Structural Equation Models of Asian American Political Participation

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What is the relationship between a particular factor, such as party identification, and political participation? Given the prior lack of nationally representative survey data on Asian American politics prior to the 2008 National Asian American Survey (NAAS), much of the book has explored the distribution of various factors that prior scholarship has hypothesized to be of importance to political behavior, and has examined the bivariate relationships between these factors and political participation. In Chapter 7 and Appendix D, these various factors are brought together in a set of multivariate regressions, where singular relationships between each predictor variable and various outcomes are established, all while holding all other predictor variables constant. As noted in their book, Wong et al. (2011) have no strong theoretical priors to assume a causal ordering of the pathway factors outlined in the book.

Still, using a latent variable (and structural equation model, or SEM) approach to explain Asian American participation has two important advantages: it decomposes variances and helps to clarify and illustrate ways in which the pathways may be plausibly ordered in a causal process. Here, we discuss methodological issues with model estimation and the use of SEM and present the results of our model estimation. This approach is not strictly confirmatory; the process developing these structural models was iterative. The latent structures were investigated initially prior to the development of regressions between latent variables. The purpose of structural regression modeling is to develop causal processes that structure the data in a way that

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reproduces the variances and covariances of the data—in essence, we are partitioning variances as well as analyzing regression to the mean. Structural equation modeling uses the data to generate estimates, and it subsequently tests the model's results by assessing how well the results can replicate the actual characteristics of the data.

There are numerous benefits to constructing latent variables as opposed to multiple regression techniques. Several authors have theorized that the use of latent constructs assists in moving beyond controlling for demographic factors and theorizing how demographic factors are part of a latent construct that impact behavior (see, for example, Timpone 1998 and Johnson 2001). Common multiple regression techniques make the assumption that independent variables do not covary, and thus multicollinearity produces inaccurate estimates of standard errors (Gujarati and Porter 2009). The estimation of standard errors is generally larger, and this results in greater type-II errors: falsely rejecting a hypothesis. This is problematic in multiple regression if researchers use variables that have a high degree of overlap. As opposed to using "kitchen-sink" or "garbage-can" models (Achen 2005), SEM collapses numerous variables that covary into latent factors, and enables an examination of potentially causal relationships between these latent variables.[3] This is beneficial, as prior research may have used collinear control variables as evidence that their causal variables are statistically significant while other variables from "the canon" are not (e.g., party identification and ideology). Also, the benefit of SEM is that it provides an estimation of measurement error along with estimated relationships; this generally corrects for any attenuation of effects (Hatcher 1994).

The use of SEM is not widespread in political science; indeed, one of the most recent major methodological publications for quantitative political science research advises against the

[3] Relationships can also be investigated between measured variables and latent variables. Structural regression models are a combination of factor analysis and path analysis.

use of SEM (Gelman and Hill 2007, p. 226). Gelman and Hill (2007) see promise with the estimation of multi-level models; however, they neglect to identify the close relationship between multi-level models and SEM (see, for example, Heck and Thomas 2009). Since such an oversight may result in devaluation and misuse of SEM techniques; this appendix attempts to make as much of a methodological contribution as a substantive reinterpretation of data.

There are two attributes to a SEM: a *measurement model* and a *structural model*. The measurement model is the composition of the measurement of latent constructs. This is basically the "factor analytic" attribute of SEM; variables are specified to have a common relationship caused by the latent variable, which is the basic structure behind confirmatory factor analysis (CFA). The latent variable represents the commonality between the variables that load onto it. When the observed variable is continuous, then a factor loading is a regression coefficient, and when the observed variable is categorical, then the factor loading is a logit (or probit) coefficient. The structural model draws relationships between the latent factors (e.g., causal and correlational). The benefit of modeling such relationships is that independent variables are allowed to covary with one another, overcoming the modeling limitations of multivariate regressions that prevent such relationships.

Tenko Raykov and George A. Marcoulides (2006) advise that without a well-fitting measurement model, there is little likelihood that the proposed structural model will fit the data well. Also, Hatcher (1994) advises steps that should be taken in the development of a SEM model: first, to develop confirmatory factor analytic models of all the latent variables separately to make certain that the measurement model fits the data well; and second, to develop a structural regression model that proposes relationships between these latent variables. Though

Raykov and Marcoulides (2006) make no advisement of this process in their text, we follow the Hatcher (1994) approach.

We used the *Mplus* statistical program to model these relationships; this program is quickly growing as one of the most popular for structural equation models—it allows for the analysis of categorical data, and does not require prior knowledge of LISREL language. One of the essential assumptions of maximum-likelihood estimation on factor analytic and SEM models is that dependent variables are continuous (Hatcher 1994; Raykov and Marcoulides 2011, 2008, 2006). Gary King (1986) warned against such violations with SEM and Path Analysis more commonly in political science. As opposed to using maximum-likelihood estimation, Muthén and Muthén (2010) developed a weighted-least squares (WLSMV) estimator that conducts probit regressions on the dependent variables that are ordinal (p. 58; Muthén 1984, Muthén, de Toit, and Spidic 1997). This is an iterative estimation process that takes into account violations of assumptions of continuous dependent variables. The only deficiency is difference testing—Muthén and Muthén (2010) advise using a general weighted least squares (WLS) estimator for difference testing and WLSMV for all other parameter estimates. Another feature of *Mplus* is the ability to conduct an analysis of missing data to incorporate all observation with no casewise deletion. The program reports the degree of overlap of observed variables and the number of missing data patterns. By incorporating missing data, *Mplus* allows for model estimation without having to rely on multiple imputation or casewise deletion.

Our Model of Political Participation

In the following, we present the overall model fit, the measurement model and define the latent variables. Subsequently, we present the SEM and a discussion of structural model. This step-by-step approach from Hatcher (1994) insures that the latent variables are identified. The model schematic is presented in Figure 1.

Model Fit

There are many ways to assess the overall model fit, and we will present and discuss the common ones in this section. Model fit is important as it similar to an F-test is multiple regression—it is an assessment of whether or not the relationships you propose exist overall before analyzing the estimated relationships in the model. The baseline model (i.e., if there were no relationships between the variables) has a $\chi^2_{351} = 46{,}616.611$. This is statistically significant, which indicates that there are relationships between these variables. The proposed model reduces the variability to $\chi^2_{308} = 4271.428$. Though this test statistic is statistically significant (it is preferred that the chi-square test statistic is not significant), it reduces the variability in the model substantially.

