We Don't Need No Education: Reconstruction and Conflict across Afghanistan

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Abstract

Field interviews conducted by the author in Afghanistan suggest current theories linking conflict to development do not adequately account for ideological drivers of resistance. We present a model demonstrating how reconstruction/development led by a foreign occupier can exacerbate violence through popular discontent, if projects are ideologically controversial. We test the model using detailed data on military-led reconstruction and public opinion from NATO, and a US-Government violence log covering Afghanistan from 2005 until 2009. We find projects in the health sector successfully alleviate violence, whereas those in the education sector actually provoke conflict. The destabilizing effects of education projects are strongest in conservative areas, where public opinion polls suggest education projects breed antipathy towards international forces. Further underscoring the role of local perceptions, project-driven violence appears to be homegrown, rather than sourced externally. Our findings do not support competing theories; are not driven by reverse causation; and are robust when considering many sources of endogeneity.

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"We're invariably going to get it wrong. Let's be honest, it's almost impossible to avoid unintended consequences of our work here. I think that's a really important premise." (major reconstruction donor, field interview 2013)

"Education can be the cause of violence in some Southern provinces... If there is no school, no teacher, no education, they will not target that village!" (Afghan NGO, field interview 2013)

More than a decade of Western engagement in Afghanistan and Iraq has brought not even a semblance of peace and security to either country. The ongoing conflicts have collectively claimed the lives of over 180,000 civilians and over 8,000 foreign troops, and casualty rates are not in systematic decline.[1] In conjunction with military force operations, a major cornerstone of both interventions has been reconstruction activity. To this end, the US Government alone has doled out over USD 80 billion in Iraq (SIGIR 2013), and over USD 100 billion in Afghanistan (SIGAR 2014). This endeavour is guided by the 'hearts and minds' credo, which maintains that development improves community cooperation in the fight against rebels, and provides alternative economic opportunities for would-be insurgents.[2] But to this end, the effort has met little apparent success. As of 2015, ISIS controlled numerous population centers in Iraq (CFR 2015), and the Taliban governed significant portions of Afghanistan (TLWJ 2015). Between 2003 and 2007, attacks on coalition forces exhibited an accompanying rise with the upward trend in reconstruction work carried out in both countries, and yet reconstruction proceeded unabated thereafter (ACSP; FPDS; GTD).

In recent years, occupation forces have re-engaged in Iraq, and progressively withdrawn from Afghanistan. As international security forces draw down in Afghanistan, reconstruction and aid programs follow suit. Internationally funded development spending has constituted a considerable share of total Afghan economic activity in recent years, so many fear its contraction will have unwanted security ramifications. Importantly though, it is debatable whether reconstruction work was ever helpful to stability in the first place.

Government officials, political pundits, think tank analysts, military personnel, and many academics maintain Western intervenors have learned much from their experiences. The importance of community involvement, cultural sensitivity, and intel-based combat tactics are often discussed in this respect. Western governments have long been aware of these, at least since military engagements in Malaya and in Vietnam (Gentile 2013). Yet there is scant

[1] Number of civilian deaths is aggregated across https://www.iraqbodycount.org and UNAMA (2016). Foreign troop deaths are calculated from http://icasualties.org.

[2] In fact, the U.S. Army Marine Corps Counterinsurgency Field Manual explicitly incorporates reconstruction work as a mainstay of COIN strategy. Civil Security, Civil Control, *Essential Services*, Governance, and *Economic and Infrastructure Development* comprise the Stability pillar of COIN strategy (see Figure 1-1, U.S. Army, emphasis added).

empirical evidence that soft counterinsurgency (i.e. reconstruction) has become effective at inducing stability. To date, in the public domain there exist very few evidence-based assessments of reconstruction efforts (Zyck 2011). Raw data on US project outlays in Iraq are available for analysis only by researchers pre-authorized by US-military. Data on NATO-country reconstruction spending in Afghanistan is unclassified, but the required clearance is prohibitive (data used herein was physically procured from an extant, official hardcopy source in Kabul). Military data on violence in both Afghanistan and Iraq is classified. The limited body of research on this topic supports military and government rhetoric asserting reconstruction enhances stability. The work presented in this paper explores instead the antithesis - reconstruction can foment violence.

