Appendix to:
"FEAR OF PERSECUTION: Forced Migration, 1952-95"
Will H. Moore & Stephen M. Shellman
Forthcoming, *Journal of Conflict Resolution*, October 2004

In this appendix we discuss the robustness checks we conducted for the results reported in Table 2 in the text. We begin with an additional model specification and follow with a discussion of missing case analyses and fixed effects estimation results.

Additional Model

We chose to include population in the model given the arguments in the article. However, we found that population had no effect on forced migration flows. Inclusion of the variable shrunk our sample, so we chose not to report the model in the article. The do-file includes a model including population in it and the results can be replicated using the accompanying replication dataset.

Missing Data

We are also concerned that missing data and/or sample selection bias might influence our findings. To explore that possibility, we created three new data sets, each of which filled in missing data (one using interpolation, another using both interpolation and extrapolation, and a third using Stata's imputation routine). We estimated parameters using each of the three data sets where we filled in missing values. The purpose is to determine whether the findings are robust to these changes, and we find that—by and large—they are.

To begin, the imputations are basically regressions run using all the independent variables in the dataset (those included in the model plus additional variables not included in the model such as secondary education and trade openness) which insert predicted values

into missing data cells based on the estimates. This approach is more efficient than simply using the variables in the model of interest (Raghunathan & Paulin 1998).

The other approaches to filling in missing data are based on linear interpolation and extrapolation. Interpolation fills in missing data when one has a series of observations with one or more missing observations within the series itself. Consider a country that has valid observations for the years 1965 through 1974 and 1976 through 1992. Our sample covers the years 1952 through 1995, so in this example the country is missing data for 1952 through 1964, 1975, and 1993 through 1995. When we interpolate we would create a value for 1975, thus creating a sample of valid observations for the years 1965 through 1992. Alternatively, when we extrapolate we fill in the missing observations prior to 1965 and after 1992 (in time in addition to filling in data between series observations). Thus, the extrapolated data set would cover the full sample: 1952 through 1995. One can observe the difference in the number of cases analyzed across approach and the percentage of cases filled in to each data matrix in Table A1. We compute relatively few cases across approaches for Model 1. However, the extrapolated and imputed data matrices for Model 2 only contain 36% to 38% of the original collected data. With that as background, we provide a general discussion of the results.

First, very few coefficients change signs and those that do are not statistically significant. Several variables that are significant in Table 2 are not significant in one or more robustness analysis, and some variables that are not significant in Table 2 are significant in one or more robustness analyses. But the vast majority of coefficients match the statistical significance reported in Table 2.

Specifically, the interpolated data results for Models 1 and 2 are virtually identical to those reported in Table 2 with and without robust standard errors. No inferences are

changed except that transition is now positive and statistically significant in the count equation.

The extrapolated results for Model 1 show that democracy is no longer significant with and without robust standard errors. The other coefficients decline a bit in magnitude and transition becomes positive and significant. In the inflate equation of Model 1, dissident violence, transition, and GNP are no longer statistically significant but all other coefficients are very similar in magnitude and significance to those in Table 2 with and without robust standard errors.

With respect to Model 2, the political terror scale variable does not garner statistical significance in either the inflate or the count equations when we use the extrapolated data set. However, as we will see below, the variable does garner statistical significance with the imputed data. The effects of international war on territory and civil war are more pronounced, and war on territory garners statistical significance, in the count equation for Model 2 when we substitute the extrapolated data. Transition is positive and statistically significant in the count equation but does not achieve statistical significance in the inflate equation. Democracy is now significant and in the anticipated positive direction and transition is no longer significant in the inflate equation. GNP also fails to garner statistical significance when calculating robust standard errors for the extrapolated inflate equation. However, by and large, the extrapolated results are very similar to those reported in Table 2.

Finally, the imputed data analyses are also very similar to those reported in Table 2. For example, the coefficient for genocide in Table 2 for Model 1 is .067 and .060 when we use the imputed data. The dissident violence coefficient decreases from .10 to .08, the civil war coefficient decreases from 1.63 to 1.35, the coefficients for war on territory are exactly the same and the coefficients on GNP and lag forced stock decrease slightly. The only

significant differences across the results for the count equation are that democracy becomes insignificant and transition is positive and significant. The results are similar as well across the inflate equations. Only GNP loses statistical significance; inferences do not change across the other parameter estimates. These findings hold with and without robust standard errors.

