Aid Under Fire: Development Projects and Civil Conflict

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October 6, 2013

1 Appendix - for online publication

This appendix presents the results of a number of robustnes tests of our empirical approach.

1.1 Sensitivity to Choice of Bandwidth

As mentioned in Section 2, there is currently no widely agreed-upon method for selecting the optimal bandwidth for local linear regressions. We therefore follow Ludwig and Miller (2007) and report results for a wide range of bandwidths. The tradeoff when choosing a bandwidth is that the estimates from smaller bandwidths have higher internal validity since they focus on observations close to the threshold, but are less precisely estimated since they are informed by smaller samples. Table 1 shows that our results are qualitatively robust to changes in the bandwidth. Point estimates for the program's effect during the entire program phase and the social preparation phase and the remaining program period become larger for smaller bandwidths, which suggests that the estimates reported in section 4 constitute conservative estimates of the program's effect. Point estimates for the pre-program period become more negative for smaller bandwidths, but are not statistically significant for any bandwidth between 2 and 6. Overall, the robustness test increases our confidence that our findings are not dependent on the choice of a particular bandwidth for the RD design.

Table 1: Robustness to Choice of Bandwidth

	Local linear regressions with bandwidth:				
	2	3	4	5	6
Panel A: Entire program period					
Poisson QMLE	0.176***	0.131***	0.115***	0.099***	0.091***
	(0.049)	(0.038)	(0.034)	(0.032)	(0.031)
OLS	0.221***	0.175***	0.127***	0.103**	0.090**
	(0.059)	(0.051)	(0.046)	(0.044)	(0.042)
Control Mean	0.090	0.083	0.077	0.075	0.076
	(0.016)	(0.012)	(0.010)	(0.009)	(0.008)
Panel B: Pre-program period					
Poisson QMLE	-0.049	-0.033	-0.024	-0.014	-0.007
	(0.083)	(0.049)	(0.039)	(0.035)	(0.032)
OLS	-0.104	-0.065	-0.045	-0.033	-0.024
	(0.080)	(0.069)	(0.054)	(0.045)	(0.040)
Control Mean	0.081	0.074	0.064	0.063	0.059
	(0.022)	(0.018)	(0.014)	(0.012)	(0.011)
Panel C: Social preparation phase					
Poisson QMLE	0.505	0.444**	0.558***	0.520***	0.488***
	(0.337)	(0.222)	(0.193)	(0.155)	(0.135)
OLS	0.735**	0.671***	0.556**	0.484**	0.449**
	(0.289)	(0.249)	(0.219)	(0.201)	(0.187)
Control Mean	0.057	0.066	0.064	0.064	0.065
	(0.021)	(0.018)	(0.017)	(0.015)	(0.014)
Panel D: Rest of program period					
Poisson QMLE	0.100**	0.063*	0.048	0.038	0.031
	(0.044)	(0.036)	(0.033)	(0.030)	(0.029)
OLS	0.118**	0.075*	0.041	0.027	0.018
	(0.054)	(0.045)	(0.041)	(0.039)	(0.037)
Control Mean	0.097	0.087	0.080	0.077	0.078
	(0.018)	(0.013)	(0.012)	(0.010)	(0.009)
Municipalities	88	129	166	195	222

The table reports results of the Regression Discontinuity design described in Section 2. The running variable is the distance between the municipality's poverty rank and the provincial eligibility threshold. All reported results are estimates of the effect of eligibility from local linear regressions that use triangular kernel weights with bandwidths between 2 and 6. All models control for flexible trends of the running variable on each side of the eligibility threshold. For Poisson models, reported values are marginal effects. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels. Standard errors are clustered at the municipality level. All specifications include the control variables shown in Table 1 and year and province fixed effects.