The greater reconstruction effort is comprised of projects carried out in a number of sectors including agriculture, health, education, security, and transport, amongst others. We postulate that local communities welcome the involvement of foreign military forces in some spheres of development activity, but oppose it in other, more controversial areas. Some projects have an ideological charge - they change institutions reflecting cultural, social, or political sensitivities. These types of projects may evoke popular resistance, which can manifest as either material, informational, or participatory support for the insurgency. Other projects are ideologically neutral, whose benefits are universally accepted. Those types of projects are more readily welcomed, and are therefore more likely to mitigate conflict in the manner typically conceived from the hearts and minds perspective. By consequence of these opposing forces, we expect security to ebb and flow in response to the overarching character of the reconstruction effort.

We formalize our theory by building a model of reconstruction spending, insurgency, and community preferences, from which we derive testable implications. To operationalize our model's predictions, we conjecture that security and education are two controversial sectors, whereas health interventions are welcomed by local communities. This intuition is reinforced by field interviews conducted by the author with key reconstruction stakeholders in Kabul, in November 2013. This fieldwork comprised 21 unstructured on-site interviews with major government donors (9); private companies in receipt of reconstruction contracts (3); local NGOs (2); foreign NGOs (2); local research organizations (2); journalists (2); and a special forces operative (1). The material gleaned from the recorded interviews is used to support the theoretical foundation of our formal theory, to guide our analysis, and to interpret our findings.[3]

The bulk of this paper lies in our empirical analysis for Afghanistan. We merge together a variety of unique datasets, including: reconstruction and development data from the NATO C3 Agency's *Afghanistan Country Stability Picture*; public opinion data from the NATO

[3]The specific identities of interviewees is withheld; we cite them instead in general terms (e.g. Foreign Company M 2013; Afghan NGO J 2013). Some exact identities may be available, however, upon request.

Communications and Information Agency's *Afghanistan Nationwide Quarterly Research*; violence data from the National Counterterrorism Center's *Worldwide Incidents Tracking System*, and the US Department of Homeland Security's *Global Terrorism Database*; and district characteristics from the Afghanistan Central Statistics Organization's *National Risk and Vulnerability Assessments*. The combined panel data covers 398 districts across Afghanistan, from 2005 until 2009.

We measure the impact on violence of military-led Provincial Reconstruction Team (PRT) projects. Health projects appear to improve stability; education projects have the opposite effect. The findings are economically significant. Specifically, in an average-sized district of 63,000 inhabitants, a one-standard-deviation increase in the number of health projects (corresponding to 1.6 projects/month) led to a reduction in expected violence by one-third (from an average of 1 incident per 5 months). On the other hand, a one-standard-deviation increase in education programming (1.4 projects/month) is associated with a 20% escalation in violent incidents. We find these effects to be exacerbated in the South of the country, where conservatism is most pronounced. Across the South, we also provide evidence that education programming breeds popular antipathy towards the international forces (ISAF). Moreover, our spatial analysis suggests project-fuelled violence is sourced within-district, rather than attracting Taliban from outside. This lends credence to our theoretical interpretation highlighting the importance of local community preferences. By contrast, we are unable to provide evidence in support of other prevailing theories linking conflict to development (such as opportunity cost or rent seeking models) in the short- to medium-run. We demonstrate our findings are not explained by reverse causation or missing data; and we rule out civil society development aid and time invariant district characteristics as confounding factors. In the Appendix we employ instrumental variables by exploiting PRT command shifts as a source of exogenous sectoral spending. Our results are also robust to this alternative identification strategy.[4]

We formally introduce the possibility that foreign-led development can be opposed on ideological grounds. This constitutes a sharp theoretical departure from a literature which consistently characterizes insurgent activity as a financial decision. Guided by theory, we evaluate differential effects across reconstruction sectors. Another contribution lies in our use of quarterly public opinion polls conducted across Afghanistan. We are the first to analyze such dynamic public opinion data in a conflict zone. Finally, we contribute to identification by discussing the presence of, and potential confound arising from, other independent development programs. This is an outstanding concern in both observational studies, and studies based on interventions where treatment was randomly assigned *at the time of*

[4]In the appendix we also show our results are not driven by any individual region, nor by female-oriented projects. Further, significant differences do not exist between the impact of construction- and service-type projects.

implementation. By virtue of our database, which ostensibly covers all military and civil reconstruction and development activities, we are able to account for such complications.

