Supplemental Analysis on Drone Strikes for "Economic Migration and Communal Violence in Pakistan"

This supplement to "Economic Migration and Low-Intensity Conflict in Pakistan" further probes the effects of drone strikes on economic migration in Pakistan. As discussed in the main paper, *Strike* is a count of strikes by district-year, and it has the theoretically-expected positive association with *Migration*. Drone strikes disrupt militant capabilities, bolstering local incentives to travel overseas for work. This result was robust to corrections for extreme covariates and unit interdependence. However, the LASSO selection process found that *Strike* was potentially an outgrowth of other underlying factors.

This supplement suggests two, possibly complementary ways to interpret this result, using additional statistical analysis to probe the data. First, we could be misconstruing *Strike's* causal mechanism. Rather than directly degrading militant capabilities through destruction of weapons, materiel, fighters, or leadership, drone strikes instead have an indirect, and perhaps even stronger, chilling effect on militant planning and coordination. To assess this possibility, I replace *Strike* with casualty estimates from NAF. *Civilian*, *Militant*, and *Leader* capture the civilian deaths, militant casualties, and militant leaders killed by drone strikes, respectively. We might expect that militant deaths of any kind degrade these groups' capabilities, and particularly leadership deaths. By contrast, civilian casualties might enhance militant power, as local residents fear they could be inadvertently or intentionally targeted by unmanned platforms. But, if the indirect mechanism is correct, then these casualties should have no effects on migration. Instead, strikes make it harder to meet, plan, acquire resources, and execute their operations, effects that would not necessarily show up using casualties as a measure of efficacy.

However, as mentioned in the main paper, U.S. and Pakistani forces do not conduct or have not released after-action analysis from these strikes. Consequently, militant groups typically frame the strike results, biasing any data in their favor. Strikes should have higher civilian casualties and lower militant ones. It is more difficult to hide leadership deaths, as terrorist groups must name successors. In the models below, I exacerbate this bias, taking the highest civilian casualty listings and the lowest militant ones. The popular controversy over these strikes typically assumes that they have widespread and negative effects on socioeconomic and political dynamics in Pakistan, as well as potentially driving militant recruitment. If the quantitative analysis still contradicts this bias, the results should be considered a substantive rebuke of this position.[1] Nevertheless, I find that strike casualties have no statistically significant effect on employment migration.

For brevity, Tables I and II present only the results for *Civilian*, *Militant*, and *Leader*, which capture the civilian deaths, militant casualties, and militant leaders killed by drone strikes, respectively. Table I uses present-year variables, while Table II uses lagged-year measures. As seen, only lagged *Leader* deaths have a significant effect, but that disappears once we account for unit interdependence.

A second, possibly complementary, possibility suggested by the LASSO process is that drone strikes are endogenous to another, underlying conflict variable. While *Warfare* and *Tribal* are externally valid, drone strikes occur only because of the unique combination of legal, political, and ethnic structures in FATA. Perhaps the cleanest way to assess this issue is by re-examining the matching results. I rerun the matching process, this time including *FATA* as a variable on which the algorithm will attempt to balance the samples. Substantively, by doing this, the algorithm is attempting to correct for *FATA*'s unique influence on strikes. If the casualty variables

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[1] In unreported analysis, I exacerbate the bias in the other direction and nevertheless find similar results. As an additional robustness check, I use data on drone strikes from the Bureau of Investigative Journalism. However, their methodology is not as clearly stated nor as rigorous, leading to wider ranges in reported deaths. Nevertheless, parallel analysis found similar effects as with the NAF data.

Table I: *Effects of Strike Casualties on Migration, Present-Year Variables.*

	Observed Data	*Matched Data*	*Spatial Model*
Militant	2.99	15.46	2.50
	(7.69)	(8.05)	(7.60)
Civilian	-15.17	-10.04	-21.18
	(23.84)	(24.82)	(23.12)
Leader	-35.89	286.88	-78.30
	(213.24)	(231.17)	(208.45)

Table II: *Effects of Strike Casualties on Migration, Lagged-Year Variables.*

	Observed Data	*Matched Data*	*Spatial Model*
Militant	-18.23	13.05	-20.86
	(15.36)	(15.79)	(15.07)
Civilian	51.10	26.28	51.15
	(44.02)	(43.30)	(43.55)
Leader	220.69	737.62 *	176.43
	(254.74)	(266.03)	(249.80)

lose significance, then *FATA* is both correlated with the other controls and was driving the results. Using this new dataset, the casualty variables do indeed lose significance, as seen in Table III. At the least, FATA's unique characteristics – whether political, administrative, or cultural – intermediate the effects of drone strike casualties on *Migration*, rendering them moot.[2] The contradictory results found in the literature may be due to how different scholars specify their models and account (whether in a quantitative or qualitative sense) for FATA's unique characteristics and dynamics.

Also, λ – the coefficient on the spatial error term – is negative and insignificant. Substantively, casualties and strikes in one district do not have a significant effect on those in another. Even if they did, the effect would be negative, meaning that such events would reinforce isolation between districts. This further supports the idea that district-specific characteristics, not province or general Pakistani traits, are driving the results, and also that the inclusion of fixed effects may bias estimates by modeling unit interdependence where none exists.

