### How Party Platforms on Immigration become Policy – Supporting Information

This supporting information provides a set of additional analyses and robustness checks. This appendix is structured as follows:

1. We have replaced the outcome variable with the **level of immigration-policy restrictiveness.**
2. We disaggregate the salience variable into **positions** on **immigration and integration**.
3. We focus on the **share of restrictive policies of all migration policies** implemented in a given country-year.
4. We **weighed** *Immigration Salience* by **cabinet parties’ seat share**.
5. A **simultaneous equations model** is presented, which addresses potential simultaneity between policy outputs and governing parties’ manifesto salience.

**A.1: Level of Immigration Policy Restrictiveness**

In the main text, we focus on the implementation of any immigration laws as coded by the DEMIG. We also assessed the robustness of our unconditional result with different data. The Immigration Policies in Comparison (IMPIC) project offers a detailed conceptualization of immigration policies across four dimensions in OECD countries between 1980 and 2010. The data set makes a broad distinction between regulations and control mechanisms, internally and externally, while regulations refer to eligibility, conditions, status, and rights. In each area, the IMPIC project measures on a quasi-continuous scale between 0 and 1 for how restrictive a policy is. The IMPIC also includes an aggregated variable, i.e., an average across all items in the data set to capture the total level of restrictiveness of immigration policies in a country. *Immigration Policy Restrictions* is the variable we focus on for our robustness check below (which is now based on OLS regression as we no longer have a count item), and we replace the main explanatory variable as well to reflect cabinet parties’ positions on immigration restrictiveness. Specifically, Lehmann and Zobel (2018) have coded *Immigration Position*, which is calculated by subtracting the share of skeptical quasi-sentences from the share of supportive quasi-sentences, and dividing this by the share of these two plus the share of the neutral quasi-sentences. Higher values pertain to more positive immigration attitudes of parties.

**Table A1. Level of Immigration Policy Restrictiveness**

|  |  |
| --- | --- |
|  | Model A1 |
| Immigration Policy Restrictionst-1 | 0.124 |
|  | (0.013) |
| Immigration Position | -0.011\*\*\* |
|  | (0.003) |
| Obs. | 82 |
| RMSE | 0.008 |
| Country Fixed Effects | Yes |
| Year Fixed Effects | Yes |

Table entries are coefficients; robust standard errors clustered on country in parentheses; the dependent variable is *Immigration Policy Restrictions;* constant and control variables included, but omitted from presentation; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

As in the main text, we aggregate this information for a country’s governmental parties by estimating the mean. All other specifications remain unaltered. As demonstrated in Table A1, the main finding remains robust. Governments fulfill their pledges, and more positive migration positions of the executive are associated with less restrictive migration regimes. In an unreported model, we also modeled the interactions, which are statistically significant (as expected).

**A.2: Disaggregation of Immigration Salience**

The main explanatory variable in our analysis captures salience, which is estimated by the proportion of immigration and integration related quasi-sentences in relation to the total number of quasi-sentences in cabinet party manifestos. Lehmann and Zobel (2018) also offer disaggregated versions of this, i.e., one on only immigration, and a second measure that captures the proportion of integration related quasi-sentences in proportion to the total number of quasi-sentences. We have re-estimated our unconditional model with both disaggregated versions of our main independent variable and, as demonstrated in Table A2, we can show that both dimensions are significantly related to the number of migration policies implemented in a given country-year, i.e., it is not just one of these dimensions that drives our results.

**Table A2. Level of Immigration Policy Restrictiveness**

|  |  |  |
| --- | --- | --- |
|  | Model A2 | Model A3 |
| Immigration Policiest-1 | -0.068\*\*\* | -0.068\*\*\* |
|  | (0.013) | (0.013) |
| Only Immigration Salience | 0.078\* |  |
|  | (0.045) |  |
| Only Integration Salience |  | 0.115\*\* |
|  |  | (0.058) |
| Obs. | 137 | 137 |
| Log Pseudolikelihood | -328.039 | -327.782 |
| Country Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |

Table entries are coefficients; robust standard errors clustered on country in parentheses; the dependent variable is *Immigration Policies;* constant and control variables included in both models, but omitted from presentation; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**A.3: Share of Restrictive Migration Policies**

It may well be the case that the government introduces softer legislation or policies that are neither more nor less restrictive. The DEMIG data also code this information, which we used in turn to create a metric variable ranging in [0; 1] that captures the share of restrictive polies of all migration policies introduced in a given country-year. Due to the different outcome variable resulting from this change in the research design, we employ OLS regression with panel-level heteroskedastic errors to address country-specific idiosyncrasies. Concerns over serial autocorrelation are addressed by including a temporally lagged dependent variable. As the number of observations in our sample decreases significantly when this alternative outcome variable is included, we omit the substantive controls. Table A.3 presents the corresponding results, and our main finding remains robust.