1 LITERATURE

The large theoretical literature on civil conflict (surveyed by Blattman and Miguel 2010) attributes violence almost exclusively to economic motives. Opportunity cost models portray conflict as an economic activity. The more attractive are employment options in the licit sector, the more likely are insurgents to defect from paid rebellion. Reconstruction and development projects increase the payoff and prevalence of formal sector work, and would thus be expected to increase stability. While this theoretical characterization of violent political resistance is readily embraced by economists, the empirical evidence for economic drivers of conflict is highly contested. Collier and Hoeffler (2004) present cross-sectional country level evidence that conflict negatively correlates with economic aggregates; the result was overturned by Djankov and Reynal-Querol (2010), however, by introducing country fixed effects. Some micro-level studies have supported opportunity cost models of rebellion (Iyengar, Monten, & Hanson 2011; Dube & Vargas 2013), but many others have cast doubt on their external validity (Krueger & Malecková 2003; Berrebi 2007; Berman, Callen, Felter, & Shapiro 2011).

Rent seeking models - a separate theoretical camp - consider violence as a competition over resources. The greater is the economic value of the territory being contested, the stronger is the incentive to gain control over that territory, and therefore the more intense the conflict will be. In this framework, reconstruction/development programming could actually spur violence as it increases the rents associated with victory in a conflict. Some recent empirical studies support the reduced form relationship between development spending and violence predicted in this framework (Dube & Vargas 2012; Nunn & Qian 2013; Crost, Felter, & Johnston 2014). These studies do not, however, test the causal channel driving those results.

As distinct from the above characterizations, an 'information-centric' theory has been formalized for specific application to the context of post-conflict reconstruction. Berman, Shapiro, and Felter (BSF 2011) suggest reconstruction efforts mitigate violence by winning over the hearts of community members with public goods. In exchange for development projects, the populace shares information with the government in the fight against insurgents, thereby enabling it to more effectively quell insurgency.

BSF (2011) provide evidence that Commander's Emergency Response Program (CERP) spending mitigates violence in Iraq, but the effect is concentrated in a period of increased troop strength (and statistically insignificant in the remaining sample years). The paper does not test whether community-provided information is more forthcoming in face of increased

reconstruction spending, or whether information indeed tempers the effectiveness of counterinsurgency.[5] Chou (2012), Child (2014), and Adams (2015) all replicate the analysis of BSF (2011) for Afghanistan, examining separate time periods by use of different data sources. The impact of CERP programming on violence in Afghanistan is statistically indistinguishable from zero in the first two replication studies. Adams (2015) provides some evidence that small CERP projects reduce violence while large projects actually *increase* violence. Sexton (2015) suggests CERP activity generally exacerbates violence in districts not fully controlled by international forces. The findings offer support for a theory which casts insurgency as a strategic response to the entrenchment of control by international/government forces. Still other work suggests National Solidarity Program (NSP) spending in Afghanistan improves community perceptions of government, and translates into reduced violence (Beath, Christia, & Enikolopov 2016).[6] Importantly, the NSP is of an altogether different nature than the CERP; while NSP is locally administered, the CERP is carried out by foreign commanders. From our theoretical perspective, this difference can reconcile the divergent outcomes we observe across these programming efforts.

To be sure, the state of empirical work on this topic is largely divided, failing to provide general support for any existing theory of violence. A flurry of evidence alternately supporting and refuting existing theoretical work has left this vein of inquiry in a state of uncertainty. We suggest the empirical link between violence and development (and reconstruction in particular) is unresolved because the accompanying theory has not acknowledged ideological drivers of conflict. In what follows, we set out to help remedy this deficiency.

2 THEORETICAL FOUNDATION

We introduce a general theoretical framework in which reconstruction affects violence through community perceptions. From our model we derive testable implications. Community members are the support upon which rebellion rests. The size of the insurgency in equilibrium therefore depends on how ideologically controversial the reconstruction effort is perceived to be. Not all spending is equivalent in the view of the community. A foreign built police station may elicit an ideological opposition amongst the populace that a road construction project would not. Depending on how mismatched are an occupier's objectives with preferences of community members, occupiers choose equilibrium spending patterns that engender resistance to a greater or lesser degree. Violent equilibria are feasible because, pragmatically, the occupier pursues overarching political and economic goals through the reconstruction

[5] Berman, Felter, Shapiro, and Troland (2013) provide evidence for complementarity between military control and service provision in reducing violence.