As a further check, I draw upon Altonji, Elder and Taber (2005) to estimate model sensitivity to omitted variable bias and, by extension, selection bias(Heckman, 1979) While this issue cannot be addressed directly, Altonji, Elder and Taber (2005) develops a process that can determine how strong these omitted variables or selection effects must be to wipe out the effects of the main explanatory variable in each model. I leverage this process to determine whether models that include FATA are more or less sensitive to omitted variables than those that do not. If they are significantly less sensitive, then FATA is largely responsible for the null effects we see.

To formalize their process, Altonji et al state the following condition:

$$\frac{\mathbb{E}(\epsilon|\text{Predictor}=1)-\mathbb{E}(\epsilon|\text{Predictor}=0)}{\text{Var}(\epsilon)}=\frac{\mathbb{E}(X'\gamma|\text{Predictor}=1)-\mathbb{E}(X'\gamma|\text{Predictor}=0)}{\text{Var}(X'\gamma)} \tag{1}$$

where X is the matrix of control variables for the outcome equation, γ is a vector of their coefficients, and ϵ is a vector of the residuals from the unobservables. While

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[2] As an additional, unreported robustness check, I use a two-stage least squares model with *FATA* as my instrument. There, too, the casualty measures do not have significance.

Table III: Results of Spatial Error Models using Matched Data. DV = Overseas Employment Migration. Models 1 and 2 use data where *FATA* was not included in the matching process. Model 1 uses present-year values for the casualty variables, while Model 2 uses one-year lags. Models 3 and 4 include *FATA* in the matching process, with Model 3 using present-year values and Model 4, lagged. The differences across these models demonstrate the sensitivity of the results to model specification, specifically how FATA is being incorporated.

	Matching Process without FATA				Matching Process with FATA			
	Present-Year		*Lagged-Year*		*Present-Year*		*Lagged-Year*	
	Model 1		**Model 2**		**Model 3**		**Model 4**	
Militant	3.79		-16.09	*	0.31		-3.30	
	(4.84)		(7.71)		(15.76)		(25.87)	
Civilian	-40.42	*	41.11	*	19.98		50.94	
	(17.21)		(20.78)		(49.71)		(64.45)	
Leader	-76.33		250.04	*	208.99		486.47	
	(148.25)		(127.52)		(444.81)		(441.72)	
Tribal	-1066.70	*	-1055.90	*	-2377.30	*	-4368.20	*
	(341.72)		(519.40)		(1014.80)		(1095.80)	
λ	-0.15		-0.25		-0.01		0.25	
	(0.14)		(0.15)		(0.14)		(0.14)	

* indicates significance at $p < 0.05$

this condition holds, the relationship between the main explanatory variable and unobserved confounders is identical to the relationship between that same variable and the observed covariates, once we adjust for the variance of those two sets of variables. Using this relationship, we can ask how large the left hand ratio must be to nullify the main variable's significance and effect.

I run this process on present-year and lagged spatial error models for three sets of data:

1. Matched data where on *FATA* was included in the matching algorithm (Set 1);
2. Matched data where *FATA* was not included (Set 2); and
3. The raw observational data (Set 3).

This progression should allow us to determine the cumulative effects of each sensitivity correction. Table IV presents the results. Starting with models with present year variables, the casualty variables in Set 1 are significantly more robust to omitted variable bias than either of those in Sets 2 or 3, by multiple orders of magnitude. Recall also that only the Set 3 models had significant results. This implies, first, that it is much more likely that there is no statistically significant relationship between the casualty variables and *Migration*. Second, FATA is generally responsible for these null effects. The models become more robust to missing variables and selection effects the more directly that FATA is accounted for in model assumptions. In the lagged models, the estimates are not quite as strong, but the results in Set 1 are generally three times more robust than those in Sets 2 and 3. Moreover, there is no statistical difference between the robustness of the variables in Sets 2 and 3. Moreover, within each set, the lagged models are substantially less robust than the present-year ones. This implies that, while the drone program may face a long-term versus short-term strategic trade-off, the longer-term consequences are more strongly intermediated by other, unaccounted factors.

In total, this sensitivity analysis suggests an important caveat on any studies of the U.S. drone program in Pakistan. Failing to account for FATA's unique characteristics may over-emphasize the program's effects. If, for example, the data is only drawn from that region and makes no comparisons with other Pakistan provinces, then it can

Table IV: Sensitivity of Casualty Variable Estimates to Omitted Variables

	Set 1		Set 2		Set 3	
	Matching Process with FATA		**Matching Process without FATA**		**Observed Data**	
	Present-Year	*Lagged-Year*	*Present-Year*	*Lagged-Year*	*Present-Year*	*Lagged-Year*
Leader	4.72×10^{28}	1.37×10^{-30}	6.19×10^{-30}	8.89	7.88	1.91
Civilian	4.43×10^{4}	2.76×10^{-4}	1.06×10^{-4}	1.51×10^{-3}	17.03	-11.78
Militant	5.72×10^{5}	7566.69	6.56×10^{5}	5.67×10^{-4}	-0.65	0.4
Average Robustness	1.57×10^{28}	2522.23	2.19×10^{5}	2.96	8.09	-3.16

fail to account for selection bias, that militant groups chose FATA as a safe haven for a reason. Although this study is only partially explores this issues, the region's unique characteristics appears to drive the military, strategic, and socioeconomic effects of drone strikes. To assess the program's efficacy, we should first theorize for how strikes interact with these local conditions.

References

Altonji, Joseph, Todd Elder and Christopher Taber. 2005. “Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools.” *Journal of Political Economy* 113(1):151–184.

Heckman, James. 1979. “Sample selection bias as a specification error.” *Econometrica* 47(1):153–61.