Economic Competition and Civilian Support for Rebel Reintegration

Amanda Kennard* Konstantin Sonin† Austin L. Wright‡

October 2022

Abstract

Terminating a violent conflict requires support of the civilian population. It is well-documented that economic considerations play a critical role in the outbreak and continuation of conflicts. We bring novel evidence to bear on a related, but understudied question: do economic considerations impact civilian support for conflict termination? When civilians fear that reintegration of ex-combatants threatens their economic security, their support for peace may diminish. We investigate localized effects of the 2015 Hindu Kush earthquake and individual-level survey data on support for Taliban reintegration. The earthquake reduced support for reintegration into disproportionately impacted economic sectors, while there was no change in support for reintegration into unaffected sectors. These results are robust to a battery of tests including a novel spatial randomization leveraging geocoded fault line segments representing the universe of counterfactual earthquakes. Our findings provide a new insight into resolution of conflicts: economic considerations undermine civilian support for rebel reintegration.

Keywords: Civil conflict, peace, ex-combatant reintegration, Afghanistan.

JEL Classification: D74.

*Department of Political Science, Stanford University.

†Harris School of Public Policy, University of Chicago.

‡Harris School of Public Policy, University of Chicago.

1 Introduction

An extensive literature argues that economic considerations play a role in combatant decisions to participate in civil conflict (Collier and Hoeffler, 1998, 2004). Empirical studies document a robust relationship between negative income shocks and the onset of conflicts: individuals are more likely to take up arms when their economic alternatives are bleak (Dal Bó and Dal Bó, 2011; Dube and Vargas, 2013; Miguel et al., 2004). Conflict provides a means for individuals to improve their economic prospects by overthrowing existing regimes, gathering spoils of war, or opening up new opportunistic forms of revenue (Kalyvas, 2006; Hirshleifer, 2001; Besley and Persson, 2011).

This work explores a related question, though one which has received less attention in the literature to date. What role do economic considerations play among citizens who choose *not* to take up arms? How do income shocks affect citizen support for peaceful conflict resolution? We argue that a poor economic outlook may undermine conflict termination through a novel channel. Citizens will be less likely to support the peace process if they expect to face new economic competition from former combatants reentering the workforce.

Peaceful resolution to intrastate conflict does depend on effective reintegration of ex-combatants (Humphreys and Weinstein, 2007; Blair et al., 2021). Economic incentives are required to persuade combatants to lay down their arms and to prevent a resurgence of violence once peace is attained (Archambault, 2012). Supported both financially and politically by a number of international organizations, reintegration programs provide both training in new skills and the provision of start-up capital to draw insurgents away from conflict and back into peace-time society (United Nations, 2009). Yet these reintegration efforts rely on community support. Without the buy-in of peaceful citizens, ex-combatants struggle to build the social ties and support needed to reestablish themselves as lawful members of the community (Specht, 2010).

When will citizens support reintegration of ex-combatants? To analyze the impact of economic considerations, we use a general equilibrium model with heterogeneous agents, and elicit agents' preferences over the number of reintegrees in their sector. In short, our model predicts that an adverse economic shock leads to lower overall support for reintegration. Reintegration implies greater—and potentially less fair—economic competition as governments and international organizations alike subsidize ex-combatant reentry, most often into agricultural sectors. The influx of the new labor reduces the demand, and hence income, for those who are already in the market, or drives them from the market altogether. When times are good, the benefits of conflict cessation for citizens will outweigh the adverse economic impact of increased competition. Yet when times are bad citizens may oppose reintegration if it threatens an already-precarious economic livelihood.

In the empirical part of our investigation we focus on the case of ex-Taliban combatants in Afghanistan. The nature of our substantive settings—as well as the questions at issue more broadly—raises immediate concerns about the appropriateness of standard regression techniques. Bad economic times may themselves be induced by high levels of conflict or damage to local property which may itself undermine support for reintegration. In this context, traditional regression analysis is likely to deliver biased estimates as well as limited insights into the precise causal mechanisms at work (Samii, 2016; Angrist and Pischke, 2008).

For this reason, we adopt a quasi-experimental approach, leveraging localized economic effects of the 2015 Hindu Kush earthquake which devastated Afghanistan's north eastern provinces and disproportionately impacted citizens engaged in the agricultural economy. We combine geocoded data on earthquake severity along with individual-level survey responses measuring support for Taliban reintegration into a range of economic sectors. By comparing the causal effects of negative economic shocks on support for reintegration into a range of sectors—some affected, some not—we are able to distinguish the economic competition mechanism from other mechanisms, including psychological channels.

Statistical analysis supports our prediction that the earthquake reduced support for reintegration into adversely-affected sectors while having no discernible impact on overall support for reintegration nor reintegration into less-affected sectors. Employing a difference-in-difference approach we estimate a precise and substantively large negative impact of the earthquake on support for reintegration of Taliban fighters into agricultural occupations. Placebo tests uncover no change in support for reintegration into unaffected sectors of the economy. Shedding further light on the mechanism at work, we provide suggestive evidence that the reduction in support for reintegration to agricultural professions is strongest within districts most reliant on cash crops and subsistence farming.

Our core results are robust to a battery of alternative specifications including alternative treatment measures based on distance and remote sensor observations of seismic activity across the country. In addition, the nature of our survey data allows us to account for numerous potential confounders at both individual and province levels. Finally we employ a novel spatial randomization technique which leverages geo-coded fault line segments to construct a counterfactual universe of earthquake epicenters. The resulting randomization inference provides additional support for our findings.

The rest of the paper is organized as follows. In Section 2 we introduce the substantive setting. Section 3 contains a theoretical model. Section 4 describes our data and empirical strategy, while Section 5 reports the main results. Section 6 discusses robustness of the empirical results and Section 7 concludes.

2 Reintegration of Taliban Ex-combatants

We study the impact of the 2015 Hindu Kush earthquake on Afghan support for reintegration of former Taliban combatants (Humphreys and Weinstein, 2007). Reintegration is one of three core pillars – along with disarmament and demobilization – which together form the basis of contemporary efforts at conflict resolution. Disarmament, demobilization, and reintegration (DDR) programs have been studied extensively by experts in the field and also widely implemented in conflict settings. Civilian and community support for reintegration represents a key precondition to the success of these efforts as such support provides ex-combatants with an accepted place within society, access to mentorship and knowledge capital within the community, and other informal benefits (Cilliers et al., 2016).

Reintegration policies have a long history within the Afghan conflict. One of the first attempts at reintegration, the Afghan New Beginnings Program (ANBP), was initiated as early as 2003 before coming to an end in 2006. The ANBP focused its reintegration efforts on the northeastern province of Konduz – one of the primary regions we study below – yet was beset by criticism of patronage on the part of its organizers and a lack of transparency in the selection of ex-combatants receiving support for reintegration. Despite this early failure, more recent efforts have garnered broad-based support among the Afghan populace. The 2010 the Afghan government established the nation-wide Afghanistan Peace and Reintegration Program (APRP). Coupled with national amnesty legislation passed around the same time, the APRP adopts a holistic approach to reintegration, including strengthening of community political institutions as well as support for combatant reintegration (Hanasz, 2012).

Following the introduction of the APRP, public approval of reconciliation efforts and reintegration increased to 83%, up from 71% the previous year. Support is particularly strong amongst male respondents with 88% supporting the approach. This is despite the fact that male citizens are overwhelmingly engaged in productive economic activities and are thus most likely to be impacted by reentry of ex-combatants into the economy.[1] Importantly, when asked whether they agreed or disagreed with the statement "anti-government elements who lay down arms and express willingness to reintegrate into society should be provided with government assistance, jobs and housing," 81% of the respondents replied in the affirmative (Tariq et al., 2010).

In October 2015 the north eastern provinces of Afghanistan were hit by a severe earthquake. While earthquakes are historically common within the region, this particular quake was notable for its intensity, reaching 7.5 on the Richter scale.[2] The epicentre of the quake - the village of Jurm - lies within Badakhshan, one of the northern-most provinces of Afghanistan. UN incident reports indicate that the majority of damage resulted in Badakhshan itself as well as neighboring provinces including Takhar, Baghlan, and Konduz (UN OCHA, 2015a,b).[3] The timing of the earthquake placed it in the midst of winter planting season, with significant repercussions for agricultural activity in the region.