[6] The effect on violence is reversed, however, in two districts near the Pakistan border.

effort, which are only indirectly related to security of the host nation.

This theoretical framework characterizes insurgency as a response to reconstruction programming. But importantly - by adopting this perspective, we by no means refute the existence of other drivers of conflict, which can be independent of government and occupier actions. To the contrary, we acknowledge sectarian strife, warlordism, ethnic tensions, and even economic greed are in many cases stronger determinants of insurgency in both Iraq and Afghanistan than the explanation we proffer here. However, the margin on which the occupier can influence outcomes in this context is arguably restricted to military posturing and reconstruction. Given the invocation of 'hearts and minds' doctrine to justify the latter (to the tune of USD 100 billion for the US in Afghanistan), we endeavour to explore the validity of that approach. Therefore, we theoretically abstract from conflict drivers which may be considered exogenous as we discuss the marginal impact reconstruction can have on violence. In what follows, we present the theoretical motivation for our formal model by substantiating its foundational assertions with material gleaned from field interviews conducted by the author in Kabul, Afghanistan (November 2013), as well as empirical evidence drawn from the literature.

2.1 Ideological controversy

The first critical assumption of our theory is that reconstruction activities can be unwelcome by some community members on ideological grounds. Intercepted correspondence between high-level al-Qaeda members reveals their opposition to Western-led development (CTC 2007a). A Taliban night letter, for example, warned Afghans against opening schools, and working with foreign companies (CTC 2009). Some Taliban opposed PRT projects on face value, because they are seen as ideologically driven (Research Organization C 2013); and any project tied to the military carries potential to elicit conflict (Donor D 2013). But also across the broader community, reconstruction work can be ill-perceived. Böhnke, Koehler, and Zürcher (2010) indicate development aid in northeast Afghanistan, from 2007-2009, is negatively correlated with approval of foreign forces, and congruence with Western values.[7] Moreover, Böhnke and Zürcher (2013) show that development projects have (if any) a negative effect on Afghan attitudes towards foreigners. In sum, evidence suggests reconstruction and development can be perceived as ideological, and can generate unfavourable views towards foreign forces and the intervention.

Our model is further premised on the notion that reconstruction work is perceived differently across sectors. Records of al-Qaeda correspondence reflect sensitivity to foreign involvement in the oil industry (CTC 2007c; CTC 2006), in the media (CTC 2007b), and in

[7]The same analysis suggests development aid from 2005-2007 had no impact on how foreign forces are perceived, and is positively correlated with Western values.

education (CTC 1999). The magazine *Jihad* stated "among the most dangerous things that the West introduced in order to put an end to Islam in the long-term are the curriculums that concentrated on demolishing the language, the religion and Islamic history" (CTC 2007b, 2). Many field interviews by the author with reconstruction stakeholders in Kabul support the notion that security and education programming can be particularly controversial (Afghan Company 2013; Donor E 2013; Journalist F 2013; Donor G 2013; Donor H 2013).[8] Regarding education, curriculum design is a common point of contention and negotiation between insurgents and the international community (Foreign NGO I 2013; Research Organization C 2013). Frictions are exacerbated when education projects become associated with military, as one local NGO contends - three of their staff were killed after a successful project in the South was monitored by armoured vehicles (Afghan NGO J 2013). We do not contend education or security development is controversial in its own right, but can become controversial when perceived to be undertaken by an occupying force. Field interviews substantiate the notion that projects tied to foreign military face resistance on that basis (Foreign Company P 2013; Journalist F 2013). By contrast, health programming provides immediate concrete benefits (Foreign NGO K 2013), and is far more innocuous from an ideological perspective (Journalist F 2013; Donor G 2013; Donor H 2013). Interview respondents generally agree that health projects provide basic services that even Taliban members appreciate for their families, and for themselves (Afghan NGO J 2013). Such projects are not overly controversial, regardless of implementing agent.