Model fit indices and evaluation of root mean square error of approximation (RMSEA) have become a standard in model fit evaluation. The chi-square test statistic is an unstable parameter estimate; it is commonly reported but little weight on model fit is based on it (see Byrne 2012; Raykov and Marcoulides 2006; Hu and Bentler 1999; Hu, Bentler, and Kano 1992). If more than one fit index is used, then Hu and Bentler (1999) recommend that both are above 0.90. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) both have values above that cutoff ($CF\quad = 0.923; TLI = 0.912$). Also, Hu and Bentler (1999) recommend that a small RMSEA ought to be present with its value and confidence interval below 0.05. The present model has an RMSEA= 0.047 with a 90%-CI $[0.046, 0.049]$. According to traditional evaluation of covariance structure analyses, this model has a good fit. The parameter estimates within the model ought to be reliable considering the overall model fit. The subgroup models have varying ranges of model fit with the models for the Korean and Japanese subsample evidencing less than adequate fit.[4]

Measurement Model

The following latent variables were developed in congruence with the concepts developed in the text: political participation, indigenous resources, party identification, racial identification, immigrant related factors, and socio-political contexts. We identify what variables were grouped together to form these latent constructs; all variables loaded onto single factors (i.e., no cross-loadings). At times, variables have error correlations due to theorized relationships between these variables beyond the relationship identified by the latent variable.[5] These error correlations improve the fit; however, model identification becomes an issue when errors are correlated. The use of correlated errors was used in every model, and they were used to modify models once the overall measurement and structural models were developed. The following latent constructs and structural model were developed without considering controls for ethnic subgroups. This approach provides an overall image of Asian-American political participation. We provide analyses of different ethnic groups within the data after the overall

[4] The results for the Korean and Japanese subgroups need further investigation, and may indeed be attributable to the smaller number of respondents in these groups or other characteristics of the sample.
[5] For the sake of brevity and space, the full model will not be provided (i.e., factor loadings and error correlations). For full model estimates and outline of correlated errors, please contact the authors.

model, and find some consistent patterns as well as some significant deviations from the overall model.

As Byrne (2012) and others advise, the measurement model was initially fit. For fully saturated latent variables (i.e., three indicators for a latent variable), the model was constrained in order to produce an over-identified model. These approaches stem from the congeneric modeling approach in psychometric theory and provide the most parsimonious analysis. Also, without an over-identified model, model fit cannot be assessed. These constraints allow for the use hypothesis tests of model fit.

Our key endogenous variable is *political participation*. The variables that were used to measure participation were the survey responses of whether or not individuals contributed to campaigns, contacted representatives, participated in protest, and participated in community organizations. Though Huckfeldt (1979) recognizes different types of political participation, a single latent construct fits the data well. As would be expected, the variable that loads least well onto participation is whether or not the respondent participated in a protest; it has a standardized[6] factor loading of 0.390 $(p < .001)$. The other factor loadings are 0.630 $(p < .001)$ for community participation, 0.716 $(p < .001)$ for contacting representatives, and 0.716 $(p < .001)$ for contributing to campaigns. With satisfactory loadings overall, the latent construct of political participation has a high level of validity and reliability. This is important because there needs to be substantial confidence in what we want to explain before we attempt to identify variables that are exogenous to it.

[6] Standardization is by the StdYX approach. This standardization incorporates the variances of the latent variables and measured variables. The interpretation of the coefficient is: "the change in y in y standard deviation units for a standard deviation change in x" (Muthén and Muthén 2010, p. 642). Standardization is used as variables are not measured on the same scale.

The latent construct of *immigrant related factors* is measured by whether or not the respondent is foreign born, the number of years the respondent has spent in the United States, the proficiency the respondent has with English, whether or not the respondent was educated abroad, whether the respondent consumes ethnic news media or general news media for political news. All of the loading are statistically significant and overall load highly onto the factor. As a result of the purpose of the factor, watching general news and years in the U.S. have negative loadings. This is an indication that the latent variable is measuring what we intend to measure as consuming English-language news is associated with a respondent having *less* immigrant related factors.

Party identification is also measured as a latent variable—this is because a respondent's partisanship is not only measured by ascribing oneself to a party. The indicators of this variable are whether the respondent has a party identification (regardless of whether it is Democrat, Republican, or other third parties), whether the respondent reports being mobilized by political parties, and whether the respondent identified differences between the parties. The factors load reasonably well, and they are statistically significant.

Racial identification is measured by the level of ingroup connectedness the respondent feels toward his or her racial group, the level of outgroup distance the respondent feels, and whether or not the respondent reported being a victim of hate motivated violence.

The latent construct of *religious and civic engagement* is measured by religious participation, membership in a civic organization, and religiosity. *Resources* is measured by family income, education, and whether or not the respondent is a homeowner.

Finally, *socio-political context* takes into account features of the respondent's social and political landscape. This includes whether or not the county is considered a "battleground", if there are local non-partisan elections, whether the respondent's state has direct democratic features (i.e., there is a statewide initiative process), if there are any Asians that are elected officials to the respondent, and if the respondent has recently moved to a new destination.

By following the Hatcher (1994) approach, each latent variable is identified and fits its respective datasets well. This approach began as confirmatory, but the model fit was improved by correlating error terms or setting factor loading to be equal. Error correlations were done with theoretically plausible reasons as to why the error terms ought to be correlated (e.g., religious participation and religious frequency). Constraining factors to be equal was done by running an initial CFA model, then constrained factor loadings of variables that evidenced similar loadings. This approach frees degrees of freedom; it allows for better model assessment and fit (e.g., Hatcher 1994; Raykov and Marcoulides 2011). Also, it provides a more parsimonious explanation. The measurement model without any relationships between the factors has a $\chi^2_{332} = 11069.711$. Considering that there is a total variation of $\chi^2_{351} = 46{,}616.611$, the measurement model organizes the data in a very cognizable and plausible way.[7]

Structural Model

The schematic of the structural results is presented in Figure 1. Any items indicated with a "ns" are estimates that are statistically *insignificant* $(p > .05)$. All remaining coefficients are statistically significant at $p < .05$ with many coefficients reaching higher levels of significance.[8] The structural model developed in an iterative process—this process employed both confirmatory and exploratory techniques. An initial model was proposed, then the model went

[7] It should be noted that though the measurement model does reduce the variability when compared to the baseline model. The measurement model has poor fit with CFI=0.768, TLI=0.755, and an RMSEA of 0.079. This is not a problem because this indicates that the latent variables ought to have relationships between them.
[8] See Table G.1 for regression output with standard errors from the SEM model.

through modification to provide the best fit. This is an exploratory approach, and future research can replicate this model with a new sample to assess its external validity.

There are many interesting relationships provided by the structural model, and we will discuss some of the most prominent. First, partisanship has the largest direct effect on participation; the standardized effect is 0.752. Second, resources have *no* direct effect on participation. Resources work through mediating variables. Those with greater resources are more likely to exhibit greater levels of partisanship, which in turn has a strong direct effect on participation. This is an important finding because it corresponds with prior work that attempts to define *why* and *how* having greater resources (e.g., income and education) leads to greater levels of participation (e.g., Verba, Schlozman, and Brady 1995). Third, immigrant related factors are exogenous to both resources and partisanship. Those who score higher on immigrant-related factors (e.g. foreign born, lower English proficiency, more ethnic media consumption) have lower levels of partisanship and resources. Though the direct effect of immigrant-related factors on participation is positive and significant, the indirect effect of immigrant related factors is both substantively significant and negatively related to participation (Total indirect effects: -0.308).

