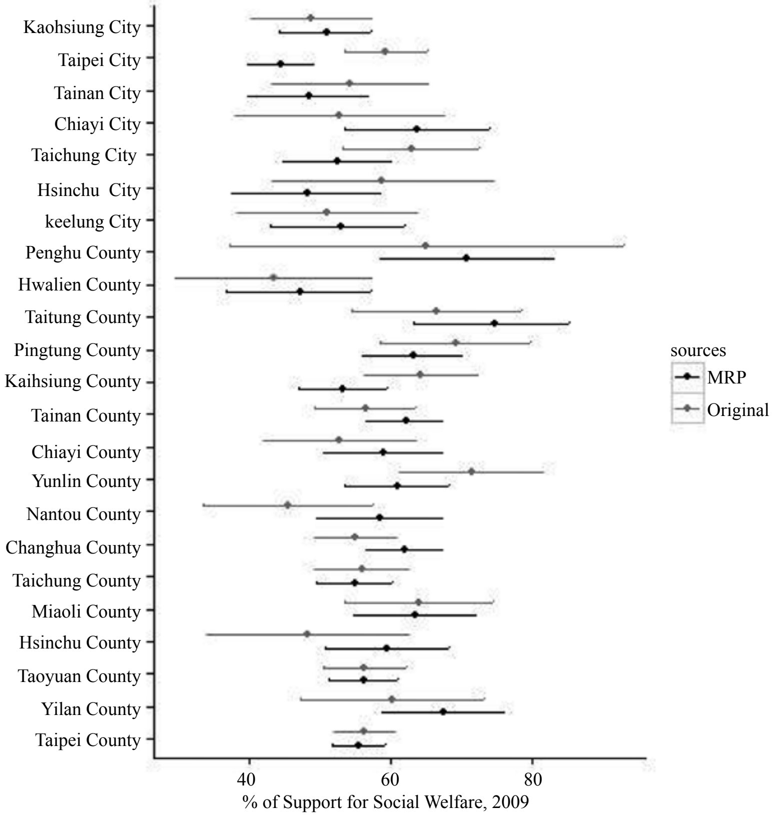
Figure 4 shows that the estimated opinion on social welfare represented by solid dots center around the interval of 50 and 70, which is much smaller than for the original data. Because MRP partially pools observations, the estimated opinion is constrained within a certain interval. Compared to disaggregated public opinion, MRP estimates are less likely to be influenced by the number of observations of sub-groups. For example, Hwalien's and Yunlin's data points are at the two extremes of the x-axis, but their MRP estimates are located closer to the other cities/counties.

Figure 3. Estimated and Original Public Opinion toward Social Welfare, 2007.



Data source: Tsai (2006).

Figure 4. Estimated and Original Public Opinion toward Social Welfare, 2009.

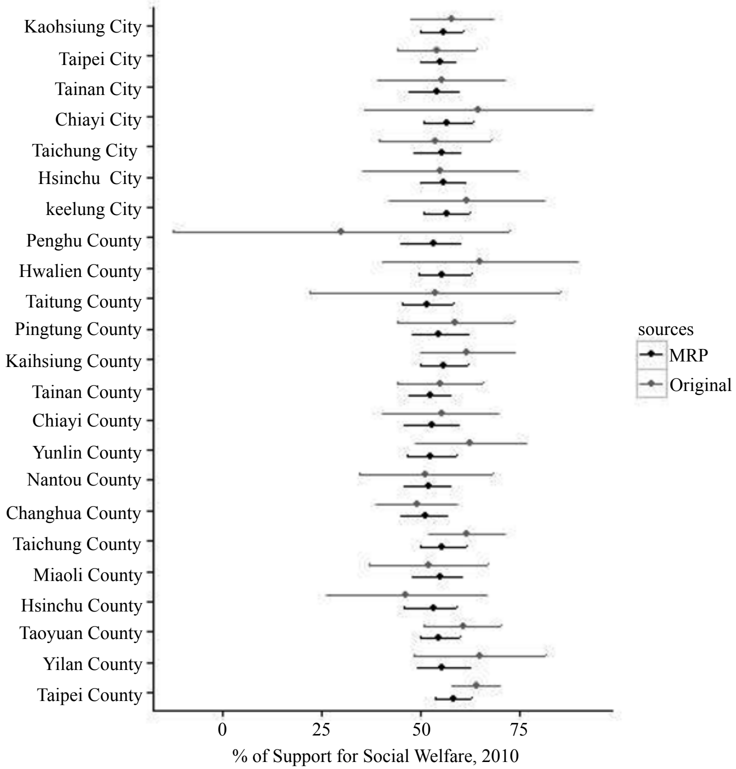


Data source: Tsai (2009).