So according to the above, community members (including extreme elements) are discerning in their perceptions among different types of development projects. Education seems to be particularly controversial (and potentially also security), whereas health is widely appreciated. Interviews conducted by Jackson and Giustozzi (2012) support this conclusion by suggesting health clinics (among other projects) are well received, while education can be controversial (depending on whether the project is oriented towards girls, and whether foreign teachers are involved).

2.2 Occupier self-interest

If it is true that certain types of foreign-led development are controversial, but others are not, then why should the occupier insist on programming in sensitive sectors? Because the occupier has its own aims regarding reconstruction spending, and these are shaped by political and economics considerations at home. Government donors face enormous pressure to expend resources as a metric for success, and so local sensitivities are secondary concerns in this pursuit (Donor G 2013; Donor E 2013). This problem is especially pronounced in the projects

[8] It should be noted, however, that some respondents claimed reconstruction unambiguously improves security (Special Forces 2013; Donor A 2013; Donor B 2013).

of PRTs (Foreign NGO I 2013). The allocation of funds across program sectors is a domestic political decision made in consultation with parliamentarians at home, and based more on national priorities (Donor L 2013; Donor H 2013) or global poverty solutions (Donor L 2013; Donor E 2013) than on local preferences. That reconstruction and development is not purely an altruistic pursuit is well understood by private contractors (Afghan Company 2013; Foreign Company M 2013), and by Afghans themselves (Donor N 2013). As one official of a major Western donor candidly admitted:

> Every project here is hugely political. It's all part of a big political process. There are many, many projects around the country which I'm sure have a strong economic justification for doing them. And maybe a strong social justification for doing them. But overriding all of that are strong political reasons for doing them (Donor E 2013).

The above sentiment is shared by a host of other development stakeholders on the ground (Afghan NGO J 2013; Journalist F 2013; Donor G 2013).

2.3 Community-supported insurgency

A final theoretical assumption is that community discontent can lead to violent resistance. That insurgents appear partly motivated by ideological grievances (CTC 1999) supports this assumption. But many interview respondents further suggest the broader community can also mobilize in response to reconstruction-related grievances (Afghan NGO O 2013; Foreign NGO I 2013; Journalist F 2013; Donor H 2013; Donor A 2013). If readers are skeptical that insurgents are drawn from the community itself, they can imagine community members simply *support* the insurgency instead. Such support could manifest as material or labour contributions, but could also be as benign as withholding information from the government and international forces. Joining the side of the occupier, in this case, would entail withdrawing support from insurgents by preventing them from entering one's village, from planting IEDs, etc (Special Forces 2013). This characterization can be reconciled with the information-centric theory of BSF (2011), with the important qualification that some types of reconstruction projects *deter* the community from co-operating with the government.

3 MODEL

Our work builds on a fully parameterized model sketched in Child and Scoones (2015). Reconstruction and insurgency is a one shot game played between two types of agents: a single occupier, and a continuum of community members. All possible reconstruction output

falls into one of two 'sectors' - g or b. The occupier seeks to maximize utility through its allocation of reconstruction spending across these two sectors. Each community member either supports the insurgency or co-operates with the occupier, depending on their relative distaste for the mix of reconstruction projects chosen by the occupier. As above, 'supporting the insurgency' implies a contribution to violence which reduces reconstruction output. The occupier moves first in anticipation of the reaction of the community; individual community members then choose whether or not to resist reconstruction by supporting the insurgency. The combination of occupier spending and community resistance determines the level of reconstruction output and payoffs, and the game ends.

3.1 Preferences & Technology

Utility of the occupier in our model, $V(g, b)$, depends positively on reconstruction output in both sectors, but exhibits decreasing marginal returns (hence $V_g > 0$, $V_b > 0$, $V_{gg} < 0$, and $V_{bb} < 0$). Utility of all community members i, $U^i(g, b; \alpha_i)$, depends positively on provision of sector g projects ($U^i_g > 0$), and negatively on the presence of sector b activities ($U^i_b < 0$), to an extent determined by the preference parameter α_i. So there is a tension between occupier and community preferences, and the notation g and b is used as a shorthand for 'good' and 'bad' in accordance with the community's perception of the reconstruction effort. Community member utility exhibits decreasing marginal returns to both the good and the bad (hence $U^i_{gg} < 0$ and $U^i_{bb} < 0$). In this sense, the bad sector is similar to a pollutant whose marginal damage becomes more severe at high levels of output. For simplicity, marginal utility of the good also declines with greater output of the bad (i.e. $U^i_{gb} \leq 0$), implying it becomes difficult to appreciate beneficial projects in the presence of ever more controversial reconstruction activities. Later we demonstrate an equilibrium based on a parameterization which relaxes this condition. Lastly, the individual parameter α_i positively affects the marginal utility derived from reconstruction (in particular, $U^i_{b\alpha_i} > 0$, and $U^i_{g\alpha_i} \geq 0$), and is drawn from a distribution such that $\alpha_i \in [0, \infty)$.[9]

