Supplementary Materials for: Remittances, Terrorism, and Democracy (Not for publication)

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A Countries in the data

Table A.1 lists how many times each country is observed in the main sample along with how many terrorist attacks we observe for each of these countries.

| Country | Number of years | Number of attacks |
|----------------------------------|-----------------|-------------------|
| Algeria | 43 | 1258 |
| Angola | 6 | 6 |
| Argentina | 35 | 58 |
| Armenia | 18 | 1 |
| Australia | 43 | 1 |
| Austria | 43 | 9 |
| Azerbaijan | 18 | 2 |
| Bangladesh | 34 | 326 |
| Belgium | 38 | 31 |
| Bolivia | 37 | 68 |
| Brazil | 38 | 30 |
| Burundi | 9 | 39 |
| Canada | 18 | 8 |
| Central African Republic | 16 | 1 |
| Chad | 8 | 2 |
| Chile | 18 | 1080 |
| China | 31 | 66 |
| Colombia | 43 | 5114 |
| Congo | 35 | 1 |
| Costa Rica | 34 | 8 |
| Cyprus | 37 | 8 |
| Democratic Republic of the Congo | 8 | 52 |
| Dominican Republic | 43 | 27 |
| Ecuador | 28 | 33 |
| Egypt | 36 | 346 |
| El Salvador | 37 | 3719 |
| Estonia | 17 | 1 |
| Ethiopia | 31 | 38 |
| France | 38 | 1100 |
| Gabon | 34 | 1 |
| Georgia | 16 | 16 |
| Germany | 22 | 30 |
| Ghana | 34 | 7 |
| Greece | 37 | 518 |
| Guatemala | 36 | 490 |
| Guinea | 26 | 1 |

Table A.1: Countries included in the data

| Country | Number of years | Number of attacks |
|------------------|-----------------|-------------------|
| Haiti | 29 | 4 |
| Honduras | 39 | 110 |
| India | 38 | 4057 |
| Indonesia | 30 | 251 |
| Iran | 22 | 102 |
| Iraq | 3 | 768 |
| Ireland | 23 | 1 |
| Israel | 43 | 1345 |
| Italy | 43 | 682 |
| Ivory Coast | 21 | 3 |
| Jamaica | 37 | 2 |
| Japan | 30 | 77 |
| Jordan | 37 | 12 |
| Kazakhstan | 18 | 1 |
| Kenya | 43 | 52 |
| Laos | 28 | 1 |
| Latvia | 17 | 2 |
| Lebanon | 8 | 42 |
| Lesotho | 38 | 12 |
| Macedonia | 17 | 42 |
| Madagascar | 32 | 2 |
| Malaysia | 31 | 3 |
| Mali | 38 | 63 |
| Mexico | 34 | 111 |
| Morocco | 38 | 14 |
| Mozambique | 32 | 207 |
| Myanmar | 26 | 140 |
| Nepal | 20 | 329 |
| Netherlands | 43 | 38 |
| Nicaragua | 24 | 244 |
| Niger | 39 | 25 |
| Nigeria | 36 | 935 |
| Pakistan | 37 | 1791 |
| Panama | 34 | 46 |
| Papua New Guinea | 34 | 34 |
| Paraguay | 38 | 22 |
| Peru | 23 | 1250 |
| Philippines | 36 | 2653 |
| Portugal | 38 | 62 |
| Russia | 19 | 401 |
| Rwanda | 37 | 70 |
| Senegal | 39 | 83 |
| 0 | | |

Table A.1: Countries included in the data

| Country | Number of years | Number of attacks |
|--------------------------|-----------------|-------------------|
| Sierra Leone | 33 | 79 |
| South Africa | 43 | 742 |
| South Korea | 37 | 5 |
| Spain | 38 | 2432 |
| Sri Lanka | 38 | 2355 |
| Sudan | 36 | 98 |
| Suriname | 36 | 49 |
| Swaziland | 26 | 1 |
| Sweden | 43 | 8 |
| Switzerland | 36 | 4 |
| Tajikistan | 11 | 2 |
| Tanzania | 18 | 4 |
| Thailand | 38 | 174 |
| Togo | 39 | 6 |
| Tunisia | 37 | 16 |
| Uganda | 14 | 108 |
| United Kingdom | 26 | 1414 |
| United States of America | 36 | 542 |
| Uzbekistan | 7 | 2 |
| Venezuela | 28 | 19 |
| Zimbabwe | 22 | 18 |