There is a significant difference between the disaggregated and MRP estimates for Taipei City. Considering that Taipei City has a large number of observations in the national sample, the difference is surprising. One of the possibilities is that the multi-level regression pulled the estimates to the mean of the overall estimates, which also takes place in Tainan City, Taichung City and Hsinchu City. Another possibility is that the 2000 census data contain incorrect information so that post-stratification produces erroneous aggregate public opinion based on multi-level regression estimates.

In Figure 5, the MRP estimates for the 2010 survey are located in a more constrained interval than Figure 3 and Figure 4. However, cities/counties of smaller sample size like Penghu, Hwalien and Taitung have very wide credible intervals. This is probably because certain counties with large sample sizes happen to be less extreme. In this case, the MRP estimates are less variable than in the case of other data.

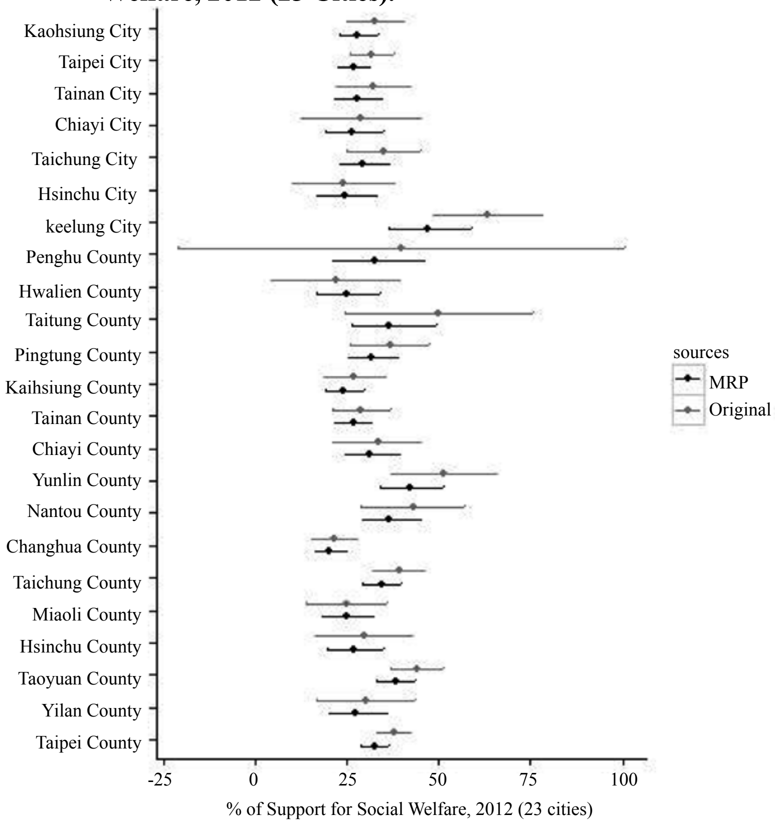
Figure 5. Estimated and Original Public Opinion toward Social Welfare, 2010.



Data source: Tsai (2009).

Figure 5 shows that the estimates fall within the interval of 50 percent and 75 percent in the 2010 survey. The MRP and disaggregated estimates are more centralized than in 2007 and 2009. Again, it seems that some of the counties with smaller sample sizes have MRP estimates close to those for other cities/counties. For example, Penghu County has a wide credible interval and its disaggregated mean falls between 25 and 50 percent. However, its MRP estimate is close to those for larger cities like Taipei and Taichung.