The occupier faces convex reconstruction costs $C(G, B)$, such that $C_G > 0$, $C_B \geq 0$, $C_{GG} \geq 0$, $C_{BB} \geq 0$, and $C_{GB} \geq 0$. G is sector g spending, and B is sector b spending; both of which ultimately translate into output. The output $g(G, R)$ depends on sector-spending and the level of community resistance in R, such that $g_G > 0$ and $g_R < 0$. We impose $g_{GG} \leq 0$, implying constant or decreasing marginal returns; and $g_{RG} < 0$, implying the resistance becomes absolutely more destructive in the presence of greater reconstruction spending. The conditions on output $b(B, R)$ are defined analogously. The level of resistance R is calculated as

[9] One class of admissible utility functions adequately fulfilling these criteria are $U^i = \alpha_i f(g, b) - h(b)$, where f is positive, concave, and increasing in both its parameters, and h is positive, convex, and increasing. For example, $U^i = \alpha_i \sqrt{gb} - b^2$, or $U^i = \alpha_i[\ln g + \ln b] - b^2$. Alternatively, the following class is also admissible: $U^i = f(g, b) - (1/\alpha_i)h(b)$, under the same conditions.

a population share, based on the individual participation decisions r^i which will be discussed in what follows.

3.2 Equilibrium

An equilibrium is a utility maximizing choice by the occupier of a spending bundle (G^*, B^*); and a utility maximizing decision by each community member whether to resist reconstruction, characterized by a threshold value α_i^* in the set of community members. Community members observe the spending allocation of the occupier before deciding whether to support the resistance; the occupier knows this and chooses an allocation with rational expectations of the coming level of resistance. The equilibrium obtained is a Stackelberg (subgame perfect Nash) equilibrium. To solve the model, we first calculate the response of community members to a given reconstruction spending: this determines R as a function of B and G. Using this and the output functions, we characterize the occupier's optimization problem. From this, the occupier chooses the optimal spending mix, which ultimately depends on its preferences, community preferences, and the relationship between output and violence.

3.2.1 Resistance

Substituting the output functions into the community member utility function, we can express $U^i(g(G,R), b(B,R); \alpha_i)$. We can then determine the impact of the insurgency on individual utility through the total derivative:

$$\frac{dU^i}{dR} = \frac{\partial U^i}{\partial g}(g(G,R), b(B,R); \alpha_i)\frac{\partial g}{\partial R}(G,R) + \frac{\partial U^i}{\partial b}(g(G,R), b(B,R); \alpha_i)\frac{\partial b}{\partial R}(B,R) \quad (1)$$

where the first term on the right-hand side is negative, and the second term is positive. The sign of dU^i/dR indicates whether community member i would perceive himself to be better or worse off with a marginal increase in the size of the insurgency. By setting $\frac{dU^i}{dR} = 0$, we can extract the identity of the marginal insurgent (MI), described by α_i^* (herefrom α^*), who is just indifferent between a larger and smaller insurgency. It is straightforward to show the marginal benefit of insurgency (dU^i/dR) is monotonically decreasing in α_i,[10] and so it follows that the MI - α^* - is unique (if it exists, for a given R). Therefore, all community members for whom $\alpha_i > \alpha^*$ will not support the insurgency, and those for whom $\alpha_i < \alpha^*$ *will* support the insurgency. Thus, each individual's binary decision regarding whether to participate in the insurgency can be described by the assignment rule:

$$r^i = \begin{cases} 1 & \text{if} \quad \alpha_i < \alpha^* \Leftrightarrow dU^i/dR > 0 \\ 0 & \text{if} \quad \alpha_i \geq \alpha^* \Leftrightarrow dU^i/dR \leq 0 \end{cases}$$

[10]Note that R is not a function of the individual α_i parameter.