Afghanistan's north eastern provinces rely predominantly on cash-crops and subsistence agriculture. Among the provinces most negatively impacted, Badakshan relies most heavily on cash crop farming which provides 52% of local income (UNHCR, 2016). Cash crops are similarly significant as an income source in Baghlan, Konduz, and Takhar. Wheat, rice, and corn make up the vast majority of crops though nearly all households also raise livestock as a means of supplementary income and food security (Central Statistics Organization of Afghanistan, 2018).

[1] Lower support amongst female respondents, 78% supportive, is widely attributed to repressive attitudes of the Taliban regime towards women and resultant fears of any negotiated settlement.

[2] Appendix depicts the historical distribution of earthquakes experienced in the region.

[3] Due to non-linearities in earthquake intensity Kabul was also significantly impacted despite its distance from the epicenter. We address this irregularity in more detail below.

Households are typically large with an average of nine members and between one and four income earners over the age of sixteen. In Badakshan and Baglan province a two room dwelling on average housed up to eight family members.[4] Moreover, agriculture is predominantly a family endeavour with able-bodied household members assisting with planting, reaping, and maintenance throughout the year (UNHCR, 2016).

The earthquake devastated infrastructure and housing throughout the affected region. Humanitarian organizations report that the destruction or partial destruction of family dwellings were among the most significant impacts, with over $20,000$ homes either damaged or destroyed. Of the affected provinces described above, Badakshan and Baghlan suffered the greatest infrastructure losses. Early assessments noted that in the aftermath of the quake, many families were forced to abandon their homes, moving in with extended family or friends in over-crowded and unsanitary living conditions (UNHCR, 2016).

In economic terms the earthquake represented a significant shock to the financial resources of affected households. Surveys after the fact reveal that families receiving humanitarian cash grants directed those funds predominantly towards the costs of building materials and - in some cases - hiring of unskilled labor to assist with reconstruction.[5] Costs of capital were further increased by damage to infrastructure, including roads, and the remoteness of impacted regions which required the redirection of expensive, specialized vehicles to transport building materials into affected communities.

Despite cash and other forms of assistance from government and non-governmental sources a

[4] One room dwellings on average house up to seven members of the immediate and extended family. Similar figures are unavailable for other affected districts.

[5] In Badakhshan province the dominance of agricultural households created a shortage of unskilled labor, driving up wages and further increasing costs of reconstruction.

large majority of affected households reported being unable to complete the necessary repairs. According to reports based on a survey of affected families, 29% of homes continued to lack doors, a roof or both while another 39% remained fully uninhabitable. In Badakshan province 53% of impacted dwellings were reported to remain uninhabitable months after the quake itself. 92% of survey respondents who had not been able to complete necessary repairs cited an inability to afford the necessary building materials. 83% reported that they could not afford the necessary manual labor despite its wide availability (UNHCR, 2016).

3 Theoretical Model

We model a simple agricultural economy in which agents produce a single good employing productive capital and subsequently compete to sell their good in the marketplace. The structure of the economy reflects the predominance of household-based cash crop farming prevalent throughout the region we study. Agents are strategic in their production decisions, taking into account their capital endowment as well as the anticipated equilibrium price of the good. In turn, equilibrium price reflects both supply and demand, varying as a result with both aggregate capital in the community and the number of agents engaged in production of the agricultural good. While the number of agents is exogenously fixed throughout the game, analysis of equilibrium behavior provides insights into the likely impact of increases in the population of agents engaged in agriculture both before and after a negative shock to productive capital.

Let there be a continuum of heterogeneous agents $[0, 1]$. Each agent is exogenously endowed with productive capital, $k_i \in \{k_L, k_H\}$ with $k_H > k_L$. The share of high-capital workers is $\alpha_H \in (0, 1)$. Agents select the amount of household labor, l_i, to devote to agricultural production, paying linear cost $c > 0$ for each unit of labor. Parameter c represents the opportunity cost resulting from the allocation of productive labor to agricultural activities rather than other household economic activities. Production is Leontieff and given by the function $f(l_i, k_i) = \min\{l_i, k_i\}$.[6] Market demand for the agricultural good is exogenous and given by inverse demand $q(p) = a - bp$, where q represents aggregate production. We focus on the case in which $a - bc > 0$.

Utility for each agent is given by $u_i = \max\{p(q)f(l_i, k_i) - cl_i, r\} + \varphi(m)$, where $\varphi(m)$ is a single-peaked function representing the common preference for investment in peaceful conflict resolution, represented by the presence of a continuum of reintegrees, $m \times [0, 1]$ with $m \in [0, M]$, who may potentially (re-)enter the community; the reintegress have the same distribution of productive capital. In addition, $r > 0$, is a reservation utility available to any agent who chooses not to engage in agricultural production (for example by engaging in subsistence farming only).

Analysis

We first describe equilibrium behavior in the game before analyzing how a shock to agents' productive capital impacts their reaction to the entrance of new agricultural agents. Let q^* denote the equilibrium output. For any agent engaged in agricultural production, $i \in \{L, H\}$, optimal labor dedicated to agriculture is $l_i^* = k_i$. Whether they posses high or low levels of productive capital, agents optimally employ the smallest amount of labor necessary to maximize output. Lowering output strictly reduces profits as agent i's individual production decision has a negligible impact on price. Resulting output for an agent with endowment, k_i, is $f(l_i^*(k_i), k_i) = \min\{l_i^*, k_i\} = k_i$. An agent optimally chooses to engage in the agricultural economy provided that profits exceed the reservation utility, $\big(p - c\big)k_i > r$.

[6] We employ a Leontieff production function throughout though results generalize to any production function with constant elasticity of substitution (CES). Note that Leontieff is a special case of a CES production function, in which the substitution parameter approaches $-\infty$ (Mas-Colell et al., 1995).

We focus on the most salient case in which $(p-c)\,k_L > r$. In the absence of an exogenous shock to productivity, both high and low capital agents optimally engage in agricultural production.

Suppose that the agents who populate the community are asked about their attitude towards reintegration. Specifically, we will look at their preferences over m, where $m \times [0,1]$ is the mass of reintegrees. With this amount of reintegrees, the supply of the product is $(m+1)\,(\alpha_P k_P + \alpha_R k_R)$. The equilibrium condition is given by the intersection of supply and demand, $(\alpha_P k_P + \alpha_R k_R)\,(m+1) = a - bp$. Solving for the market price we have,

$$p^*(m) = \frac{1}{b}\left(a - (m+1)\left((1-\alpha_H)k_L + \alpha_H k_H\right)\right).$$

Given the dependence of equilibrium price on population size (including reintegrees) and the distribution of capital endowments, individual equilibrium utility u_i can be expressed as function of these same parameters,

$$u_i(m, k_i) = \big(p^*(\alpha_H, m, \bar{k}) - c\big)k_i + \varphi(m)$$

Now, for each agent with capital k_i we have

$$\begin{aligned} u_L(k_L) &= \left(p^*(m) - c\right)k_L + \varphi(m) \\ &= \frac{1}{b}\left(a - (m+1)\left((1-\alpha_H)k_L + \alpha_H k_H\right)\right)k_i + \varphi(m). \end{aligned}$$

Maximizing with respect to m, and analysing the first order condition, we could state our first result. Let $m_i^o(k_i) = \arg\max_m \{u_i\,(m, k_i)\}$ denote the optimal number of reintegrees from the perspective of an agent of type $i \in \{L, H\}$; our assumptions imply a unique optimum.

Proposition 1 *Agents with high productive capital prefer lower levels of ex-combatants reintegration than agent with low productive capital:* $m^o(k_L) > m^o(k_H)$.

The economic mechanism behind the political preferences over the reintegration that are described in Proposition 1 is intuitive. The owners of more productive capital (or simply more skilled workers) are more exposed to competition from potential reintegrees. In equilibrium, they supply a higher amount of labor and therefore are more sensitive to the fall in the price of their product, which results from increased labor force. While we demonstrate our results for two types of capital-owners, the result is robust to any number of classes. In the limit, with a continuous type space, opposition to reintegration is strictly increasing in productive capital.

Next, we consider how a negative capital shock affects agent attitudes towards reintegration, that is, the optimal number of reintegrees $m^o(k_i)$. The shock produces a proportional decrease in productive capital across classes. Let $1 - \delta$ denote the share of productive capital remaining following a destructive natural disaster such as the one we study, so that the magnitude of the shock is represented by $\delta \in (0, 1)$. For any δ two effects will shape the market response of economic agents. First, a fall in the capital stock results in reduced aggregate supply as agents have less capital with which to complement their labor. With less supply, the market price will increase. At the same time, individual market participation decisions may shift as destruction of capital endowment will imply less willingness to participate among agents who now find the reservation value, r, relatively more attractive. For simplicity we focus on the median or representative agent's preferences. The following result establishes conditions under which this representative agent's support for reintegration will decline following a negative capital shock.