Another interesting finding is the dual relationship immigrant related factors has with partisanship and racial identification. Those who score higher on immigrant-related factors are less likely to have greater racial identification and an even lower likelihood of partisanship. This is in line with past studies of Latino and Asian American party identification (Wong 2000; Hajnal and Lee 2006, 2011), which show that immigrants are much less likely than the native born to have a clear impression of what differentiates the two major political parties and are much less likely to hold an attachment to either party. Party identification is particularly weak among recent immigrants, and strengthens with time spent in the United States. Similarly, our model also shows that racial identification gets stronger among with higher English proficiency, more education in the United States, and more time spent in the U.S. Finally, racial identification and party identification also bear a strong relationship to each other. The relationship is modeled here as a correlational one instead of causal because we have no strong theoretical priors on which should appear first in a causal order—while it may be tempting to think that early encounters with race once immigrants arrive in the United States should make racial identification first in causal priority, the data from the NAAS indicate that immigrants gain attachments to parties faster then they do a strong sense of racial identification. Regardless of the causal relationship, we find that racial identification is not a direct cause of political participation but is instead a correlated cause (through party identification).

A final notable feature of these overall results is the effect of partisanship on civic and religious engagement. As the partisanship score increases, the more likely a respondent is to be engaged in civic and religious communities. Surprisingly, however, religious and civic engagement has a weaker-than-anticipated effect on political participation. Considering the role partisanship plays in both religious and civic engagement and party identification, it is likely that the sources of both participation and engagement are similar (with unmeasured factors such as political motivation perhaps also playing a role). Still, the relatively muted relationship between civic engagement and political participation among Asian Americans suggests a process of political and civic socialization that may be different from those found among the general population (Verba et al. 1995; Putnam 2000; Ramakrishnan 2005).

Subgroup Models

Figures 2 through 7 are schematics of the structural models of subgroups of the data. Every racial group was analyzed by initially developing a measurement model. The indicators for the overall model were all used in the measurement model of each subgroup, and the same indicators loaded onto the same factors. The measurement models of each subgroup evidenced good fit, and structural paths were developed between the variables. Following the structure of Hatcher (1994) and Byrne (2012), measurement models were developed for each subgroup, and then structural models were developed and modified. The theorized overall model provided a starting place, but there were paths that were insignificant, these paths were constrained to 0 (i.e., the path was deleted from the model). In addition, other paths were added based upon plausible theoretical relationships and modification indices. With each subgroup model required changes from the overall model indicates that there are commonalities and significant differences between Asians of different national origins. There was heterogeneity among the subgroups as well as with the overall model. All structural estimates with standard errors are in Tables 2-7. The following reports overall similarities as well as unique differences that are notable. Readers are encouraged to analyze the figures and tables to draw out further implications from these results.

Though some models do not fit to the appropriate requirement for a tenable model, all of the models fit better than simply applying the overall model to each subgroup. Tables 8 through 13 show the results and fit-statistics for the overall model applied to subgroups—these models are somewhat tailored to each subgroup as some errors were allowed to co-vary to increase the model fit. Even with this adjustment, most models did not reach satisfactory model fit.

Overall—partisanship remains to be a significant predictor of political participation. In all subgroups except for the Japanese sample, partisanship has the largest direct effect on political participation. However, the role that resources and immigrant factors play in partisanship is varied. At times, resources are positively related to partisanship, and at other times the relationship is non-existent. For the Japanese sample, partisanship has no direct effect on participation, and racial identification is significant predictor of participation. Partisanship operates through racial identification, and this correlated cause is substantively significant ($0.713, p < .001$). For cases where resources appears to not matter (i.e., the path is constrained to zero), immigrant related factors is exogenous to both resources and partisanship. However, the effect of immigrant-related factors is both *positive and significant* for Korean and Vietnamese Americans. The relationship between immigrant-related factors and resources also varied by subgroups. For the Chinese and Filipino samples, greater immigrant related factors leads to lower resources; however, for the Vietnamese, Indian, and Korean samples, greater immigrant related factors leads to *greater* resources. However for those groups, resources have no direct effect on political participation, and indirect effects are either attenuated or non-existent. So, even though the relationship between partisanship and participation is consistent across groups, the relationships (direct and indirect) between resources and participation vary across groups raising important questions about the applicability of socioeconomic theories of political participation to Asian Americans, as noted in the Wong et al. (2011) book.

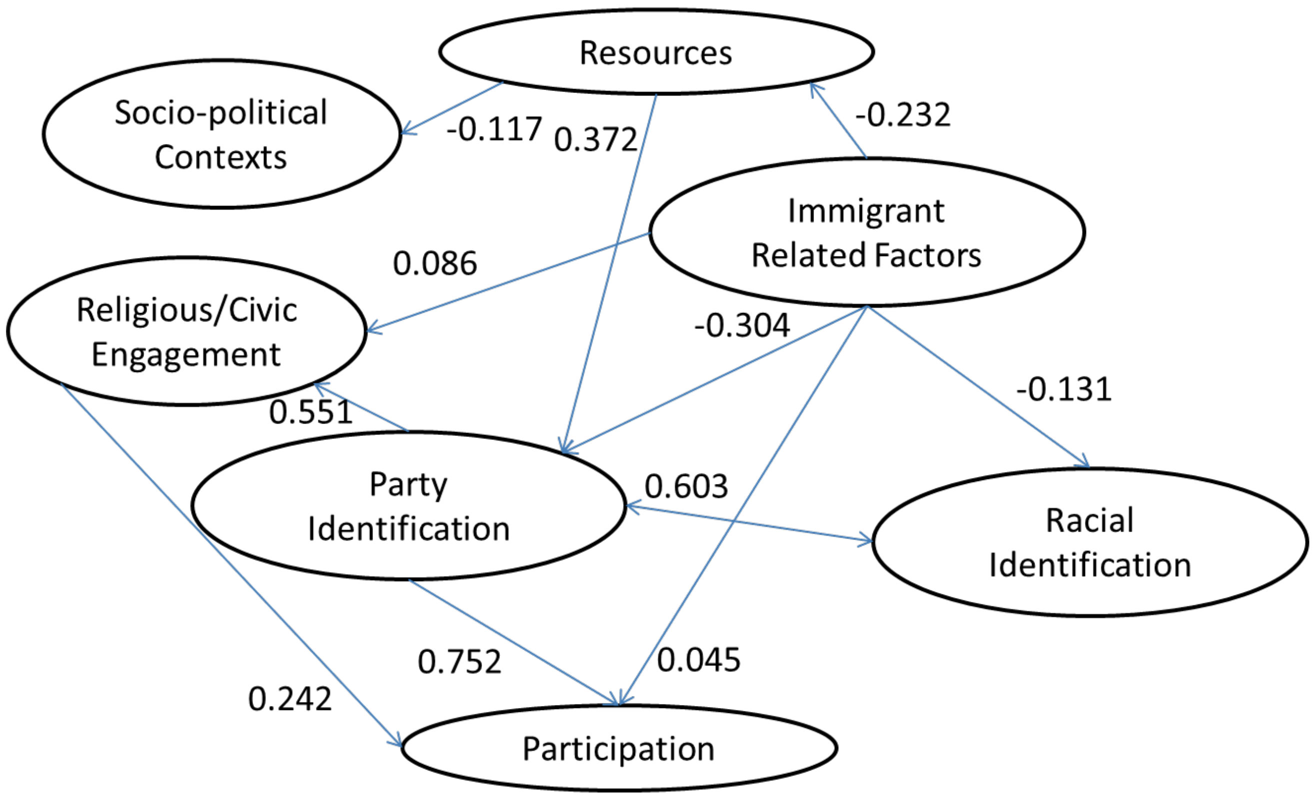
Another notable feature of all the models presented is the null relationship between socio-political contexts and participation. It appears that there is little relationship between the contextual variables used to measure socio-political contexts and participation. It also appears that this variable matters little in the causal process. What is most apparent are the effects of immigrant related factors, partisanship, and resources are statistically and substantively meaningful even if their estimates are not all in the same direction. The interplay between these three variables is integral in the prediction of participation.