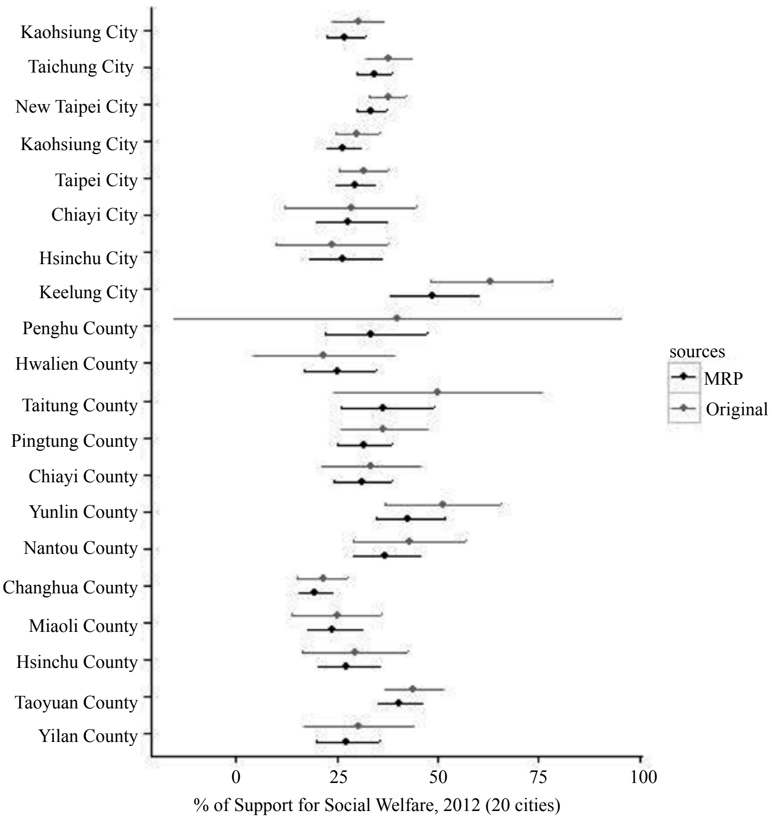
Figure 6. Estimated and Original Public Opinion toward Social Welfare, 2012 (23 Cities).



Data source: Tsai (2012).

Because of the changes that took place in several local governments in 2010, I estimate the preferences in 23 and 20 cities/counties based on the 2012 data. Although both figures present the MRP estimates from the same survey, the three new metropolitan cities, Taichung, Tainan, and Kaohsiung, seem to have a minimal influence on the results. It is difficult to tell the difference between Figure 6 where there are 23 cities/counties and Figure 7.

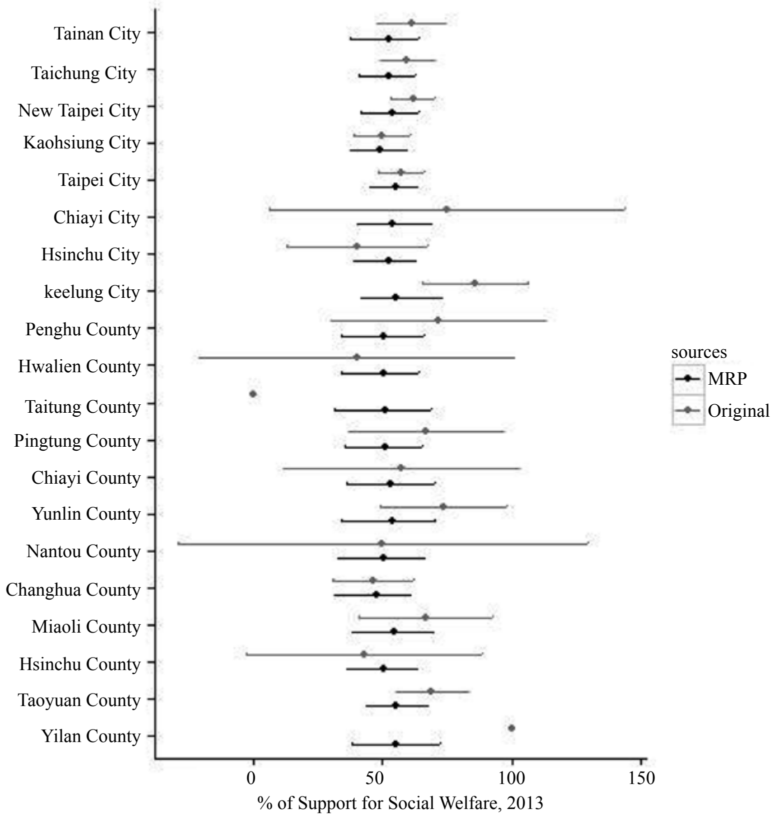
Figure 7. Estimated and Original Public Opinion toward Social Welfare, 2012 (20 Cities).



Data source: Tsai (2012).

Figure 8 shows very centralized MRP estimates in 2013. Those invariable estimates are somewhat beyond my expectations, considering the small sample sizes for each city/county. For example, Taitung County has no respondents in our dataset and Yilan has only four, but their MRP estimates are not that different from those for other cities/counties. This demonstrates the strength of the MRP estimation. As for other cities/counties, smaller credible intervals of the MRP estimates make the inference more robust.

Figure 8. Estimated and Original Public Opinion toward Social Welfare, 2013.