**Table A3. Level of Immigration Policy Restrictiveness**

|  |  |
| --- | --- |
|  | Model A4 |
| Restrictive Policies Sharet-1 | -0.045 |
|  | (0.141) |
| Immigration Position | -0.299\* |
|  | (0.155) |
| Obs. | 55 |
| RMSE | 0.265 |
| Country Fixed Effects | Yes |
| Year Fixed Effects | Yes |

Table entries are coefficients; robust standard errors clustered on country in parentheses; the dependent variable is *Restrictive Policies Share;* constant included, but omitted from presentation; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**Table A4. Weighting by Seat Share**

|  |  |
| --- | --- |
|  | Model A5 |
| Immigration Policiest-1 | -3.735\*\*\* |
|  | (0.202) |
| Weighted Immigration Salience | 19.451\*\*\* |
|  | (1.114) |
| Obs. | 103 |
| Log Pseudolikelihood | -178.552 |
| Country Fixed Effects | Yes |
| Year Fixed Effects | Yes |

Table entries are coefficients; robust standard errors clustered on country in parentheses; the dependent variable is *Immigration Policies;* constant included, but omitted from presentation; control variables omitted so model could converge; \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**A.4: Weighting by Seat Share**

Not all government parties are should necessarily be weighted equally. It is common that a larger party forms a government coalition with a junior partner, and in this context Gamson’s Law becomes relevant. The Law states that coalition governments distribute portfolios in proportion to each member party’s contribution of seats to the coalition (Gamson 1961). To assess the influence stemming from this and to assess the robustness of our main finding given Gamson’s Law, we have weighted the contribution of each cabinet member’s immigration salience to the overall score by its seat share, using data from Döring and Manow (2012). Specifically, instead of assigning equal weights to each governing party’s salience score as coded by Lehmann and Zobel (2018) for the core independent variable as done in the main text, we first multiply each governing party’s salience score by its relative seat share (in percent). In turn, we average these scores across all governing parties. Those parties with a larger vote share benefit from a larger weight and, hence, influence assigned to their migration salience in their manifestos. Once this calculation is complete, we include it instead of the core explanatory variable in our main model. The effect of our main variable remains robust and, when examining its substance, grows in size – as expected (Table A.4).

**Table A.5. Simultaneous Equations Model**

|  |  |  |
| --- | --- | --- |
|  | Model A6 | Model A6 |
|  | Immigration Policies | Immigration Salience |
| Immigration Policiest-1 | -0.333\*\*\* | -0.306 |
|  | (0.114) | (0.297) |
| Immigration Salience | 1.281\*\* |  |
|  | (0.501) |  |
| Immigration Salience t-1 |  | 0.958\*\*\* |
|  |  | (0.022) |
| Migrant and Refugee Population | -0.303 |  |
|  | (3.003) |  |
| Political Constraints | -4.289 |  |
|  | (6.142) |  |
| Population | -26.286 |  |
|  | (26.294) |  |
| GDP per capita | 0.665 |  |
|  | (6.563) |  |
| Unemployment | 0.075 |  |
|  | (0.189) |  |
| Obs. | 125 | 125 |
| Log Pseudolikelihood | -495.866 | -495.866 |
| Country Fixed Effects | Yes | No |
| Year Fixed Effects | Yes | No |

Table entries are coefficients, and robust standard errors clustered on country are in parentheses. Constants are included in both equations, but omitted from presentation.

\* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01.

**A.5: Simultaneous Equations Model**

Endogeneity in our setup is partially addressed by the inclusion of a lagged dependent variable (Keele and Kelly 2006). However, a more robust approach is necessary to deal with further concerns in this context and, thus, we have added a simultaneous equations model. Specifically, our focus in the main text is that salience in governing parties’ manifestos drives their policy output once in government. Equally plausible, though, the policies implemented once in power may well affect how migration is treated in party manifestos.

A simultaneous equations model is the appropriate estimation strategy to examine this possibility. We use three-stage least-squares (3SLS). The data are the same as in the main analysis and we considered possible specifications for the equations by running multiple models. In 3SLS, instruments for endogenous variables are generated by regressing each such variable on all exogenous variables in the system. Here, the endogenous variables are *Immigration Policies* (outcome variable in our main analysis) and *Immigration Salience* (main explanatory variable). The model summarized in Table A.5 is then a re-estimate of Model 3 in the main article using 3SLS, but we specify a second equation where we reverse the direction of influence. Note that the variables included in the equations must differ in some respects for the model to be identified. Those items included in one, but not the other then influence the other equation’s outcome indirectly through their dependent variable.

The results of Model A6 are very similar to those reported in the main text when focusing on the first equation. The findings of the second equation, which has *Immigration Salience* as its dependent variable, the coefficient associated with *Immigration Policies* is statistically insignificant. This suggests that the influence flows from *Immigration Salience* to *Immigration Policies*, and not in the opposite direction.

**References**

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