Table A.1: Countries included in the data

B Control variable estimates for the main models

Table B.1 presents the estimates suppressed from the main regressions in Table 3. There are a couple points of interest here, particularly regarding anocracies, which we do focus on in the main text. First, we find that, holding everything else constant, anocracies have a higher baseline rate of domestic terrorism than democracies and autocracies. This finding matches results from Gaibulloev, Piazza and Sandler (2017) and provides some face validity to the models. Second, across models, the combined estimate $\hat{\beta}_{\text{Remittances}} + \hat{\beta}_{\text{Remittances} \times \text{Anocracy}}$ is not distinguishable from zero. Likewise, the substantive effects within anocracies tend to have enormous confidence intervals relative to other regime types. This high-variance result is expected given the large heterogeneity among access to and efficacy of legitimate politics within anocracies.

| Dependent variable: | | Domestic ter | rorist attacks | 1 |
|---------------------------------|---------------------------------|---------------------------------|---|---------------------------------|
| | (1) | (2) | (3) | (4) |
| Remittances × Anocracy | -0.17^{*} | -0.27** | -0.24** | 2.13 |
| Remittances × Anocracy × GPP pc | (0.09) | (0.09) | (0.09) | (1.29) -0.30^{*} (0.16) |
| Democracy \times GDP pc | | | | 0.22 |
| Anocracy \times GPP pc | | | | (0.29) 0.35 (0.28) |
| Democracy | 0.46 | 0.46 | 0.43 | (0.20) -0.83 (2.07) |
| Anocracy | (0.33) 1.59^{**} (0.32) | (0.30) 1.38^{**} (0.27) | (0.25) 1.28^{**} (0.27) | (2.07) -1.17 (2.06) |
| Military personnel | (0.32) | (0.27) 2.05^{**} (0.57) | (0.27) 1.61^{**} (0.50) | (2.00) 2.24^{**} (0.58) |
| Population | | (0.57) 3.70^{**} (0.00) | (0.59) 2.77^{**} (0.84) | (0.58) 4.25^{**} (0.02) |
| GDP growth | | (0.90) -0.02 (0.01) | (0.84) -0.01 (0.01) | (0.92) -0.02 (0.01) |
| GDP per capita | | (0.01) 0.88^{**} | (0.01) 0.75^{*} | (0.01) 0.71 (0.50) |
| Free Press | | (0.41) 0.27 (0.10) | (0.42) 0.27 (0.10) | (0.50) 0.15 |
| GINI | | (0.19) -0.001 (0.02) | (0.19) -0.01 (0.02) | (0.19) -0.01 (0.02) |
| Horizontal inequality | | (0.02) 2.20^{**} (0.20) | (0.02) 2.10** (0.22) | (0.02) 2.19^{**} (0.20) |
| Excluded population | | (0.50) -0.14 (0.58) | (0.32) -0.21 (0.57) | (0.29) -0.01 (0.55) |
| # of ongoing civil conflicts | | 1.04^{**} (0.14) | (0.01) 0.74^{**} (0.12) | (0.00) 1.01^{**} (0.14) |
| Lag attacks | | (0.14) | $\begin{array}{c} (0.12) \\ 0.01^{**} \\ (0.001) \end{array}$ | (0.14) |
| Country Fixed Effects | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes |
| Controls | NO 2 070 | Yes | Yes | Yes |
| Ubservations | 2,979 | 2,979 | 2,979 | 2,979 |
| θ | -5,010.71 0.44 | -5,407.17 0.55 | -5,406.32 0.62 | -5,450.49 0.57 |

Table B.1: Regression coefficients for the control variables in the main model

 $p^* > 0.1$, $p^* > 0.05$. Coefficients from negative binomial models. Standard errors in parentheses clustered on country. Other coefficients for each model are presented in Table 3 (main text).