Conclusion

The goal of this chapter is to apply Structural Equation Models (SEM) to the National Asian American Survey, and to explore the causal processes between several of the concepts that lead to political participation. This analysis is a “first cut” at something that will need further study and verification. SEM is rooted in a psychometric tradition and is conventionally used in numerous test-retest practices to construct reliable and valid concepts and processes. This work is an initial step in measuring latent variables and estimating relationships between variables. For those interested in learning more about SEM techniques and methods, helpful resources include Raykov and Marcoulides (2005), Byrne (2012), and the *Structural Equation Modeling* journal.

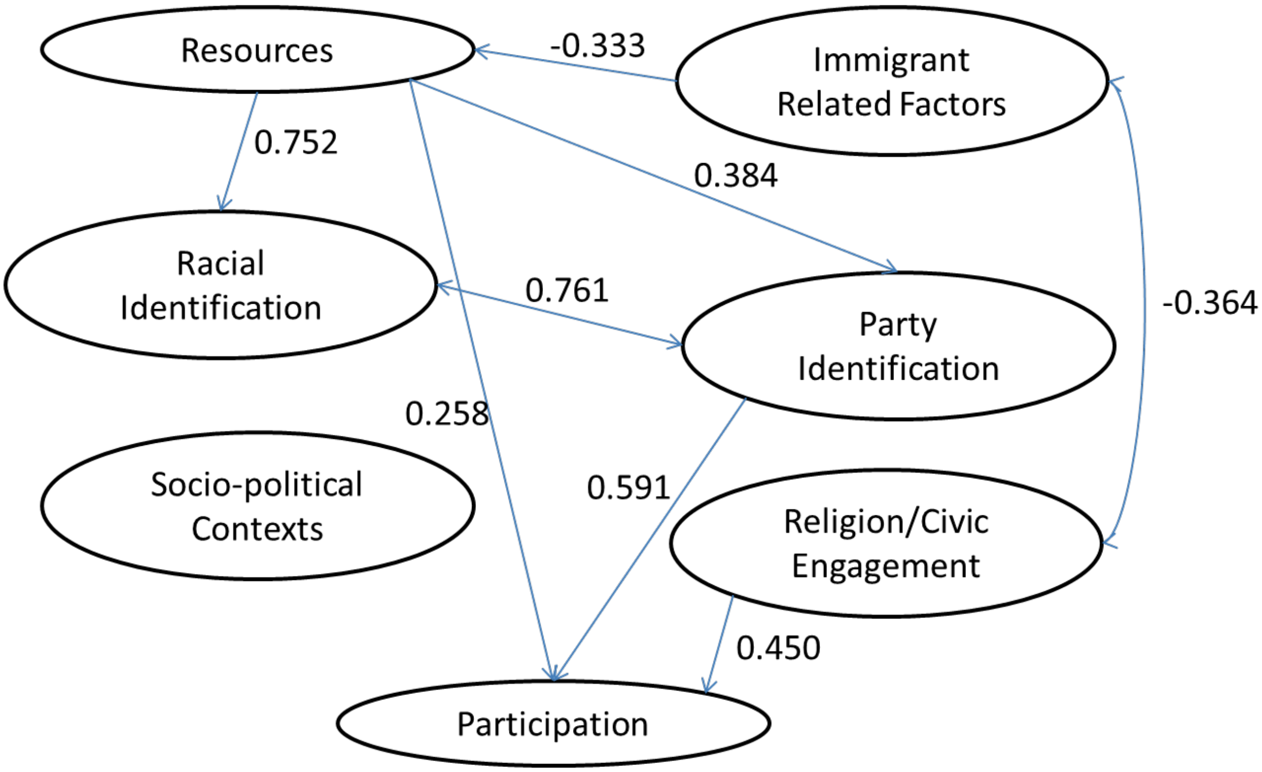
Substantively, the analysis in this appendix generates as many questions as it seeks to answer. Why is it that immigrant related factors leads to greater resources for some groups and less in others? How is the immigrant experience unique for these subgroups and how are they similar? Why is it that partisanship continues to be a reliable predictor of political participation—in fact, the only consistent predictor of participation while other features such as civic engagement appear to play an insignificant role? Is it possible to predict the political participation of immigrants and subsequent generations by knowing their immigrant related factors, resources, and partisanship (i.e., a highly constrained model with only those causal processes modeled)? Finally, under what conditions do immigrant related factors actually lead to benefits (e.g., Koreans and Indians) as opposed to costs in political participation?

Figure 1 Structural Model of Political Participation (All respondents)