The total share of insurgency can then be calculated by integrating the individual participation decisions over the entire population distribution:[11]

$$R = \int_0^{+\infty} r^i(\alpha_i; g, b) f(\alpha_i) d\alpha_i = F(\alpha^*)$$

where $f(\cdot)$ is the density function pertaining to the distribution of α_i. In Appendix A we prove the solution above exists and is unique under some additional assumptions. It is worth mentioning that the model can also be solved in discrete form. In that case, $R = \sum_{i=1}^{N} r^i/N$, where N is the finite population measure. Under this discrete framework the individual contribution to insurgency is positive and measurable. We can then solve the model by eliciting the MI instead from the micro-founded condition: $\frac{dU^i}{dr^i} = \frac{\partial U^i}{\partial g}\frac{\partial g}{\partial R}\frac{dR}{dr^i} + \frac{\partial U^i}{\partial b}\frac{\partial b}{\partial R}\frac{dR}{dr^i} = 0$, which yields an analogous outcome since $\frac{dR}{dr^i} = \frac{1}{N} > 0$.[12] Having established that the two formulations are qualitatively equivalent, we proceed under the simpler and more elegant continuous framework.

Our primary concern is how the insurgency responds to sector-specific outlays. To see this, we first calculate the rate of change in the returns to insurgency with respect to spending on the bad sector. Because the MI alone contributes zero mass to the total size of insurgency, we examine the *instantaneous* rate of change in incentives for the MI, fixing the existing level of insurgency.[13] Using equation 1, we evaluate

$$\frac{d}{dB}\left(\frac{dU^i}{dR}\right) = U_b^i b_{_{RB}} + U_{bb}^i b_{_B} b_{_R} + U_{gb}^i b_{_B} g_{_R} > 0 \tag{2}$$

The first term on the right-hand-side is positive because the resistance is able to destroy more of the public bad (in an absolute sense), the more widespread it becomes ($b_{_{RB}} < 0$). The second and third terms capture second-order effects on marginal utility. The second term is positive because marginal destruction of sector b output yields greater utility benefit under comparatively higher levels of output ($U_{bb}^i < 0$). The third term is positive or zero, depending on whether additional output in b negatively influences the benefits derived from g ($U_{gb}^i \leq 0$). In sum, the individual returns to insurgency are higher (for the MI, and for all i of the community in fact) in response to larger injections of B spending. Accordingly, it must be true that the marginal insurgent faces *positive* returns to insurgency with an incremental increase in B, and therefore supports the insurgency. For the allocation with comparatively larger B, the

[11] $R = \int_0^{+\infty} r^i(\alpha_i; G, B) f(\alpha_i) d\alpha_i = \int_0^{\alpha^*} r^i(\alpha_i; G, B) f(\alpha_i) d\alpha_i + \int_{\alpha^*}^{+\infty} r^i(\alpha_i; G, B) f(\alpha_i) d\alpha_i = \int_0^{\alpha^*} (1) f(\alpha_i) d\alpha_i + \int_{\alpha^*}^{+\infty} (0) f(\alpha_i) d\alpha_i = F(\alpha^*)$

[12] Through this alternative framework, we could also account for participation costs to insurgency which, until now, have been assumed to be zero. The introduction of such costs would simply reduce the size of the insurgency in equilibrium, without affecting the tradeoffs central to our analysis.

[13] Imagine we take an injection to B sufficiently small to just suade the MI. In this case it is obvious the MI takes the prevailing level of R as given.

new marginal insurgent (α^{**}) lies somewhere further to the right on the distribution of α_i (i.e. $\alpha^{**} > \alpha^*$), and the insurgency is larger since $R = F(\alpha^{**}) > F(\alpha^*)$.

Hypothesis I: For a fixed level of spending in the good sector, and fixed community member preferences, an increase in outlays to the controversial sector will lead to growth of the resistance. Ceteris paribus, $\Delta R/\Delta B > 0$.