Data source: Tsai (2012).

B. Stability of Public Opinion

After examining the MRP estimates and disaggregation means of preference in every city/county, I look at the stability of public opinion. A simple regression allows us to assess the association between two variables. In this study, they consist of the attitudes toward social welfare across the same administrative units at two time points. Table 1 presents the results for the four waves of MRP estimates predicted by the prior ones. Notice that I predict the 2012 estimates based on the 2010 data for 23 cities/counties, and use the 2012 estimates for the 20 cities/counties to predict the 2013 estimates.

Table 2. Continuity of Public Opinion toward Social Welfare, 2009-2013.

	2009	2010	2012	2013
Intercept	106.437***	60.767***	0.354	0.478***
	(25.530)	(2.606)	(0.430)	(0.021)
2007 Preference	−0.635$ (0.334)			
2009 Preference		−0.108* (0.045)		
2010 Preference			−0.001 (0.008)	
2012 Preference				0.145*
				(0.065)
R^2	0.147	0.217	0.001	0.219
Adj. R^2	0.106	0.180	-0.047	0.176
Num. obs.	23	23	23	20

Data source: Tsai (2006), Tsai (2009), Tsai (2012).

Notes: ***p < 0.001$, **p < 0.01$, *p < 0.05$, $p < 0.1.

The first column of Table 2 shows the weak correlation between the 2009 and 2010 estimates. The *p*-value is 0.07. The correlation between the 2009 and 2010 MRP estimates is statistically significant. The coefficient is -0.108 and the standard error is 0.045. The negative signs of the regression coefficients mean that there has been a decreasing demand for social welfare; support for more social welfare steadily decreases in 23 cities/counties.

Using the 2010 estimates to predict the 2012 estimates, however, gives rise to the null result. Nevertheless, the 2012 estimates successfully predict the 2013 estimates; the coefficient is 0.145 and the standard error is 0.065. The negative coefficients of the 2009 and 2010 models suggest that the general public has been against more social welfare from 2007 through 2010. The positive coefficient in the 2013 model, however, implies that citizens have changed their minds. On the one hand, it may reflect the economic downturn in 2013 when the economic growth rate was less than 2%. The general public could react to the worsening economic situation by asking for more subsidies. On the other hand, there may be a cycle of attitudes; citizens vacillate in terms of their attitudes every few years. This pattern confirms Wlezien's theory (1995) that people will turn around their preferences when they feel there has been too much government spending in certain policy fields. Knowing the real cause of the change in public opinion will allow policy-makers to respond to it. The bottom line of this finding is that the social welfare preference in time *t-1* has unstable impacts on preferences in time *t* across the period of time. This data analysis shows mixed results regarding the stability of public opinion in Taiwan.

VI. Validation

How well do we measure citizens' preferences toward social welfare? Are there any indicators related to them? It is necessary to conduct a validation test before drawing a conclusion. In considering Tsai and Yu's (2011) finding that social welfare opinion failed to predict government spending, I assume that the "demand side" is more important to the support for social welfare. Because the government has not released the statistics in 2013, I only test four years of the MRP estimates. First of all, I use the percentage of households with low income to predict the estimated public opinion. Table 3 gives rise to mixed results. Only in 2009 can the independent variable predict the dependent variable, the MRP estimate of social welfare support.

Table 3. Validation of Estimates by Low-income Households

	2007	2009	2010	2012
Intercept	76.371***	57.028***	54.607***	29.669***
	(1.035)	(1.585)	(0.393)	(2.808)
2007 Low Income	0.002			
	(0.077)			
2009 Low Income		0.231$		
		(0.120)		
2010 Low Income			−0.019 (0.030)	
2012 Low Income				1.046
				(1.302)
R^2	0.000	0.150	0.019	0.035
Adjusted R^2	-0.048	0.110	-0.028	-0.019
N	23	23	23	20

Notes: ***p < 0.001, **p < 0.01, *p < 0.05, $p < 0.1.

Data source: Tsai (2006), Tsai (2009), Tsai (2012).

Table 4. Validation of Estimates by Household Average Income

	2007	2009	2010	2012
Intercept	74.150***	73.837***	52.549***	38.547***
	(3.395)	(4.374)	(1.184)	(7.944)
2007 Household Income	0.022 (0.032)			
2009 Household Income		−0.159*** (0.042)		
2010 Household Income			0.020$ (0.011)	
2012 Household Income				−0.064 (0.071)
R^2	0.022	0.407	0.128	0.043
Adjusted R^2	-0.025	0.379	0.087	-0.010
N	23	23	23	20

Notes: ***p < 0.001, **p < 0.01, *p < 0.05, $p < 0.1.