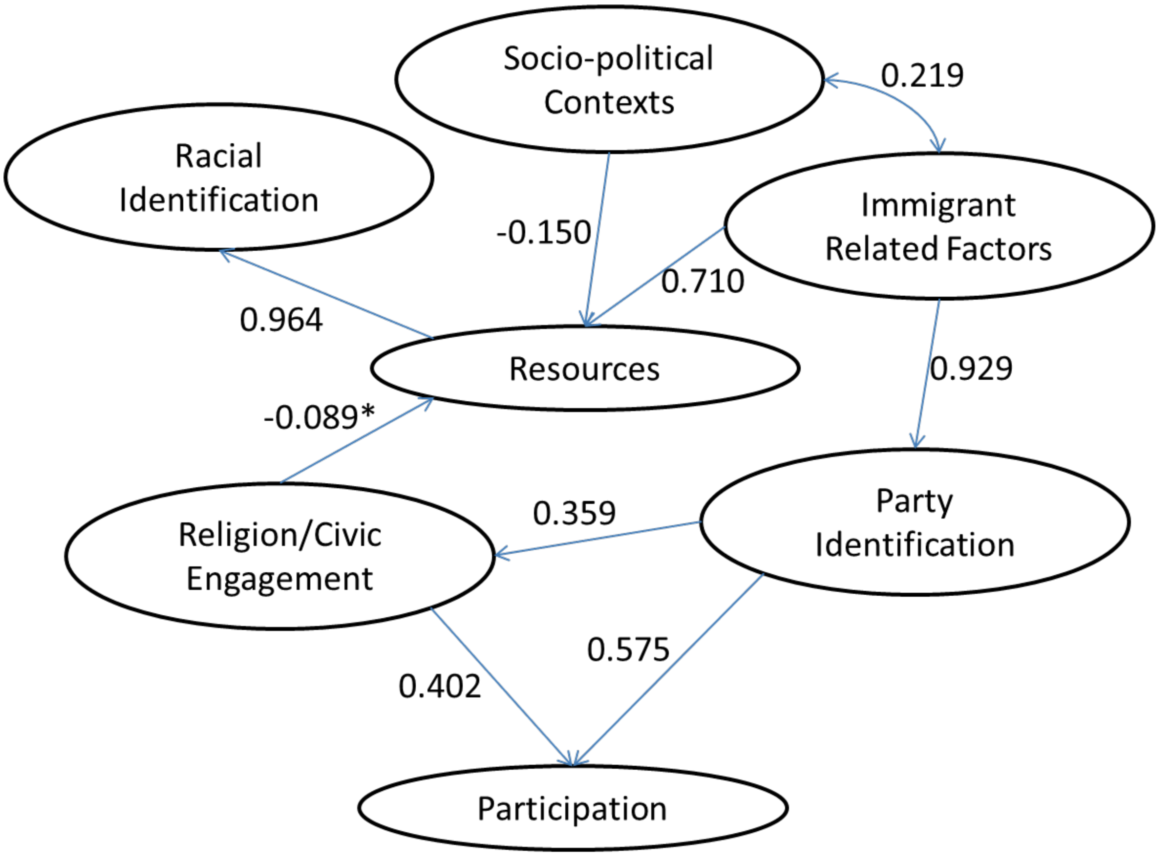
$\chi^2_{307} = 3857.792$, CFI=0.923, TLI=0.912, RMSEA=0.047, 90%-CI: [0.046,0.049]

Figure 2 Structural Model of Political Participation (Chinese Sample)



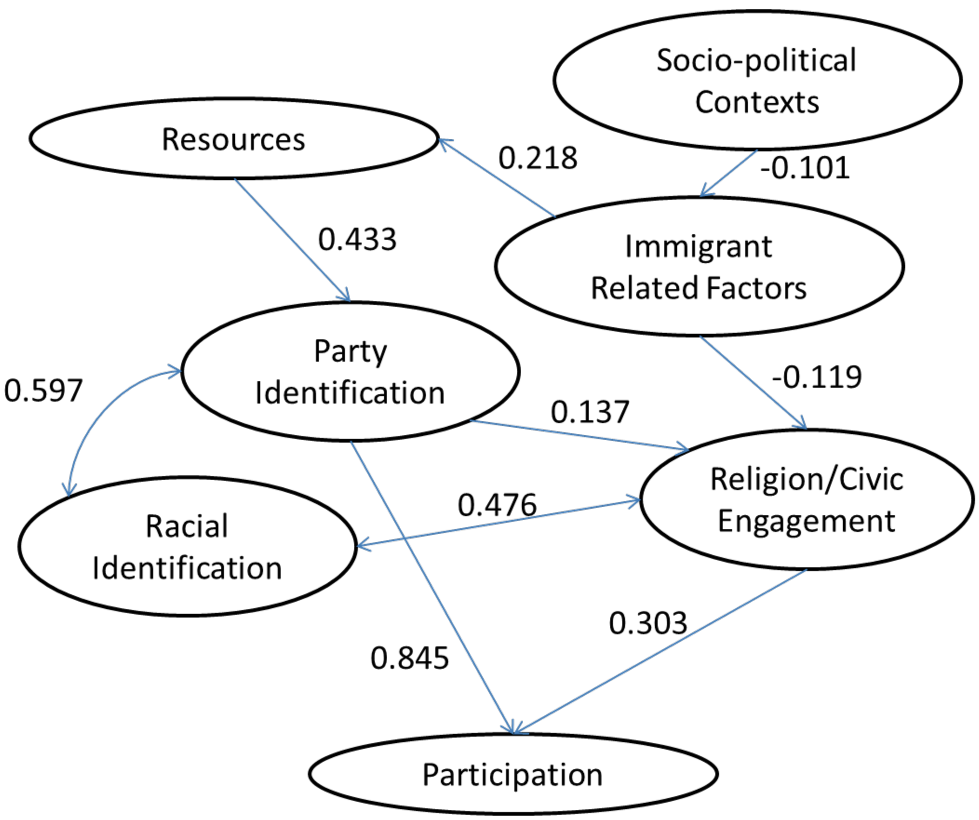
$\chi^2_{241} = 530.619$ CFI=0.949, TLI=0.941, RMSEA=0.038, 90%-CI: [0.034,0.042]
Chinese Sample

Figure 3 Structural Model of Political Participation (Vietnamese Sample)



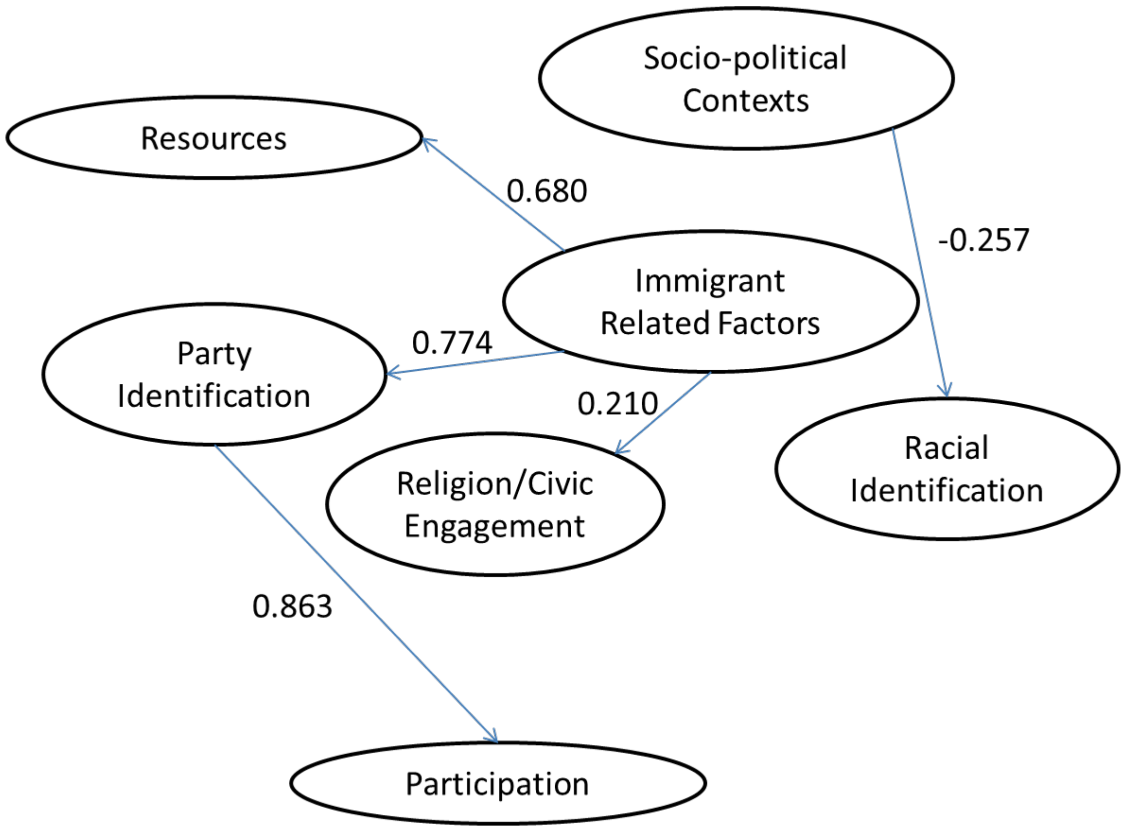
$\chi^2_{303} = 574.491$ CFI=0.916, TLI=0.903, RMSEA=0.035, 90%-CI: [0.031,0.040] *p=.071
Vietnamese Sample