Proposition 2 *If the capital losses due to an earthquake are relatively large, $\delta > \delta^*$, and the capital inequality is relatively significant, $\gamma > \gamma^*$, the earthquake results in increasing share of those who oppose reintegration.*

The basic logic of this result is straightforward. Consider $\delta > \delta^* = 1 - r \times \left(\frac{1}{b}a - \alpha_R k_R - c\right)^{-1} k_P^{-1}$. For those δs that satisfy this condition, the poor will be out of the agriculutral production. Comparing the first-order condition for the post-earthquake preferred number of reintegrees with a similar condition without the earthquake, we obtain that if $\alpha_H \left(k_H(1-\delta)\right) k_H > \left((1-\alpha_H)k_L + \alpha_H k_H\right) k_L$, then $m^o\left(\delta\right) < m^o$. Further, there exists some ratio γ^* such that for any capital ratio $\frac{k_H}{k_L} > \gamma^* = \gamma^*\left(\delta, \alpha\right)$, the new optimal choice is strictly lower. The threshold is decreasing in δ, the parameter that reflects damage, and in increasing in α_R, the relative share of high capital types.

Intuitively, the first condition in Proposition 2 implies that the shock is large enough to deter low capital workers from engaging in agricultural production. When this is the case and capital inequality is sufficiently high, this disruption in the labor market will lead to overall higher levels of opposition to reintegration. The impact of capital scarcity outweighs the impact of labor market losses resulting in a higher overall price, and greater competitive opposition to reintegration for the median economic agent. Furthermore, it is interesting to note that γ^*, the necessary level of capital inequality for the result to hold, is decreasing in the share of low-capital workers in the population, $1-\alpha_H$. As we will see in Section 5, the main predictions of the theoretical model are supported by the data in our substantive setting.

4 Data and Empirical Strategy

We estimate the impact of the earthquake and its economic consequences by comparing changes in survey responses in affected areas. Our survey data consists of waves 29 and 30 of the Afghanistan Nationwide Quarterly Research (ANQAR) survey collected in August and November 2015. The North Atlantic Treaty Organization (NATO) contracted the Afghan Center for Socio-Economic and Opinion Research (ACSOR) to design and implement the survey. ACSOR selected enumerators from the sampled regions and trained them in proper household and respondent selection, recording of responses, culturally appropriate interview techniques, and secure use of respondent information. The survey follows a standard multi-stage randomized sampling procedures, and enumerators use random walk and Kish grid techniques to select respondents. ANQAR survey respondents are representative of other nationwide data collection platforms in Afghanistan (Condra et al., 2018; Condra and Wright, 2019; Fetzer et al., 2020).[7]

The administrative district is the primary sampling unit, and districts are selected via probability proportional to size systematic sampling. We rectify the sampling frame used by ACSOR with the administrative map produced by the Empirical Studies of Conflict (ESOC) group. Among sampled districts, secondary sampling units (villages/settlements) are randomly selected from a sampling frame based on records from the Afghan Central Statistics Organization. A random walk method is used to identify target households and a Kish grid technique is used to randomize the respondent within each target household.[8]

We employ a difference-in-difference design to estimate the impact of the Hindu Kush earthquake on support for reintegration. Because no comprehensive data on damage exists, our main specification is a distance-based measure (300 kilometer buffer around the epicenter). This measure is informed by field reports and damage data on the impact radius of the earthquake (United Nations Office for Disaster Risk Reduction, 2015). As robustness exercises we supplement this specification with two additional distance-based measures (linear distance and

[7] See Figure A-2.

[8] Figure A-1 visualizes data on refusal rates, non-contact rates, and overall cooperation rates across ACSOR-enumerated waves of ANQAR for which data are available (Waves 16-38). This means we cannot produce these statistics for our study wave despite it also being conducted by ACSOR. Importantly, the survey collection critiqued in Blair et al. (2014) was conducted by Eureka Research, not ACSOR. Overall, the refusal rates observed by ACSOR are lower (∼3.6%) than those reported in a comparable survey (∼15%) conducted in Afghanistan in 2011 (Lyall et al., 2015). Figure A-2 shows that ACSOR's sampling appears to be consistent with demographic information collected across 13 years of data available from the Asia Foundation. For additional details, see Condra and Wright (2019).

logarithmic distance) as well as a measure of shaking intensity made available by the USGS Earthquake Hazards Program.[9] The difference-in-differences design yields a causal estimate of the earthquake's impact if trends in the outcome of interest in the control region represent a valid counterfactual for the treatment region ('common trends') (Donald and Lang, 2007).

Given the individual-level nature of our data we are able to further account for potential bias by including a range of covariates such as ethnicity, gender, socio-economic status, age, and educational attainment. We account for location (district) specific factors that do not change between August and November (terrain ruggedness, agricultural reliance, conflict exposure, political leadership) as well as any country-wide factors that vary across survey waves. We employ heteroskedasticity-robust standard errors, clustered by administrative district.

Our estimating equation is,(2):

$$y_i = \alpha + \beta_1 Post_i + \beta_2 Exposed_d + \beta_3 Post_i \times Exposed_i + \lambda D_i + \theta W_t + \gamma X_i + \epsilon \qquad (1)$$

where y_i is the respondent's sector-specific or - alternatively - overall support for reintegration. We rely on the following three questions for our primary and placebo analyses:

- **Overall Support:** "Do you think it is possible for former Taliban fighters to join the Afghan society that the Government is trying to build?"
- **Reintegration as Farmer:** "If an insurgent was to stop fighting against the government would you accept him back into the community if he came back as a farmer?"
- **Reintegration in Unaffected Sectors:** "If an insurgent was to stop fighting against the government would you accept him back into the community if he came back as... [a

[9] The shaking intensity measure is based on a combination of remote sensors as well as human-based reporting of earth movement. Given the potential for measurement bias in population-dense regions, our preferred specification is the fixed radius.

shopkeeper/a member of the Afghan National Police/a member of the Afghan National Army/a member of the shura/an official in the provincial or district government administration]?"

The primary outcome of interest is support for reintegration as a farmer. $Post_i$ takes the value of 1 if the respondent is surveyed after the earthquake occurred (Wave 30). $Exposed_d$ indicates that the respondent resides in a district that is classified as a earthquake-affected. $Post_d \times Exposed_i$ captures the difference-in-difference estimator of the change in y_i of the exposed subjects after treatment (the earthquake). The interaction effect is the quantity of interest in this research design and the coefficient reported. D_i indicates district-level fixed effects, W_t indicates wave (time period) fixed effects and X_i is a vector of control variables. All models include age, age squared, gender, education, and ethnicity as demographic controls. Robust standard errors are clustered by district to account for potential spatial clustering in earthquake risk, exposure to localized economic shocks (our mechanism), and the sampling design (i.e., correlation of survey timing within the primary sampling unit). All models are adjusted using population sampling weights.

5 Results

We begin by assessing the plausibility of the parallel trends assumption, examining shifts in public support for reintegration across treatment and control groups prior to the impact of the earthquake. Using our primary distance-based treatment classification, we plot these trends in overall support in Figure 1 Panel A.[10] Note that prior to treatment, the outcome measure across groups covaries as a parallel trend. This provides support for a causal interpretation of our statistical estimates.

[10]We focus on trends in overall support due to consistent placement on the survey.

Panels B and C of Figure 1 depict our primary treatment classification and the main results. Our findings are three-fold and provide consistent support for our argument across the board. First, we find no shift in overall public support for rebel reintegration after the earthquake ($\widehat{\beta} = -.001, p = 0.927$). Second, we observe a large and statistically significant decrease in public support for reintegration into the agricultural sector ($\widehat{\beta} = -.054, p = 0.039$). This represents a 5.4% reduction in public support for reintegration in the agricultural sector against a pre-earthquake baseline of 58.6% ($\widehat{\beta} = 9.2\%$ decline relative to pretreatment mean).