C Differences in terrorism by regime type



Figure C.1: Expected differences in domestic terrorist attacks by remittances and regime (Model 2)

Caption: Shaded areas represent 95% confidence intervals from a parametric bootstrap. Positive values reflect cases where there are more attacks within autocracies, on average.

In this section, we further consider the results from Figure 1, by presenting the difference in expected terrorism between democracies or autocracies, rather than separating the estimated levels by regime type. While the difference does not directly speak to our hypotheses or research question it is separately interesting from the perspective of how vulnerable regimes are to terrorism at different values of remittances. At low levels of remittances there are not strong differences in the amount of domestic terrorism in democracies and autocracies, but democracies, on average, may experience slightly more domestic terrorism. However, at values of about 250 USD/person and greater we see a significant difference where democracies experience less domestic terrorism. As remittances increase, the democratic advantage increases.

D Robustness checks

In this appendix we consider several robustness checks. Unless noted, all models use the same controls as Model 2. Across every model we find that remittances have a pacifying effect on domestic terrorism within democracies; this effect is statistically significant in all but one specification. In most models, we also find support for our finding that remittances lead to an increase in domestic terrorism with autocracies, although this result is statistically significant in fewer models. In only one model do we find that the direction of the autocratic relationship is negative.

D.1 Alternative measures of remittances

The first set of robustness checks considers alternative ways to measure or transform remittances. In the main text, we used remittances per capita measured in constant USD/person. In Table D.1, we consider a log transformation, a square root transformation, a time detrended measure, a measure of remittances as a percentage of GDP, and a measure of remittances per capita from the IMF. The detrending model uses a regression of remittances per capita on a quadratic B-spline of the current year interacted with the country fixed effects to remove any time trend within remittances country-by-country. The quadratic specification was chosen based on the AIC from various alternative specifications.

In every model the combined coefficients $\hat{\beta}_{\text{remittances}} + \hat{\beta}_{\text{remittances}\times\text{Dem.}}$ are negative and statistically significant at a conventional level. Likewise, the relationship between remittances within autocracies is positive across these other models, but only significant in 2 of the 6 alternative measurements. Using the AIC to compare these models, we find that the main model with two-way fixed effects (Model 2) is preferred when comparing all the models that use the same observations.

| Dependent variable: | | | Doi | nestic terroris | st attacks | | |
|--|---|---|---|---|---|---|--|
| Remittance measure: | Remittances per capita (Model 2) | Logged remittances per capita | Sq. root remittances per capita | Detrended remittances per capita | Logged Remittances as pct. of GDP | Logged Remittances per capita as pct. of GDP | IMF Remittances per capita |
| Remittances | 0.20^{**} | 0.06 | 0.60^{*} | 0.26 | 0.11 | 0.16 | 0.29^{*} |
| Remittances \times Dem. | (0.07) -0.48** | (0.09) -0.24** | $(0.35) -1.26^{**}$ | (0.41) - 0.58 | $(0.11) -0.27^{**}$ | $(0.10) - 0.34^{**}$ | $(0.15) -0.76^{**}$ |
| | (0.13) | (0.11) | (0.38) | (0.43) | (0.13) | (0.10) | (0.21) |
| $\hat{eta}_{\mathrm{Remittances}}+\hat{eta}_{\mathrm{Remittances}}	imes$ Democracy | -0.28^{**} (0.13) | -0.17^{*} (0.10) | -0.66^{**} (0.33) | -0.31^{**} (0.13) | -0.17^{*} (0.10) | -0.18^{**} (0.09) | -0.48^{**} (0.19) |
| Country fixed effects Year fixed effects Controls | $\begin{array}{c} Y_{\rm es} \\ Y_{\rm es} \\ Y_{\rm es} \end{array}$ | $\begin{array}{c} \mathrm{Yes} \\ \mathrm{Yes} \\ \mathrm{Yes} \end{array}$ | $\begin{array}{c} \mathrm{Yes} \\ \mathrm{Yes} \\ \mathrm{Yes} \end{array}$ | $\begin{array}{c} \mathrm{Yes} \\ \mathrm{Yes} \\ \mathrm{Yes} \end{array}$ | Yes Yes Yes | Yes Yes Yes | Yes Yes Yes |
| $\begin{array}{c} \hline \textbf{Observations} \\ \textbf{Log Likelihood} \\ \theta \end{array}$ | 2,979 -5466.17 0.55 | 2,979 -5475.76 0.55 | 2,979 - 5468.95 0.55 | 2,979 - 5477.07 - 0.55 | 2,979 -5475.44 0.55 | 2,979 -5466.56 0.56 | $\begin{array}{r}2,511\\-5035.83\\0.54\end{array}$ |
| p < 0.1, p < 0.05. Coefficients from 1 | negative binomia | ul models. Stan | dard errors in p | arentheses clust | ered on country. | | |