1.2 Are There Spillovers to Nearby Municipalities?

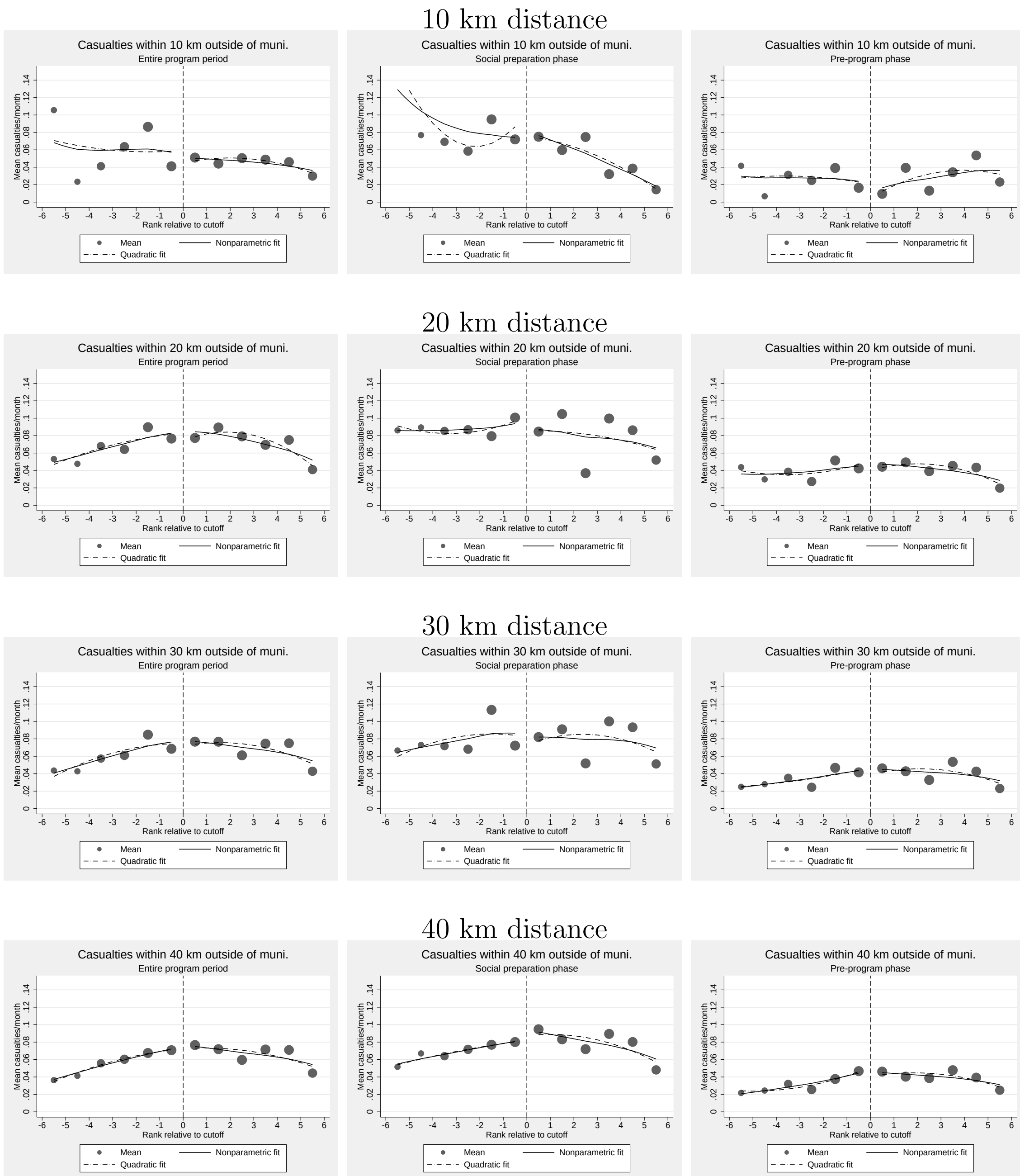
As mentioned in Section 3, it is possible that our results are due to troop movements between municipalities. For example, it is possible that the AFP moved troops towards eligible municipalities, perhaps to enhance the program's security. Eligible municipalities may therefore have experienced more casualties simply because more AFP troops were present to engage in conflict. It is therefore possible that the program did not increase aggregate conflict in the country as a whole, but merely shifted conflict from one location to another by acting as a "conflict magnet".

To explore this possibility, we estimate the program's effect on casualties in municipalities that were close to eligible municipalities but not necessarily eligible themselves. The Philippine military assigns units by geographic Areas of Responsibility (AOR). Therefore, if additional units were deployed to eligible municipalities, they would have most likely been moved from nearby municipalities in the same AOR. To do this, we define our outcome of interest as the average number of casualties within a certain radius around a municipality (not including casualties in the sample municipality itself.). If there were spillover effects due to troop movement, we would expect the program to have a negative effect on the number of casualties in municipalities close to an eligible municipality.

Figure 1 and Table 2 show no evidence of such a spillover effect. The point estimates of the program's effect on casualties within 10-40 kilometers are small relative to the program's direct effect and not statistically significant, neither for the entire program period nor the social preparation phase. Most of the point estimates are negative, but Panel C shows that this was already the case for the pre-program period.[1] Thus, we find no evidence that the program had an effect on conflict close to, but outside of, eligible municipalities.