Third, we find no consistent effects of earthquake exposure on support for reintegration across sectors that were not impacted by the earthquake (merchants, army officers, police officers, government officials, and members of the local council (shura)). Although support for reintegration of rebels as police officers increases ($\widehat{\beta} = .047, p = 0.037$), this result is not robust across treatment specifications as depicted below. These three results are consistent with our predictions and the theoretical model: overall support for reintegration and support for reintegration in unaffected economic sectors were not impacted by the earthquake; support for reintegration in the sector impacted by the earthquake declined significantly.

These results remain consistent across all three alternative treatment specifications as depicted in Figure 2. As mentioned above the primary change across treatment specifications is in the estimated effect of treatment on support for reintegration as police officers. We next introduce our supplemental controls. These include household characteristics, respondent's level of comfort and comprehension, a measure of village security, whether the government controls the village, as well as the frequency of patrols by government forces. These supplemental specifications yield evidence highly consistent with the benchmark model.[11]

[11] See A-3 for full results.

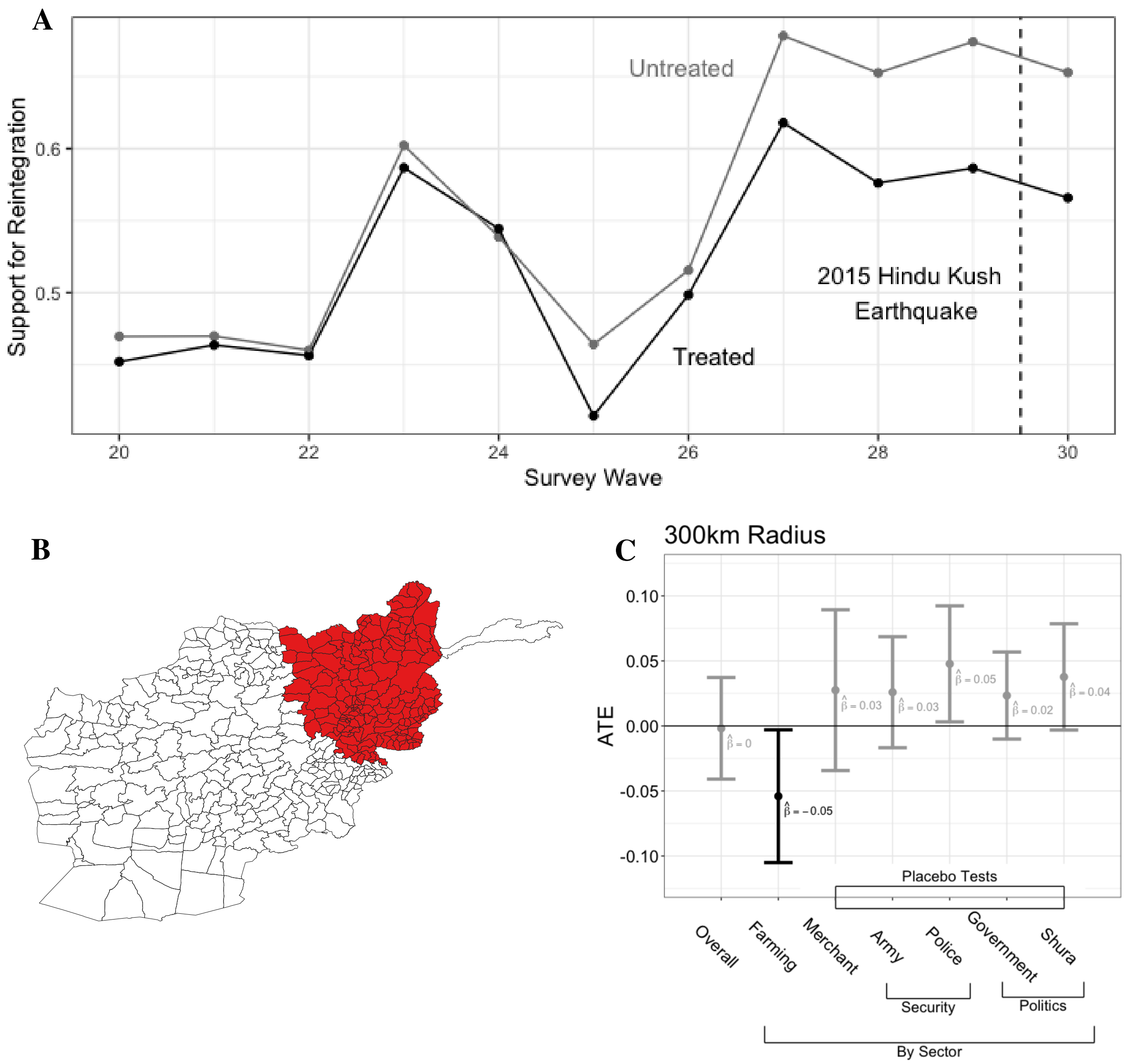


Figure 1: Parallel Trends, Treatment Classification, and Main Results

Panel (A): Over time comparison of overall support for combatant reintegration, treated versus untreated. Panel (B): Treatment classification using 300km radius from epicenter. Panel (C): Estimated effect of earthquake on overall support for reintegration, support for reintegration into agriculture, and reintegration into various non-agricultural sectors.

To further probe the mechanism at work, we next estimate the marginal effects of the difference-in-differences estimator, comparing districts where reliance on agricultural income is high versus low.[12] The quantity of interest is the marginal effect of (agricultural) income reliance, which we expect to further reduce support for agricultural reintegration in exposed districts after the earthquake occurs. To estimate this quantity we rely on a triple difference regression model (difference-in-difference-in-differences). This approach allows us to test for marginal effects consistent with the theoretical mechanism. To do this, we estimate a fully interacted version of the regression above (2) as follows:

$$\begin{aligned} y_i = \alpha + \beta_1 Post_i + \beta_2 Exposed_d + \beta_2 FarmerDependent_d + \beta_3 Post_i \times Exposed_i \\ + \beta_4 Post_i \times FarmerDependent_d + \beta_5 Post_i \times Exposed_i \times FarmerDependent_d \\ + \lambda D_i + \theta W_t + \gamma X_i + \epsilon \end{aligned} \tag{2}$$

where y_i and other comparable notation remains the same as above. $Post_i \times Exposed_i \times FarmerDependent_d$ captures the marginal effect of the difference-in-differences estimator when the additional parameter equals one. In this case, it is the effect of the differential effect of the earthquake among subjects that reside in districts that are above the mean level of dependence on farming as a source of household income.

The results are presented in Table 1. We find a large negative marginal effect as hypothesized ($\widehat{\beta} = -.094, p = 0.080$). This represents a 16.0% decline relative the baseline level of support. This suggests the overall observed decline in support for reintegration into agricultural sectors is driven by respondents who are themselves most severely impacted.

[12] To do this, we rely on data collected in earlier ANQAR waves and classify districts using the mean of the distribution.