Table D.1: Negative binomials with Different measures and transformations of remittances

| Dependent variable: | | | Dor | nestic terrorist | attacks | | |
|---|---|--|--|---|---|-------------------------------------|---------------------------------------|
| Democracy Measure: | Polity cutpoints at ±7 (Model 2) | Polity cutpoints at ±6 | Polity cutpoints at ±5 | Polity linear | Polity quadratic | V-DEM categorical | V-DEM Electoral democracy index |
| Remittances | 0.20^{**} | 0.17^{**} | 0.10 | -0.12 | -0.35^{**} | 0.13 | -0.01 |
| Remittances \times Dem. | (0.07) -0.48** | $(0.09) -0.50^{**}$ | $(0.09) - 0.40^{**}$ | $(0.08) -0.02^{**}$ | $(0.15) -0.03^{**}$ | $(0.09) -0.43^{**}$ | (0.20) - 0.29 |
| Remittances \times Dem. sq. | (0.13) | (0.13) | (0.13) | (0.01) | (0.01) 0.00^{**} | (0.14) | (0.28) |
| Remittances \times Electoral Autocracy | | | | | (0.00) | -0.40^{**} | |
| Combined coefficient on remittances | 0.20^{**} | 0.17^{**} | 0.10 | 0.10 | 0.21^{**} | 0.13 | -0.05 |
| (Autocracy) | (0.02) | (0.00) | (0.00) | (0.07) | (0.08) | (0.00) | (0.16) |
| Combined coefficient on remittances | -0.28^{**} | -0.33^{**} | -0.30^{**} | -0.33^{**} | -0.25^{**} | -0.30^{**} | -0.26^{**} |
| (Democracy) | (0.13) | (0.13) | (0.12) | (0.12) | (0.11) | (0.12) | (0.13) |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | \mathbf{Yes} | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | \mathbf{Yes} | Yes | Yes | Yes |
| Observations | 2,979 | 2,979 | 2,979 | 2,979 | 2,979 | 2,979 | 2,979 |
| Log Likelihood | -5,466.17 | -5,506.78 | -5,508.30 | -5,523.74 | -5,489.09 | -5,519.66 | -5,524.01 |
| θ | 0.55 | 0.52 | 0.52 | 0.51 | 0.54 | 0.52 | 0.52 |
| ${}^*p < 0.1, {}^{**}p < 0.05$. Regression coefficient are calculated at ± 9 . In the categorical V- model, the 10th and 90th percentile are use | s. Standard error -DEM model, the ed. | s in parentheses, c categories of non | clustered on count -electoral autocra | ry. In the linear s cy is used for the | und quadratic polit autocracy coeffici | y models, combinent. In the elector | ed coefficients ral democracy |

Table D.2: Negative binomials with different measures of democracy

D.2 Alternative measures of democracy

In this section, we consider the following alternatives to the democracy/anocracy/autocracy dummies presented in the main text

- Polity dummies with cut points at ± 6
- Polity dummies with cut points at ± 5
- Linear polity score
- Quadratic polity score
- V-DEM regime categories
- V-DEM's Electoral democracy index.

For the V-Dem dummies where we define democracy using the top two categories from their levels measure: "Electoral democracy" and "liberal democracy." The remaining regime types in this measure are "electoral autocracy" and "closed autocracy." We use closed autocracies as the omitted category. These various measures highly correlate with each other; pairwise correlations, using Spearman's ρ , range from 0.78-0.94. These results are presented in Table D.2.