Figure 4 Structural Model of Political Participation (Indian Sample)



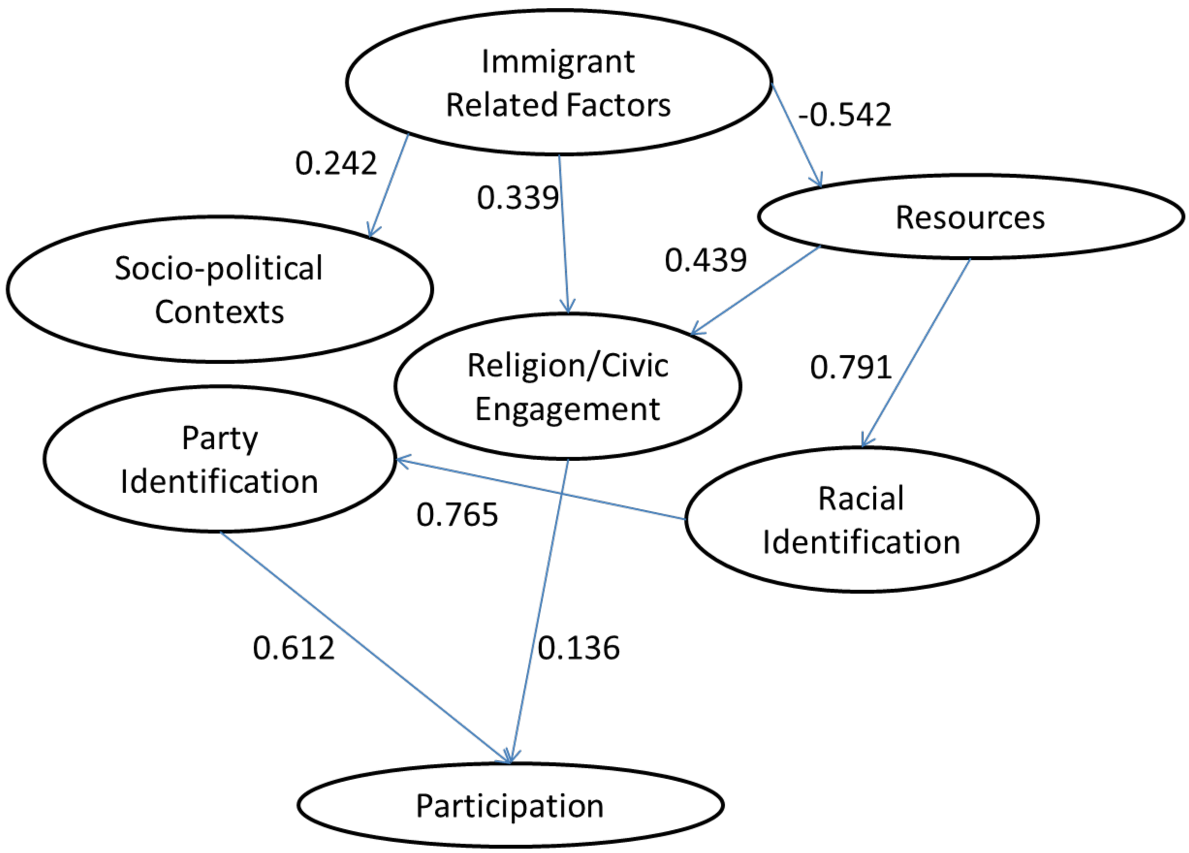
$\chi^2_{307} = 864.914$ CFI=0.909 TLI=0.896, RMSEA=0.040, 90%-CI: [0.037,0.043]
Indian Sample

Figure 5 Structural Model of Political Participation (Korean Sample)



$\chi^2_{313} = 620.549$ CFI=0.854 TLI=0.836, RMSEA=0.040, 90%-CI: [0.035,0.045]
Korean Sample