The imputed analysis for Model 2 produces a positive and statistically significant coefficient for the political terror scale in the count equation, and a negatively statistically significant coefficient in inflate equation. The only major differences are positive and significant transition and war on territory coefficients in the count equation, an insignificant violent dissent coefficient in the inflate equation, and non-significant coefficients for transition and GNP in the inflate equation. When calculating robust standard errors for the imputed data analyses, only democracy in the count equation becomes insignificant. All other coefficients and significance levels are consistent with Table 2. Generally speaking, very few inferences change across the different datasets. The imputed data probably contain the most reliable estimated data for missing cases and the results from the analyzed imputed data matrices show very similar results across both models.

Fixed Effects

We used a fixed-effects (FE) approach to re-estimate our models and see if the results held controlling for country-specific effects. We estimated a fixed-effects model, which assumes that each country in the sample has a different baseline level of forced migration and we used robust standard errors corrected with countries specified as the panels. Like the robust estimates discussed in the article, the corrected standard error models did not produce Chi

Square statistics. However, the robust estimates do not significantly alter the inferences we draw.

When performing robustness checks on Model 1, the fixed effects approach will not converge when we include country dummies in both equations. We chose to calculate the estimates after 50 iterations. When we include country dummies only in the count equation, the model converges. The estimates and standard errors reported across the two FE models are virtually identical. All variables are significant and in the predicted direction. These results are also very similar to the estimates reported in Table 2. We highlight the differences below.

In the FE analyses most of the coefficients increase in magnitude, but continue to obtain statistical significance. For example, the coefficient on genocide increases from .07 (Table 2) to .19 and the standard error increases from .04 to .05. Thus, the impact of genocide increases in the FE analyses. The coefficient on dissident violence increases from .10 to .20, the one on civil war increases from 1.64 to 1.75, the one on war on territory decreases from 1.03 to .60, and GNP decreases. Again all coefficients are statistically significant at the.05 level except war on territory which is significant at the .10 level. The only strange finding is that democracy becomes positive. However, the polity variable is fairly constant over time and may be correlated with some of the country dummy variables. When we use robust standard errors combined with the FE approach, war on territory and transition are not statistically significant, but all of the other coefficients obtain statistical significance.

In the model where we enter country dummies in both the inflate and count equations, the coefficients for the count equations are virtually identical to those described above. Only War on territory is insignificant. When we use robust standard errors war on

territory, democracy and GNP are insignificant. With regard to the inflate equations across the two FE models, GNP and dissident violence are insignificant. However, the coefficients are similar to those reported in Table 2. Genocide and dissident violence decrease, and democracy flips signs. Again, this is most likely the effect of the correlation between the polity scale and country dummies. When we calculate robust standard errors using the FE approach democracy, dissident violence, and GNP are insignificant in the inflate equation.

The FE models did not converge for Model 2. Thus we took the estimates after 50 iterations. We focus on the model in which we included country dummies in both the count and inflate equations. The coefficients in the count equation are similar to those reported above for Model 1. However, the political terror scale variable is not statistically significant. It is positively signed but does not quite reach the .10 level. In the inflate equation, all signs and significance levels are the same across Model 1 and Model 2 and the political terror scale variable is negative and statistically significant. In short, the overwhelming majority of the results are sustained when using a fixed effects approach and robust standard errors.

To summarize all of our efforts, the vast majority of the coefficients retain the levels of significance reported in Table 2 when we probed their robustness. While there were some changes, none of the changes become predominant across the multiple analyses. As such, we conclude that the results reported in the text are rather robust and unlikely due to selection bias.

TABLE A1
Number of Cases Analyzed and Percent Cases Computed Across Model & Approach

	Complete Case	Interpolated	Extrapolated	Imputed
Model 1 Cases	5,196	5,207	6,195	6,243
(% Computed)	(0%)	(1%)	(16%)	(17%)
Model 2 Cases	2,279	2,340	6,064	6,243
(% Computed)	(0%)	(3%)	(62%)	(64%)