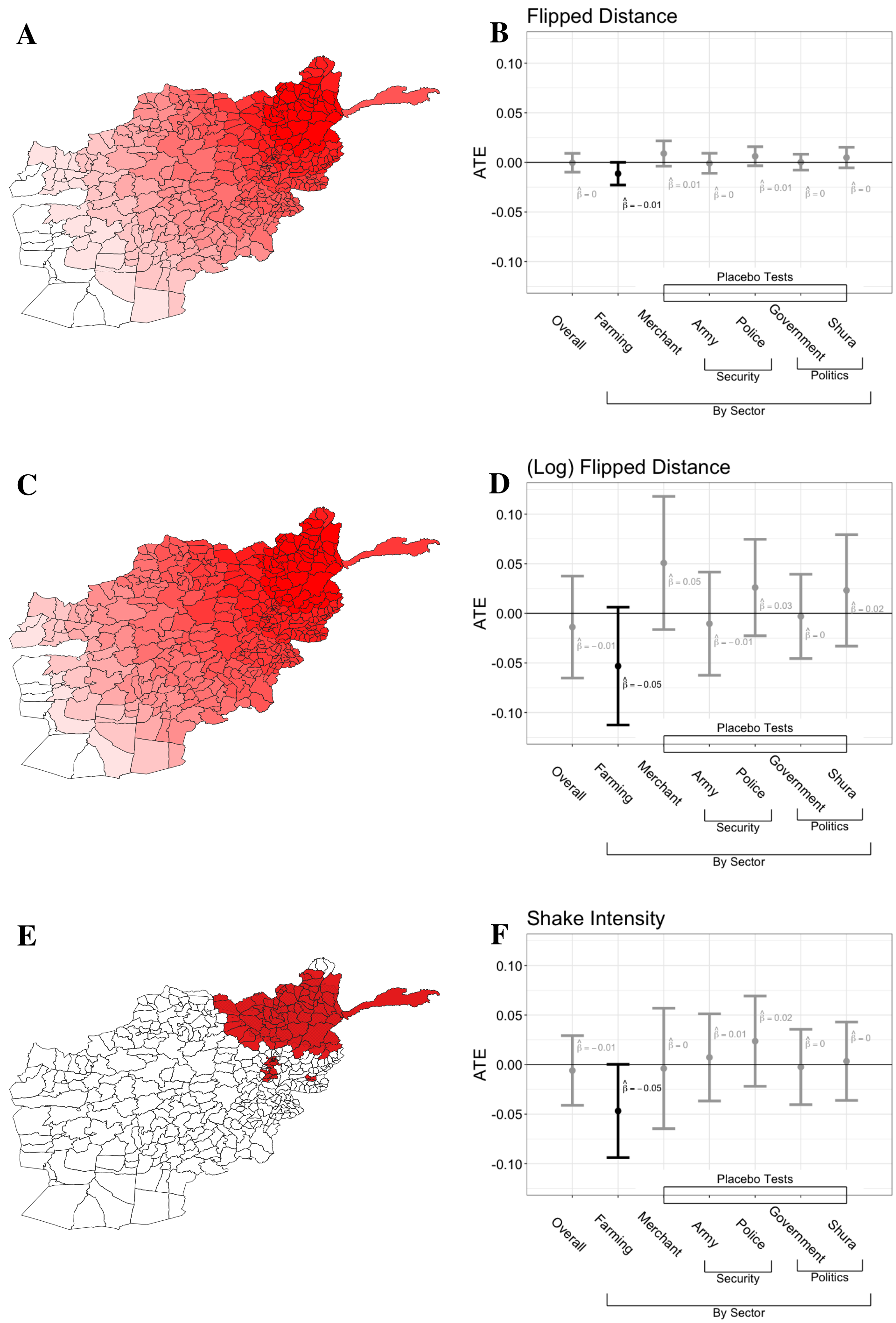


Figure 2: Coefficient Estimates using Alternative Treatment Classifications

Panel (A) illustrates a continuous measure of distance (arc degrees) that is inverted at the maximum. Panel (B) plots these estimates as the scale axis scale as the main effects in Figure 1C. Inverting the scale eases interpretation. Panel (C) illustrates the log of this measure (A) and corresponding results (Panel (D)). Panel (E) uses a shaking intensity measure drawn from USGS. Panel (F) plots these effects.

Table 1: **Heterogeneous impact of earthquake exposure on support for reintegration**

	(1) Overall Support	(2) Farmer	(3) Merchant	(4) Police Officer	(5) Army Officer	(6) Shura Member	(7) Local Official
		Impacted Sector	Placebo Sectors				
Post × Treated	-0.0194	-0.0210	0.0446	0.0421	0.0216	0.0389	0.0269
	(0.0234)	(0.0289)	(0.0338)	(0.0290)	(0.0259)	(0.0240)	(0.0223)
Post × Treated × Farming Dependent	0.0551	-0.0943*	-0.0639	-0.000826	-0.00111	-0.0166	-0.0144
	(0.0426)	(0.0537)	(0.0561)	(0.0506)	(0.0486)	(0.0452)	(0.0396)
SUMMARY STATISTICS							
Outcome Mean	0.621	0.565	0.509	0.278	0.234	0.219	0.172
Outcome SD	0.485	0.496	0.500	0.448	0.423	0.414	0.377
PARAMETERS							
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ADDITIONAL PARAMETERS							
Ethnicity	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gender	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socio-economic Status	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Education	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MODEL STATISTICS							
N	25468	26294	26280	26280	26166	26099	26044
Clusters	359	359	359	359	359	359	359

Notes: Outcome of interest is support for reintegration (=1) and varies by column. The quantity of interest is the marginal effect (highlighted row). All regressions include location and wave fixed effects as well as demographic controls (ethnicity, gender, socio-economic status, age, and educational attainment). Column 1 is for overall support. Column 2 is the primary result. Columns 3-7 report results for placebo sectors that were not impacted by the mechanism we theorize. Heteroskedasticity robust standard errors clustered by district are reported in parentheses. Stars indicate *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

6 Spatial Randomization Inference

To assess the robustness of our core results, we next perform a novel spatial randomization test. Standard randomization inference tests are conducted by shuffling treatment classification in a manner that is orthogonal to the original treatment status and subsequently reestimating the treatment effect (Abadie, 2002; Ho and Imai, 2006). The estimated treatment effect from the true data can then be compared to the distribution of estimates derived from the set of shuffled samples. Given independence of treatment status across units, the resulting empirical distribution will converge to a normal distribution with mean zero. This provides an empirical basis for comparison with the observed effect. These tests, however, are typically misspecified where treatment status is spatially correlated across units as is the case of seismic or other environmental events (Sonin and Wright, 2020).

To correct for the spatial correlation of treatment status, we gather data on all seismic fault line segments in Afghanistan and recalculate the treatment effect for the universe of counterfactual earthquake epicenters using the distance-based measure from our main specification.[13] To adjust for spatial correlation induced by our distance-based measure, we reweigh estimated effects ($\widehat{\beta}_{random}$) employing the inverse of the correlation between treatment status for each counterfactual epicenter and the true (that is, observed) treatment status.[14] We map the universe of seismic epicenters in Figure 3A. We present uncorrected estimates in 3B. The spatial clustering of red (negative coefficients) and green (positive coefficients) illustrates the failure of standard randomization inference due to correlation in seismic risk across units. In 3C, we visualize the novel spatial correlation corrected coefficient weights. The reweighted estimates are depicted in Figure 3D. In 3E and 3F, we plot the distribution of the counterfactual estimates. Notice that our estimated effect is in the tail of the counterfactual distributions with an empirical p equivalent to our main estimate (values to the left of the vertical line in 3E; the red region in 3F). This novel methodology has potential applications in a range of observational studies of environmental and climatic events, where spatial correlation in treatment classification can be modeled and corrected.

[13]The simplifying assumption is that propagation across fault lines is the same given an identically scaled seismic event. A more complex approach would model earthquake movement through soil, producing a distance-based measure that is unique to each epicenter. To maintain the tractability of the method, we leave this alternative approach to future work.

[14]This approach differs substantively from shuffling respondents into different treatments (while ignoring the spatial correlation in treatment status) or randomly seeding the study region with 'simulated' epicenters which would lead to implausible treatment classifications.

7 Conclusion

Natural disasters are economically disruptive and can prolong conflict by undermining public support for reintegration of fighters. Using individual-level data and a difference-in-differences approach, we present robust causal evidence that the Hindu Kush earthquake in Afghanistan reduced support for reintegration in one sector disproportionately impacted by the disaster: subsistence agriculture. These results also have broad implications outside the immediate study of civil conflict: the economic mechanism supported by our analysis has particular relevance for understanding the likely impact of climate change on future conflict (Hsiang et al., 2017). Historically economic losses due to drought and flood events have been similar to that of the disaster we study.[15] As the climate warms, these environmental disasters are expected to increase in frequency and intensity (Seneviratne et al., 2017). Climate-amplified disasters may similarly jeopardize the agricultural sector (Schmidhuber and Tubiello, 2007), prolonging dozens of current and future armed conflicts.

[15] See Figure A-5 for a comparison of the economic costs of earthquakes versus common climate-related natural disasters.