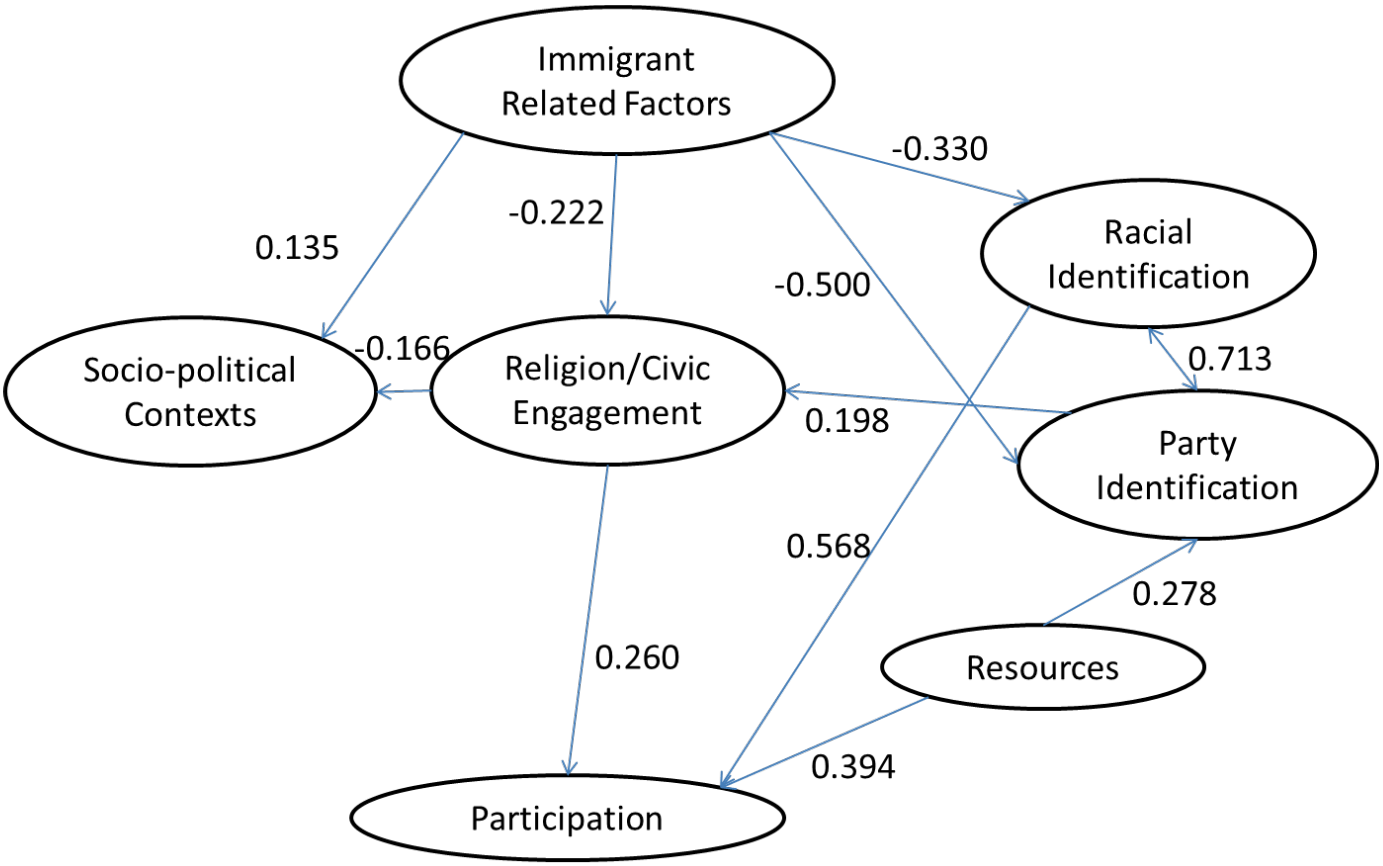
Figure 6 Structural Model of Political Participation (Filipino Sample)



$\chi^2_{311} = 505.971$ CFI=0.914 TLI=0.903, RMSEA=0.032, 90%-CI: [0.027,0.037]

Filipino Sample

Figure 7 Structural Model of Political Participation (Japanese Sample)



$\chi^2_{310} = 656.773$ CFI=0.883 TLI=0.868, RMSEA=0.045, 90%-CI: [0.040,0.050]
Japanese Sample

Table 1 Overall Model SEM Estimated Effects with Standard Errors ($N = 5159$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	--	0.372*** (0.015)	−0.117*** (0.016)	--
IMM. FACTORS	0.045* (0.021)	0.086*** (0.020)	−0.131*** (0.016)	−0.304*** (0.018)	--	−0.232*** (0.010)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	0.752*** (0.042)	0.551*** (0.034)	**0.603*** (0.092)**	--	--	--
RACIAL ID	--	--	--	--	--	--
RELIG/CIVIC ENGAGEMENT	0.242*** (0.041)	--	--	--	--	--

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items indicate estimated correlation
$*p < .05$ $**p < .01$ $***p < .001$ (two-tailed)

Table 2 Chinese Sample SEM Estimated Effects with Standard Errors ($N = 835$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	0.258** (0.079)	--	0.752*** (0.062)	0.384*** (0.050)	--	--
IMM. FACTORS	--	**−0.364*** (0.083)**	--	--	--	−0.333*** (0.079)
SOCIO-POL CONTEXT	--	--	--	**0.761*** (0.179)**	--	--
PARTY ID	0.591*** (0.084)	0.654*** (0.031)	**0.761*** (0.179)**	--	--	--
RACIAL ID	--	--	--	1.884*** (0.128)	--	--
RELIG/CIVIC ENGAGEMENT	0.450*** (0.066)	--	--	--	--	--

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items are estimated correlations
$*p < .05$ $**p < .01$ $***p < .001$ (two-tailed)

Table 3 Vietnamese Sample SEM Estimated Effects with Standard Errors ($N = 719$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	0.964*** (0.015)	--	−0.118*** (0.016)	--
IMM. FACTORS	--	--	--	0.929*** (0.055)	**0.219*** (0.060)**	0.710*** (0.045)
SOCIO-POL CONTEXT	--	−0.217*** (0.057)	--	--	--	−0.150** (0.051)
PARTY ID	0.575*** (0.061)	0.359*** (0.052)	--	--	--	--
RACIAL ID	--	--	--	--	--	--
RELIG/CIVIC ENGAGEMENT	0.402*** (0.067)	--	--	--	--	−0.089 (0.049)

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items are estimated correlations
$*p < .05$ $**p < .01$ $***p < .001$ (two-tailed)

Table 4 Indian Sample Model SEM Estimated Effects with Standard Errors ($N = 1150$)

	REGRESSAND VARIABLES						
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES	IMM. FACTORS
RESOURCES	--	--	--	0.433*** (0.041)	−0.118*** (0.016)	--	--
IMM. FACTORS	--	−0.119* (0.060)	--	--	--	0.156*** (0.037)	--
SOCIO-POL CONTEXT	--	--	--	--	--	--	−0.101** (0.034)
PARTY ID	0.845*** (0.040)	0.137** (0.197)	**0.597*** (0.084)**	--	--	--	--
RACIAL ID	--	**0.476*** (0.076)**	--	**0.597*** (0.084)**	--	--	--
RELIG/CIVIC ENGAGEMENT	0.303*** (0.050)	--	**0.476*** (0.076)**	--	--	--	--

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items are estimated correlations
$*p < .05$ $**p < .01$ $***p < .001$ (two-tailed)

Table 5 Korean Sample Model SEM Estimated Effects with Standard Errors ($N = 614$)

	REGRESSAND VARIABLES						
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES	IMM. FACTORS
RESOURCES	--	--	--	--	−0.118*** (0.016)	--	--
IMM. FACTORS	--	−0.236*** (0.021)	--	0.774*** (0.056)	--	0.680*** (0.062)	--
SOCIO-POL CONTEXT	--	--	−0.257* (0.114)	--	--	--	--
PARTY ID	0.863*** (0.069)	0.654*** (0.031)	--	--	--	--	--
RACIAL ID	--	--	--	--	--	--	--
RELIG/CIVIC ENGAGEMENT	--	--	--	--	--	--	0.210*** (0.055)

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
$*p < .05$ $**p < .01$ $***p < .001$ (two-tailed)

Table 6 Filipino Sample Model SEM Estimated Effects with Standard Errors ($N = 603$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	0.439*** (0.075)	0.791*** (0.076)	--	--	--
IMM. FACTORS	--	0.339*** (0.076)	--	--	0.242*** (0.067)	−0.542*** (0.058)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	0.612*** (0.046)	--	--	--	--	--
RACIAL ID	--	--	--	0.765*** (0.030)	--	--
RELIG/CIVIC ENGAGEMENT	0.136* (0.063)	--	--	--	--	--