Data source: Tsai (2006), Tsai (2009), Tsai (2012).

It is apparent that the percentages of low-income households have a weak association with the MRP estimates, and thus I turn to the average income of households in multiples of NTD10,000 dollars. Table 4 shows that in 2009 and 2010 the average household income predicts the MRP estimates effectively but in different ways. In 2009, the higher the average income of the city/county, the less support for social welfare that there is. In 2010, however, high household income also means support for social welfare.

The results partially confirm the validity of the MRP estimates; they are still not perfect. Certainly, it is necessary to develop better theories of social welfare before conducting more validation tests.

Moreover, the average household income may not precisely measure the demand for social welfare. At this stage, I would argue that the validity of the MRP estimates needs more checks but their reliability is out of the question.

VII. Conclusion

This paper has presented empirical evidence regarding the stability of aggregate public opinion. By investigating macro-level preferences toward social welfare across three years, I have found that the public opinion in twenty-three or twenty cities/counties is consistent. MRP implemented using Gibbs sampling as a means of Bayesian inference generates more than 15,000 random draws from the sample for each city/county. The median of a posterior distribution is chosen as the predicted probability of supporting social welfare in each city/county. Then the medians are post-stratified over the sub-groups, gender, education, age, and the interaction term of age and education using the census data in 2000 and 2010. The MRP estimates indeed correct the extreme values of some cities/counties with smaller sample sizes.

To summarize, this paper has four points to make:

1. MRP generates estimates that are more centralized than the original data points. Because MRP partially pools observations across cities, the estimates of sub-national public opinion are stronger than those obtained through the disaggregation of survey data.

2. The validity of the MRP estimates is arguable. There is no established theory to explain individual or aggregate support for

social welfare, and therefore we ought to search for better indicators to verify the MRP estimates.

3. The stability of public opinion toward social welfare is not confirmed. Even though the coefficients between the 2007 and 2009, 2009 and 2010, and 2012 and 2013 MRP estimates are significant, the size is small and the direction is either negative or positive.

4. We shall apply this model to other policy issues. As the literature review indicates, the causal relationship between policy and public opinion may not be uniform across the board. Examining policy preferences across different fields only helps us approach the true preferences of the citizens.

The over-arching question is whether the general public leads policy-making or that policy represents preferences. My findings suggest that the general public could be responsible for public policies because public opinion is stable. The question is whether the general public is informed by policies or that they can formulate policies. It is necessary to trace public opinion over longer periods and to correlate it with more policy indicators. With a rigorous estimation method like MRP, we should not refrain from investigating the complicated causal stories of public opinion and government policies, which would only benefit the prospects of democracy.

There are several limitations of this study as I noted earlier in this paper. While this research produces less uncertain estimates of public opinion toward social welfare, using a single policy to argue for the stability of general policy preferences is at best incomplete. I believe that the class of public policies can be studied in the same way and am confident that the findings would hold for other policies. Until then, however, the generalization of the stability of opinion among people in Taiwan is limited.

Moreover, this study focuses on public opinion and neglects the aspect of government. Although Tsai and Yu (2011) have investigated the link between policy and preferences, more systematic research is definitely essential for this discipline. We should also consider other demographic variables, such as occupation, to predict support for government spending. While the Bayesian statistics can reduce the uncertainty associated with the estimates by incorporating a prior distribution, better data may make the inferences more precise. Finally, the hidden internal division between two merging administrative units (e.g., Tainan City and County) may cause the fluctuation in policy preferences to be under-estimated. With a longer period of data, we can probably find the degree to which administrative mergers equalize the policy preferences of city and county.

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台灣社會福利民意的測量

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摘要

政策與偏好的關聯是政治學的重要關懷之一。過去對於政策與投票的研究偏重個體的層級，並未考慮整體層次的政策民意的穩定性。本文利用 2007 年至 2013 年所收集的電話訪問以及網路民調資料，以多層次貝氏統計模型加上事後加權（MRP），估計各縣市民眾對於增加或是減少社會福利預算的偏好，克服縣市的觀察值不一所造成的不確定性。結果發現，雖然民意的穩定程度並不高，但是這個方法可以提供相當可信的估計。各縣市的社福預算民意似乎在 2010 年之後傾向緊縮，意味著在社福預算一直增加的情況下，民眾開始持保留的態度。

關鍵字：民意、社會福利、多層次貝氏統計模型加上事後加權