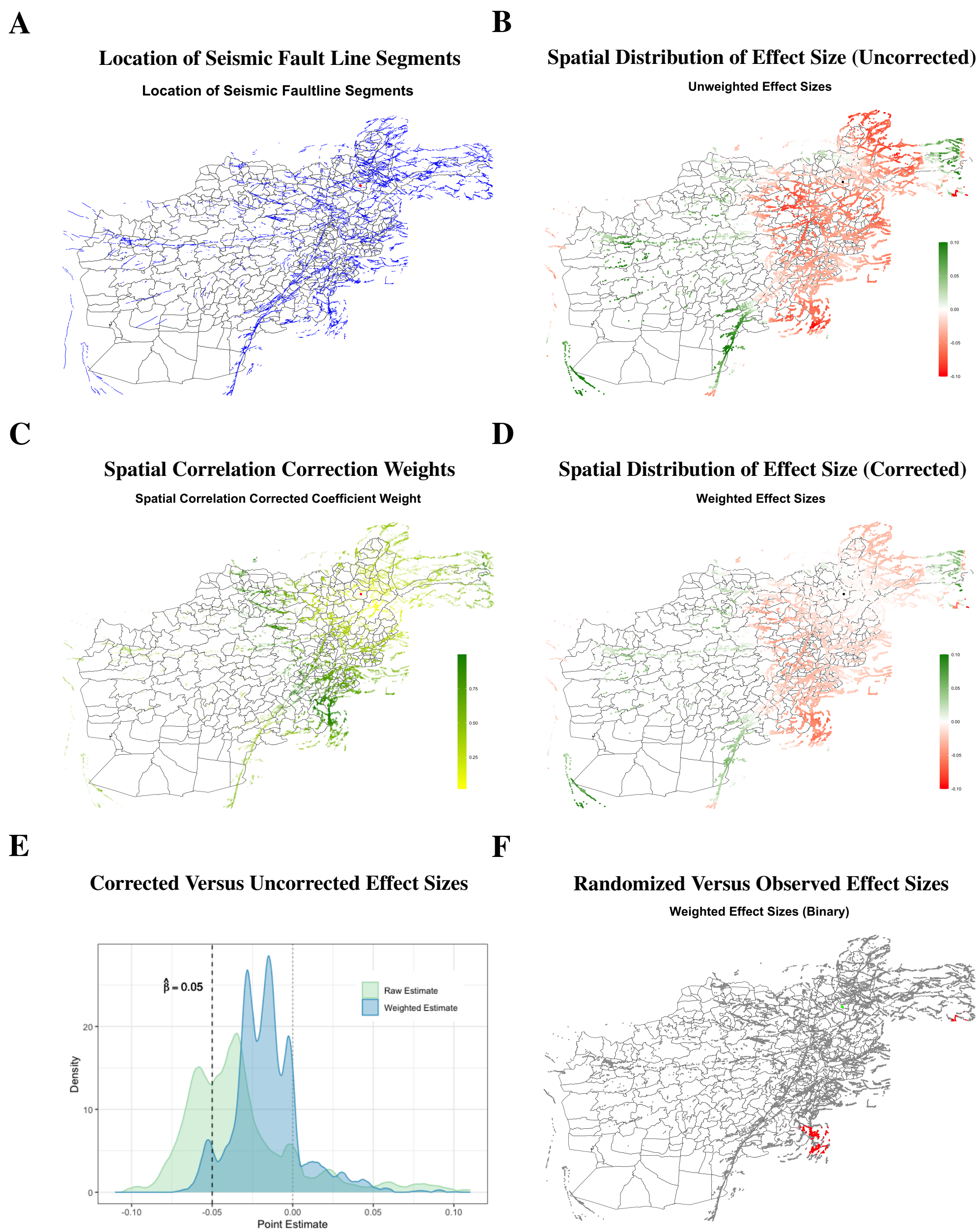


Figure 3: Spatial Correlation Corrected Randomization Inference Test

Panel (A): True location of fault lines throughout Afghanistan. Panel (B): Estimated treatment effects without correcting for spatial correlation. Panel (C): Correction weights calculated employing correlation of randomized versus true treatment status. Panel (D): Estimated treatment effects with correction for spatial correlation. Panel (E): Distribution of corrected versus uncorrected coefficient estimates. Observed estimate noted by dashed vertical line. Panel (F): Comparison of randomization-derived estimates versus observed estimate. Gray points indicate epicenters with estimated effects less extreme than the observed estimate. Red points indicate epicenters with estimated effects more extreme than the observed estimate. The majority are clustered in the vicinity of Kabul which despite its distance from the true epicenter suffered large economic losses from the 2015 earthquake.

References

Alberto Abadie. Bootstrap Tests for Distributional Treatment Effects in Instrumental Variable Models. *Journal of the American Statistical Association*, 97(457):284–292, 2002.

Joshua D Angrist and Jörn-Steffen Pischke. *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton University Press, 2008.

Angela K Archambault. Drug Treatment Centers in Afghanistan: Creating a Participatory Approach to Tackling the Drug Trade. Technical report, NAVAL POSTGRADUATE SCHOOL MONTEREY CA DEPT OF NATIONAL SECURITY AFFAIRS, 2012.

Timothy Besley and Torsten Persson. The logic of political violence. *Quarterly Journal of Economics*, 126(3):1411–1445, 2011.

Graeme Blair, Kosuke Imai, and Jason Lyall. Comparing and Combining List and Endorsement Experiments: Evidence from Afghanistan. *American Journal of Political Science*, 58(4): 1043–1063, 2014.

Graeme Blair, Rebecca Littman, Elizabeth R. Nugent, Rebecca Wolfe, Mohammed Bukar, Benjamin Crisman, Anthony Etim, Chad Hazlett, and Jiyoung Kim. Trusted authorities can change minds and shift norms during conflict. *Proceedings of the National Academy of Sciences*, 118(42), 2021. ISSN 0027-8424. doi: 10.1073/pnas.2105570118. URL https://www.pnas.org/content/118/42/e2105570118.

Central Statistics Organization of Afghanistan. Afghanistan Statistical Yearbook, 2016-2017. Technical report, Government of Afghanistan, 2018.

Jacobus Cilliers, Oeindrila Dube, and Bilal Siddiqi. Reconciling after civil conflict increases social capital but decreases individual well-being. *Science*, 352(6287):787–794, 2016.

Paul Collier and Anke Hoeffler. On Economic Causes of Civil War. *Oxford Economic Papers*, 50(4):563–573, 1998.

Paul Collier and Anke Hoeffler. Greed and grievance in civil war. *Oxford Economic Papers*, 56 (4):563–595, 2004.

Luke N Condra and Austin L Wright. Civilians, Control, and Collaboration during Civil Conflict. *International Studies Quarterly*, 63(4):897–907, 08 2019.

Luke N. Condra, James D. Long, Andrew C. Shaver, and Austin L. Wright. The logic of insurgent electoral violence. *American Economic Review*, 108(11):3199–3231, 2018.

Ernesto Dal Bó and Pedro Dal Bó. Workers, warriors, and criminals: social conflict in general equilibrium. *Journal of the European Economic Association*, 9(4):646–677, 2011.

Stephen G Donald and Kevin Lang. Inference with Difference-in-Differences and Other Panel Data. *The Review of Economics and Statistics*, 89(2):221–233, 2007.

Oeindrila Dube and Juan F Vargas. Commodity Price Shocks and Civil Conflict: Evidence from Colombia. *The Review of Economic Studies*, 80(4):1384–1421, 2013.

Thiemo Fetzer, Pedro CL Souza, Oliver Vanden Eynde, and Austin L. Wright. Security transitions. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-176), 2020.

Paula Hanasz. Appeasing 'upset brothers': an introduction to the Afghanistan Peace and Reintegration Program. *Australian Journal of International Affairs*, 66(2), 2012.

Jack Hirshleifer. *The Dark Side of the Force: Economic Foundations of Conflict Theory*. Cambridge University Press, 2001.

Daniel E Ho and Kosuke Imai. Randomization Inference With Natural Experiments: An Analysis of Ballot Effects in the 2003 California Recall Election. *Journal of the American Statistical Association*, 101(475):888–900, 2006.

Solomon Hsiang, Robert Kopp, Amir Jina, James Rising, Michael Delgado, Shashank Mohan, DJ Rasmussen, Robert Muir-Wood, Paul Wilson, Michael Oppenheimer, et al. Estimating Economic Damage from Climate Change in the United States. *Science*, 356(6345):1362–1369, 2017.

Macartan Humphreys and Jeremy M Weinstein. Demobilization and Reintegration. *Journal of Conflict Resolution*, 51(4):531–567, 2007.

Stathis N Kalyvas. *The Logic of Violence in Civil War*. Cambridge University Press, 2006.

Jason Lyall, Yuki Shiraito, and Kosuke Imai. Coethnic Bias and Wartime Informing. *Journal of Politics*, 77(3):833–48, 2015.

Andreu Mas-Colell, Michael D. Whinston, and Jerry R. Green. *Microeconomic Theory*. Oxford University Press, 1995.

Edward Miguel, Shanker Satyanath, and Ernest Sergenti. Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of Political Economy*, 112(4):725–753, 2004.

Cyrus Samii. Causal Empiricism in Quantitative Research. *The Journal of Politics*, 78(3): 941–955, 2016.

Josef Schmidhuber and Francesco N Tubiello. Global food security under climate change. *Proceedings of the National Academy of Sciences*, 104(50):19703–19708, 2007.