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
$*p < .05$ $**p < .01$ $***p < .001$ (two-tailed)

Table 7 Japanese Sample Model SEM Estimated Effects with Standard Errors ($N = 541$)

	REGRESSAND VARIABLES				
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT
RESOURCES	0.394** (0.049)	--	--	0.278*** (0.048)	--
IMM. FACTORS	--	−0.222*** (0.051)	−0.330*** (0.081)	−0.500*** (0.040)	0.135** (0.053)
SOCIO-POL CONTEXT	--	--	--	--	--
PARTY ID	--	0.198** (0.059)	**0.713*** (0.098)**	--	--
RACIAL ID	0.568*** (0.027)	--	--	**0.713*** (0.098)**	--
RELIG/CIVIC ENGAGEMENT	0.260*** (0.049)	--	--	--	−0.166** (0.065)

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items represent correlations
$*p < .05$ $**p < .01$ $***p < .001$ (two-tailed)

Table 8 Overall Model Applied to Chinese Sample ($N = 835$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	--	0.466*** (0.050)	−0.117*** (0.016)	--
IMM. FACTORS	0.199† (0.108)	−0.221* (0.101)	0.835*** (0.052)	−0.210† (0.110)	--	−0.232*** (0.010)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	0.603*** (0.122)	0.506*** (0.074)	**1.979*** (0.376)**	--	--	--
RACIAL ID	--	--	--	**1.979*** (0.376)**	--	--
RELIG/CIVIC ENGAGEMENT	0.569*** (0.151)	--	--	--	--	--
Model Fit	$\chi^2_{305} = 1001.750$*** $CFI = 0.880$ $TLI = 0.861$ RMSEA= 0.052, 90%-CI [0.049,0.056]					

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items indicate estimated correlation/covariance
†p<.10 *p<.05 **p<.01 ***p<.001 (standard errors in parentheses)

Table 9 Overall Model Applied to Vietnamese Sample ($N = 719$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	--	-0.066 (0.084)	0.104† (0.059)	--
IMM. FACTORS	-3.316 (4.856)	-1.526 (2.050)	0.966*** (0.013)	1.036*** (0.054)	--	0.695*** (0.040)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	4.009 (4.923)	1.833 (2.038)	**-3.926 (4.457)**	--	--	--
RACIAL ID	--	--	--	**-3.926 (4.457)**	--	--
RELIG/CIVIC ENGAGEMENT	0.229 (0.267)	--	--	--	--	--
Model Fit	$\chi^2_{297} = 588.139$*** $CFI = 0.910$ $TLI = 0.894$ RMSEA= 0.037, 90%-CI [0.033,0.041]					

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Model identification issues—estimates are beyond theoretical boundaries
Bold items indicate estimated correlation/covariance
†p<.10 *p<.05 **p<.01 ***p<.001 (standard errors in parentheses)

Table 10 Overall Model Applied to Indian Sample ($N = 1150$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	--	0.426*** (0.042)	−0.061† (0.034)	--
IMM. FACTORS	−0.002 (0.006)	−0.017 (0.024)	0.025 (0.031)	0.020 (0.025)	--	0.033*** (0.039)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	0.812*** (0.042)	0.301*** (0.039)	**0.780*** (0.086)**	--	--	--
RACIAL ID	--	--	--	**0.780*** (0.086)**	--	--
RELIG/CIVIC ENGAGEMENT	0.130*** (0.015)	--	--	--	--	--
Model Fit	$\chi^2_{300} = 943.554^{***}$ $CFI = 0.895$ $TLI = 0.877$ RMSEA= 0.043, 90%-CI [0.040,0.046]					

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items indicate estimated correlation/covariance
†p<.10 *p<.05 **p<.01 ***p<.001 (standard errors in parentheses)

Table 11 Overall Model Applied to Korean Sample ($N = 614$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	--	0.052 (0.236)	−0.056 (0.064)	--
IMM. FACTORS	0.108 (0.167)	0.151 (0.137)	0.954*** (0.289)	0.714** (0.250)	--	0.658*** (0.097)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	0.747*** (0.159)	0.039 (0.137)	**0.600 (*const.*)**	--	--	--
RACIAL ID	--	--	--	**0.600 (*const.*)**	--	--
RELIG/CIVIC ENGAGEMENT	0.085 (0.085)	--	--	--	--	--
Model Fit	$\chi^2_{302} = 621.528$*** $CFI = 0.848$ $TLI = 0.824$ RMSEA= 0.042, 90%-CI [0.037,0.046]					

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses

Bold items indicate constrained correlation/covariance

†p<.10 *p<.05 **p<.01 ***p<.001 (standard errors in parentheses)

Table 12 Overall Model Applied to Filipino Sample ($N = 603$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	--	0.466*** (0.050)	−0.216** (0.069)	--
IMM. FACTORS	0.087 (0.082)	0.277* (0.072)	−0.310** (0.099)	−0.210† (0.110)	--	−0.471*** (0.061)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	0.658*** (0.072)	0.372*** (0.069)	**0.600 (*const.*)**	--	--	--
RACIAL ID	--	--	--	**0.600 (*const.*)**	--	--
RELIG/CIVIC ENGAGEMENT	0.074 (0.075)	--	--	--	--	--
Model Fit	$\chi^2_{301} = 519.241^{***}$ $CFI = 0.904$ $TLI = 0.888$ RMSEA= 0.035, 90%-CI [0.030,0.040]					

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses

Bold items indicate constrained correlation/covariance

†p<.10 *p<.05 **p<.01 ***p<.001 (standard errors in parentheses)

Table 13 Overall Model Applied to Japanese Sample ($N = 541$)

	REGRESSAND VARIABLES					
REGRESSOR VARIABLES	PARTICIPATION	RELIG/CIVIC ENGAGEMENT	RACIAL ID	PARTY ID	SOCIO-POL CONTEXT	RESOURCES
RESOURCES	--	--	--	0.312*** (0.045)	−0.038 (0.058)	--
IMM. FACTORS	0.005 (0.057)	−0.221* (0.101)	−0.230** (0.089)	−0.403*** (0.048	--	−0.109** (0.035)
SOCIO-POL CONTEXT	--	--	--	--	--	--
PARTY ID	0.794*** (0.062)	0.506*** (0.074)	**0.775*** (0.150)**	--	--	--
RACIAL ID	--	--	--	**0.776*** (0.150)**	--	--
RELIG/CIVIC ENGAGEMENT	0.234** (0.080)	--	--	--	--	--
Model Fit	$\chi^2_{303} = 633.778$*** $CFI = 0.888$ $TLI = 0.870$ RMSEA= 0.045, 90%-CI [0.040,0.050]					

Standardized beta, gamma, and phi coefficients (StdYX), standard errors in the parentheses
Bold items indicate estimated correlation/covariance
†p<.10 *p<.05 **p<.01 ***p<.001 (standard errors in parentheses)

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