Across these different measurement strategies we continue to find a consistent negative and significant relationship between remittances and domestic terrorism within democracy. Beyond this, we also note that there is an equally strong and negative relationship between remittances and domestic terrorism within electoral autocracies. This interesting finding suggests that the institutional variation within autocracies has an effect on how remittances are used. Specifically, the presence of elections, even within autocracies, may be enough for groups to move away from terrorism and toward legitimate politics. This trend matches some results by Wilson and Piazza (2013), who find that electoral autocracies are associated with less terrorism and they attribute that to the electoral system being a more attractive tool for politics than ineffective terrorism.

| Dependent variable: Sample: | Domestic Attacks (main) Non-OECD | Domestic Attacks (ESG) Full sample |
|--|-------------------------------------|---------------------------------------|
| Remittances per capita | 0.14* | 0.23** |
| Remittances per capita \times dem. | $(0.08) \\ -0.85^{**} \\ (0.20)$ | $(0.05) \\ -0.38^{**} \\ (0.09)$ |
| $\hat{\beta}_{\text{Remittances}} + \hat{\beta}_{\text{Remittances} \times \text{Dem.}}$ | -0.71^{**} (0.21) | -0.16^{*} (0.09) |
| Country Fixed Effects | Yes | Yes |
| Year Fixed Effects | Yes | Yes |
| Controls | Yes | Yes |
| Observations | 2,384 | 1,233 |
| Log Likelihood | -4,203.86 | -4,012.51 |
| θ – | 0.50 | 1.74 |

 Table D.3:
 Alternative dependent variables and samples

 $p^* < 0.1$, $p^* < 0.05$. Coefficients from negative binomial models. Standard errors in parentheses clustered on country.

Turning to the autocratic measures, we see that in all but one of these models the relationship between remittances and terrorism is positive, but only in the polity models do we find a significant relationship. This difference may suggest that differences in how V-Dem and polity code levels of autocracy and/or differences between autocratic versus anocratic regimes may be influencing this result.

D.3 Alternative samples and dependent variables

In this section, we consider robustness checks based on changes to the sample and to how the dependent variable is measured. The results are reported in Table D.3. Regarding the former, we first check whether the results hold when we restrict our sample to non-OECD countries. The reason for this check is that OECD countries receive roughly twice as many remittance per capita par year as non-OECD countries. While country-fixed effects control for some of the differences between OECD and non-OECD countries, we want to be sure that these rich states are not driving the main results.

Regarding the latter, we use the domestic terrorist attack data from Enders, Sandler and Gaibulloev (2011, ESG hereafter) to code the dependent variable. Recall that we code attacks as domestic when the perpetrator nationality matches the attack location using the INT_LOG indicator within the GTD. Our approach correlates highly with the ESG approach, while allowing for the inclusion of more recent data. However, it is important to make sure that the use of one or the other aggregation method does not drive the main results.

Turning to the estimates in Table D.3, we see that the main results continue to hold. Interestingly, the democratic effect appears to be much larger in the non-OECD sample than in the main results. The results from using the ESG look very similar to the main results.

D.4 Alternative modeling choices

| Dependent variable: | | Dome | estic Attacks | |
|--|----------------------------------|----------------------------------|----------------------------------|----------------------------------|
| Specification: | Zero-inflated neg. bin. | Pooled neg. bin. | Random effects neg. bin. | Mundlak Poisson |
| Remittances per capita | 0.20^{**} | 0.18^{*} | 0.23^{**} | 0.25^{*} |
| Remittances per capita \times dem. | (0.08) -0.32^{**} (0.12) | (0.10) -0.32^{**} (0.14) | (0.07) -0.54^{**} (0.10) | (0.13) -0.47^{**} (0.24) |
| $\hat{\beta}_{\text{Remittances}} + \hat{\beta}_{\text{Remittances} \times \text{Dem.}}$ | -0.12 (0.12) | -0.15^{*} (0.09) | -0.31^{**} (0.07) | -0.22 (0.16) |
| Country fixed effect | Yes | No | No | Mundlak |
| Year fixed effect | Yes | No | No | Yes |
| Controls | Yes | Yes | Yes | Yes |
| Observations | 2,979 | 3,790 | 3,790 | 3,790 |
| Log Likelihood | -5,245.47 | -6,505.44 | -5,873.74 | -39,928.55 |
| heta – | 0.98 | 0.16 | 0.42 | |

 Table D.4:
 Alternative specifications

 $p^* p < 0.1, p^* p < 0.05$. Regression coefficients. Ordinary (Model 26) or clustered standard errors in parentheses.