Sonia I Seneviratne, Neville Nicholls, David Easterling, Clare M Goodess, Shinjiro Kanae, James Kossin, Yali Luo, Jose Marengo, Kathleen McInnes, Mohammad Rahimi, et al. Changes in Climate Extremes and their Impacts on the Natural Physical Environment. 2017.

Konstantin Sonin and Austin L. Wright. Rebel capacity and combat tactics. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2018-74), 2020.

Irma Specht. Socio-Economic Reintegration of Ex-Combatants. *London: International Alert*, 2010.

Mohammad Osman Tariq, Najla Ayoubi, and Fazel Rabi Haqbeen. Afghanistan in 2010: A Survey of the Afghan People. Technical report, The Asia Foundation, 2010.

UN OCHA. Afghanistan Earthquake: OCHA Situation Report No. 1 (As of 5 November 2015). Technical report, United Nations Office for the Coordination of Humanitarian Affairs, 11 2015a.

UN OCHA. Afghanistan Earthquake: OCHA Situation Report No. 4 (As of 23 November 2015). Technical report, United Nations Office for the Coordination of Humanitarian Affairs, 11 2015b.

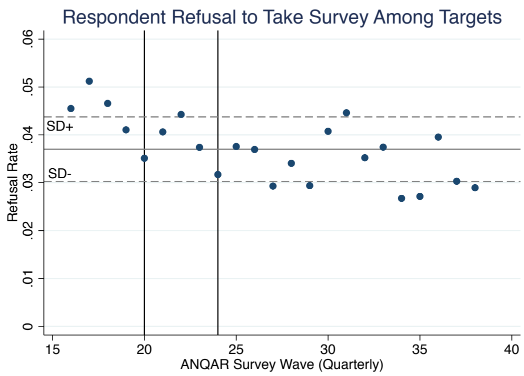
UNHCR. Badakshan Earthquake Response Evaluation Assessment. Technical report, United Nations High Commissioner for Refugees, 12 2016.

United Nations. United Nations Policy for Post-Conflict Employment and Reintegration. Technical report, United Nations Office of the Secretary-General, 2009.

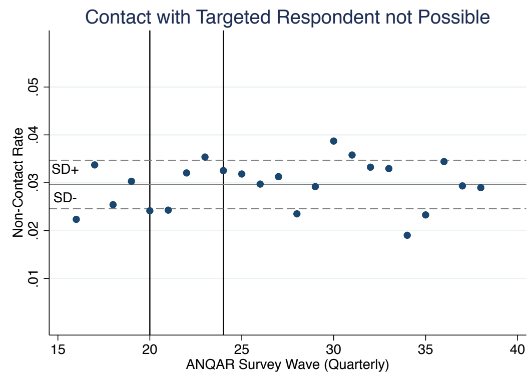
United Nations Office for Disaster Risk Reduction. 26 October 2015 Badakshan Afghanistan and Pakistan Earthquake Disaster Risk Reduction Situation Report: DRR sitrep. *Technical Report*, 2015.

APPENDIX

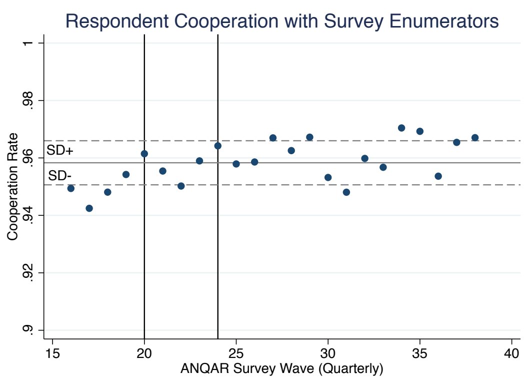
A1 Additional Figures



(a) Refusal rate



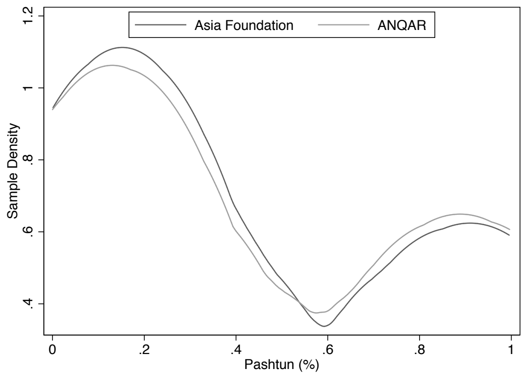
(b) Non-contact rate



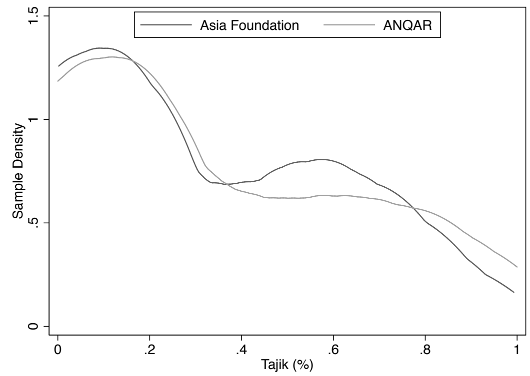
(c) Cooperation rate

Figure A-1: ANQAR diagnostics during later waves (16-38) conducted by firm collecting ANQAR (ACSOR).

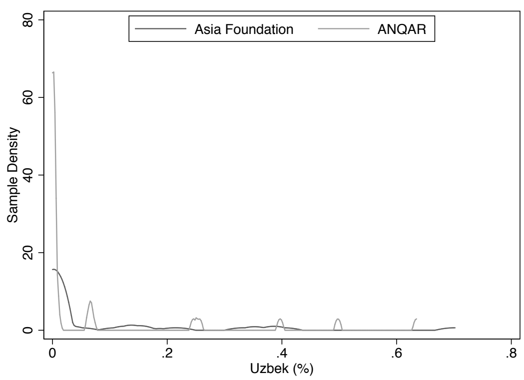
Data on refusal, non-contact, and overall cooperation were shared with the authors by NATO. Author's own calculations.



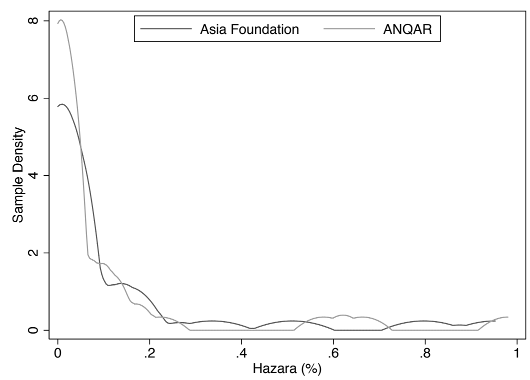
(a) Pashtun (%)



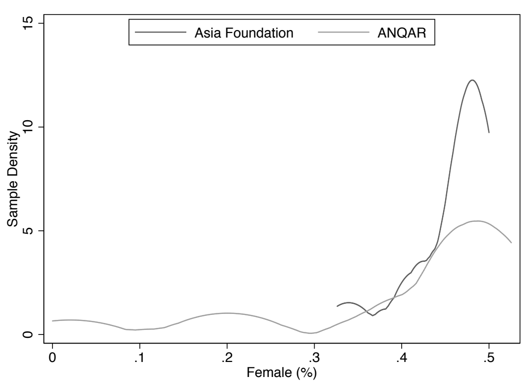
(b) Tajik (%)



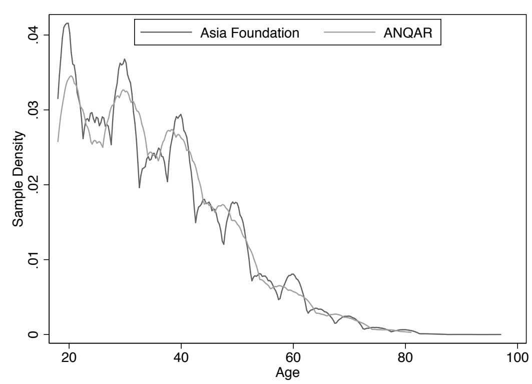
(c) Uzbek (%)



(d) Hazara (%)



(e) Female (%)



(f) Age

Figure A-2: Comparison of ANQAR and Asia Foundation Demographic Data.

Panels A-E are province averages of binary demographics; Panel F uses individual-level age data (continuous). Asia Foundation data includes information from 2006 to 2018 and is plotted in black; ANQAR is plotted in gray. Demographics are highly consistent across the two data sources.