[1] It is not surprising that many of the point estimates have the same sign, since the fact that the distance "rings" overlap leads them to be mechanically correlated.

Figure 1: Spillover Effects



The figure presents the relationship between the running variable of the RD design, which is the distance between the municipality's poverty rank and the provincial eligibility threshold, and a number of control variables. Scatter dots represent means of bins with a bandwidth of 1. Dashed lines are quadratic fits, separately estimated on both sides of the eligibility threshold. Solid lines are nonparametric fits from a local linear regression that uses triangular kernels with a bandwidth of 6, separately estimated on both sides of the eligibility threshold.

Table 2: Spillovers to Nearby Municipalities

	Dependent variable: Mean casualties within:			
	10 km	20 km	30 km	40 km
Panel A: Entire Program Period				
Eligible	0.002	-0.009	-0.007	-0.007
	(0.022)	(0.016)	(0.006)	(0.006)
Panel B: Social Preparation Phase				
Eligible	-0.009	-0.004	-0.004	-0.012
	(0.048)	(0.035)	(0.015)	(0.015)
Panel C: Pre-Program Period				
Eligible	0.006	-0.004	-0.004	-0.002
	(0.012)	(0.007)	(0.010)	(0.008)
Mean # of muni. within distance:	2.96	11.19	22.32	30.23
	[2.68]	[9.03]	[15.85]	[17.11]
Mean # of eligible muni. within dist.:	0.81	3.07	6.13	8.47
	[1.05]	[2.81]	[4.82]	[5.62]
Controls	Yes	Yes	Yes	Yes
Municipalities	222	222	222	222

The table reports results of the Regression Discontinuity design described in Section 2. The running variable is the distance between the municipality's poverty rank and the provincial eligibility threshold. All results are OLS estimates of the effect of eligibility on mean casualties in municipalities within distances between 10 and 40 km (not including the observed municipality itself). All estimates are from local linear models that control for flexible trends of the running variable on each side of the eligibility threshold and use a triangular kernel with a bandwidth of 6. *, ** and *** denote statistical significance of the underlying coefficient at the 10%, 5% and 1% levels. Standard errors, clustered at the municipality level, are reported in parentheses. Standard deviations of mean number of municipalities are reported in square brackets. All specifications include the control variables shown in Table 1 and year and province fixed effects.

1.3 Smoothness at "Pseudo-Thresholds"

We now test whether there are discontinuities in conflict casualties at other places away from the threshold. Finding discontinuities at those "pseudo-thresholds," where eligibility does not change, would raise the concern that our results are due to mis-specified non-linearities in the relationship between the running variable and the outcome (Imbens and Lemieux, 2008). Following Imbens and Lemieux's recommendation, we look for discontinuities at two pseudo-thresholds: the medians of the running variable for eligible and ineligible municipalities, located at -2 and 3 relative poverty ranks, respectively. Table 3 shows that we find no statistically significant evidence of discontinuities at these two thresholds.

Table 3: Robustness Test for Discontinuities at Pseudo-Thresholds

Dependent variable: Total casualties (entire program period)				
	Poisson QMLE		OLS	
	Local Linear	Quadratic	Local Linear	Quadratic
	(1)	(2)	(3)	(4)
Pseudo-threshold at -2 (median of eligible municipalities)				
Eligible	0.029	-0.010	0.038	0.011
	(0.041)	(0.059)	(0.037)	(0.054)
Pseudo-threshold at 3 (median of ineligible municipalities)				
Eligible	-0.052	-0.022	-0.010	0.011
	(0.058)	(0.091)	(0.096)	(0.12)
Municipalities	222	222	222	222

The table reports results of the Regression Discontinuity design described in Section 2. The running variable is the distance between the municipality's poverty rank and pseudo-thresholds at -2 and 3 poverty ranks (the respectivemedians for eligible and ineligible municipalities). Local linear regressions control for flexible trends of the running variable on each side of the pseudo-threshold and use triangular kernel weights with a bandwidth of 6 ranks. Quadratic regressions control for flexible quadratic trends of the running variable on both sides of the pseudo-threshold. For poisson models, reported values are marginal effects. *, ** *** denote statistical significance of the underlying coefficient at the 10%, 5% and 1% levels. Standard errors are clustered at the municipality level. All specifications include year fixed effects.

References

Imbens, G. W. and Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics* 142: 615–635.

Ludwig, J. and Miller, D. I. (2007). Does head start improve children's life chances? evidence from a regression discontinuity design. *Quarterly Journal of Economics* 122: 159–208.