In this section, we consider several alternative modeling choices. The results are reported

in Table D.4. The first one we consider is a zero-inflated negative binomial. To specify the binomial component we follow advice from Drakos and Gofas (2006) and focus on the regime and media aspects by using democracy, anocracy, free press, and the lagged number of attacks along with a Mundlak-specification (i.e., group-level means in the binomial stage). The count specification uses the variables from Model 2 including country and year fixed effects.

In the remaining models, we try alternatives to main modeling choice of a negative binomial regression with country dummies. To this end, we consider a pooled and countryrandom-effects model; the main results hold in these two cases. We also use a Mundlakstyle Poisson model to make sure that the results are robust to both the distributional assumption and the inclusion of the all-zero countries (Crisman-Cox 2021; Wooldridge 2010, 648). The Poisson distribution will produce consistent estimates even when the constant variance assumption is wrong, although the standard errors may be incorrect, with the clustered standard errors reported here perhaps being extra conservative. As such we are primarily interested in the sign and relative magnitude of the estimates, which are very similar to those reported in Table 3.

D.5 Controlling for increased government spending of remittance

As mentioned in the main text, it could be that remittance flows actually lead to more state resources and that what states do with these resources affects terrorism. This top-down approach could explain the trends reported in the main models. Easton and Montinola (2017) show that remittances tend to have different effects on government spending within democracies and autocracies. In the former, governments tend to spend more on social services, which may reduce the motives for terrorism and lead to fewer attacks. In the latter, governments tend to increase military spending, which may increase the motivations for terrorism and lead to more attacks. If the effect of remittances actually goes through government spending habits, then controlling for these spending levels will remove the effect of remittances that flows through spending. Any remaining effect can be attributed to factors

| Dependent variable: | Domes | tic terrorist a | attacks |
|--|--------------|-----------------|--------------|
| | (12) | (13) | (14) |
| Remittances per capita | 0.23** | 0.21** | 0.23** |
| | (0.06) | (0.08) | (0.06) |
| Remittances per capita \times Dem. | -0.54^{**} | -0.49^{**} | -0.55^{**} |
| | (0.11) | (0.13) | (0.12) |
| Infant mortality | 1.79^{**} | | 1.82** |
| | (0.63) | | (0.64) |
| Military expenditures | | -0.86 | -1.02 |
| | | (1.14) | (1.26) |
| $\hat{\beta}_{\text{Remittances}} + \hat{\beta}_{\text{Remittances} \times \text{Dem.}}$ | -0.32^{**} | -0.29** | -0.33** |
| | (0.12) | (0.13) | (0.12) |
| Country fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes |
| Observations | 2,969 | 2,930 | 2,924 |
| Log Likelihood | -5,445.32 | -5,415.33 | -5,395.91 |
| θ | 0.57 | 0.55 | 0.57 |

 Table D.5: Effect of remittances after controlling for spending

 $p^* < 0.1$, $p^* < 0.05$. Coefficients from negative binomial models. Standard errors in parentheses clustered on country. Coefficients for the control variables are suppressed for space.

outside government spending, which is consistent with our explanation.

Table D.5 considers this alternative explanation. Here, we add in logged military expenditures per capita, as measured by COW, and use logged infant mortality, as measured by the World Bank, to proxy for public health and social spending. We chose infant mortality because it has better temporal coverage than most direct measures of government social spending. Even after accounting for how governments spend the enhanced tax dollars associated with remittances, we see that remittances still have opposite effects in democracies and autocracies that go beyond their effect on government spending.

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