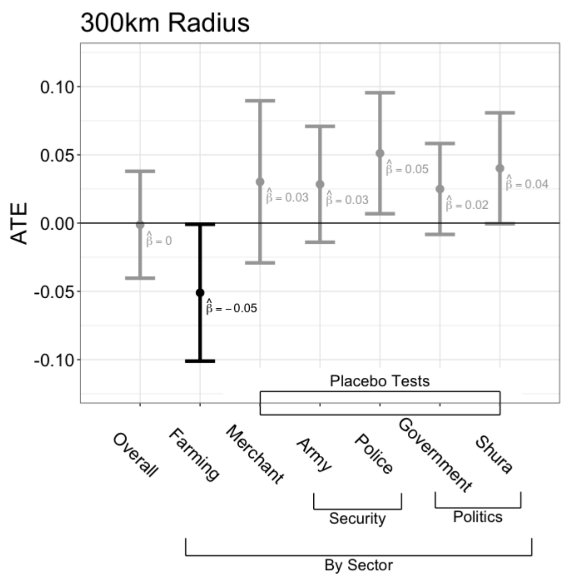


Figure A-3: Additional Sensitivity Tests for Treatment Classification using distance-based measure.

Additional regression controls include: number of persons living in the household; number of persons present during the interview; the level of comfort of the respondent; the level of understanding exhibited by the respondent; security condition in the village; government control over the respondent's village or neighborhood (mantaqa); patrol frequency of government forces.

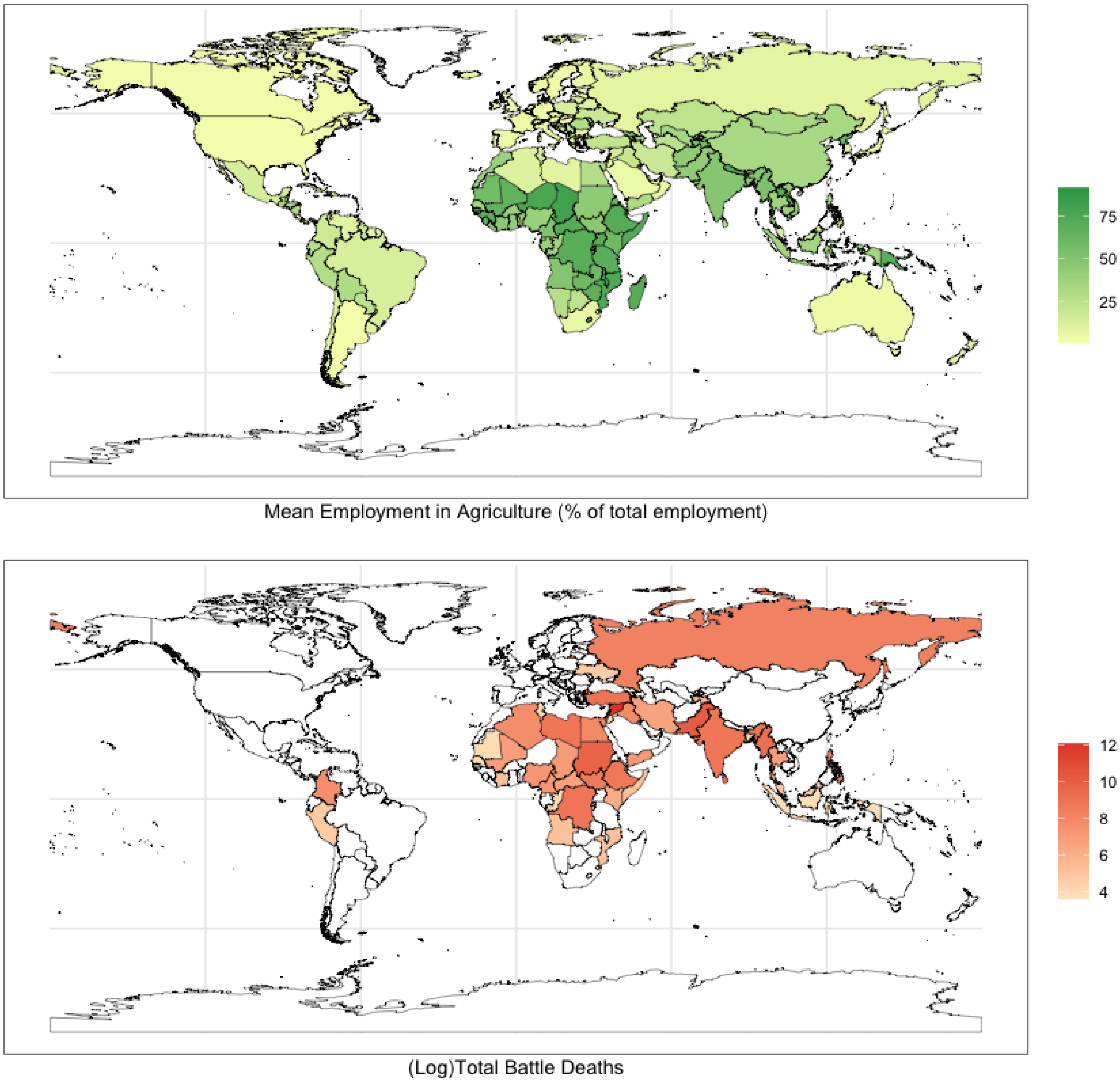


Figure A-4: Agricultural Reliance in Conflict-Prone States, 2008-2017

Agricultural employment obtained from the World Bank's Word Development Indicators database. Battle deaths obtained from Uppsala Conflict Data Program.

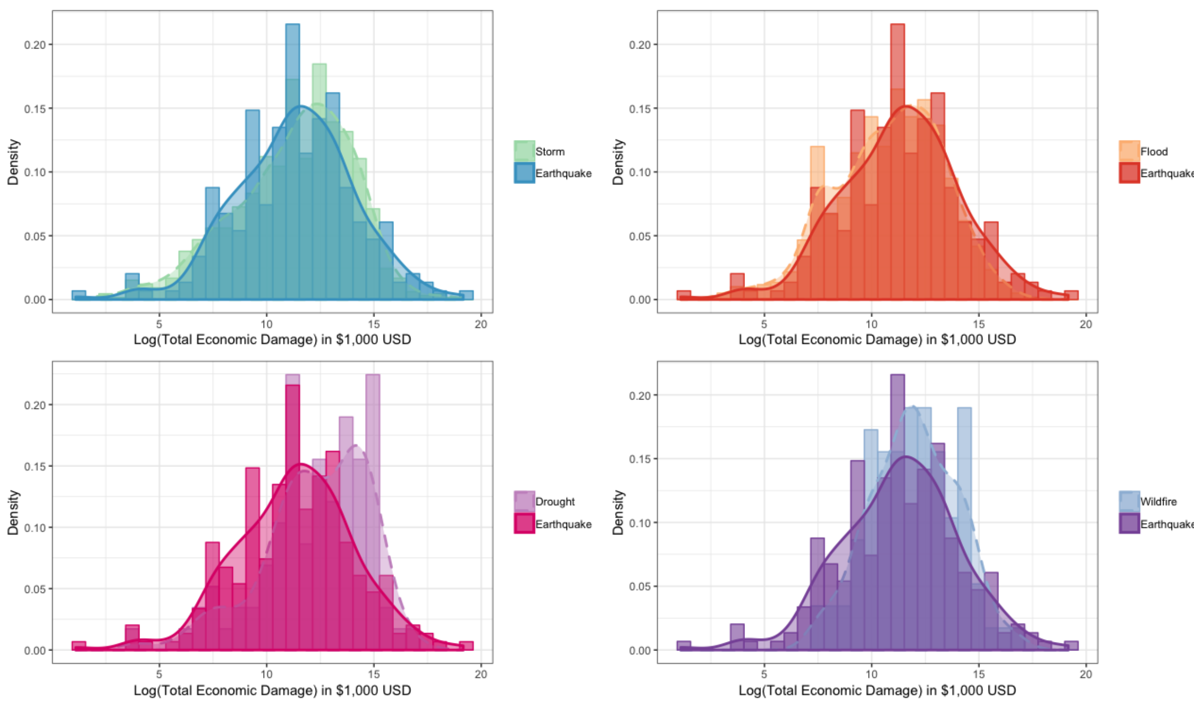


Figure A-5: Economic Damage from Earthquakes Vs. Other Disasters

Damage estimates obtained from the EM-DAT database.