By contrast, the change in incentives arising from an injection of G takes the form

$$\frac{d}{dG}\left(\frac{dU^i}{dR}\right) = U^i_g g_{RG} + U^i_{gg} g_G g_R + U^i_{bg} g_G b_R$$

The first term on the right-hand-side is negative because absolute collateral damage (or intentional destruction) of public goods increases when they are more plentiful ($g_{RG} < 0$). The second term is positive, capturing the decline in valuation of marginal public goods subject to ruin by the insurgency. The third term is either zero or positive, depending on whether the removal of public bads becomes more attractive in the presence of public goods. Together the terms imply, surprisingly, that spending on G need not actually reduce the incentives for insurgency. In case the latter two terms dominate, a counterintuitive result emerges in which more public goods fuel resistance. Ultimately, the direction of the total effect will depend on the valuation of public goods, their diminishing returns, and the technology of insurgency. Based on our fieldwork (see 2.1) and analytical results (of 3.2.4 and Appendix A), we strongly suspect the destructive effect captured in the first term will dominate the subsequent effects stemming from changes to individual marginal returns. In those cases G has the intuitive, countereffect to B. The MI would strictly prefer not to join the insurgency following a marginal increase in G, leading to a *reduction* in insurgency. Therefore, we formulate a hypothesis for empirical testing.

Hypothesis II: For a fixed level of spending in the bad sector, and fixed community member preferences, an increase in outlays to the beneficial sector will lead to a decline in resistance. Ceteris paribus, $\Delta R/\Delta G < 0$.

Let us now consider Hypothesis I in more depth. Given a change in sector B spending, the response in terms of insurgency is determined by two factors: (i) the population density at (and to the right of) the decision margin ($f(\alpha^*)$); and (ii) the breadth of the adverse reaction ($\partial\alpha^*/\partial B$). Hence we can approximate $dR/dB \approx f(\alpha^*)\frac{\partial\alpha^*}{\partial B}$, where $\partial\alpha^*/\partial B$ is ultimately a composite function of G and B, and depends on the functional forms of b, g, $f(\cdot)$, and the U^i. Precisely,

$$\frac{dR}{dB} = \int_{\alpha^*}^{\alpha^* + \frac{\partial\alpha^*}{\partial B}} f(\alpha_i)d\alpha_i = F\left(\alpha^* + \frac{\partial\alpha^*}{\partial B}\right) - F(\alpha^*)$$

Diagrammatically, the relationship above is depicted in Figure 1. From here we can see the distribution of ideological preferences is paramount in determining the community response dR/dB. This feature of our model enables interesting comparisons across local contexts.

Our focus is on the controversial nature of projects. Our field interviews suggest the friction between community preferences and development programming is stronger in some communities than in others. It is therefore instructive to compare outcomes across communities with different perceptions regarding the controversial nature of programming. Let us consider two communities, which differ according to their ideological preferences. Let the preference (α_i) distribution in conservative community c constitute a leftward shift of its counterpart in moderate community m (with first-order stochastic dominance), implying a greater concentration of ideologically sensitive community members in c. Further, let the preference distribution be unimodal. So long as there is a higher level of violence in c than in m, and so long as the MI (the most liberal insurgent) in c is more ideologically extreme than both his modal community counterpart, and the MI in m, then the violent backlash from B will be more severe in c than in m.

Hypothesis III: Ceteris paribus, the violent backlash in response to controversial projects will be more severe, the more antagonistic are the underlying ideological preferences of the community. Consider two communities (denoted by subscripts c and m) where the preference distributions differ by a constant, such that $f_c(\alpha_i) = f_m(\alpha_i + s) \ \forall \ \alpha_i$, where $s > 0$ (so that $F_m(\alpha_i) < F_c(\alpha_i) \ \forall \ \alpha_i$). If the following conditions (i)-(iv) hold, then $f_c(\alpha_c^*) > f_m(\alpha_m^*)$ and $(\partial\alpha^*/\partial B)_c > (\partial\alpha^*/\partial B)_m$, implying $(dR/dB)_c > (dR/dB)_m$.

(i) f_m is unimodal

(ii) $R_c > R_m$

(iii) $\alpha_c^* < \arg\max_{\alpha_i} f_c(\alpha_i)$

(iv) $\alpha_c^* < \alpha_m^*$

It is noteworthy that conditions (i)-(iv) above are not controversial, and can be expected to hold in practice. By imposing some additional structure, in Appendix A we analytically derive Hypotheses I through III.

3.2.2 Public Opinion

Whether an individual supports the insurgency depends on whether he/she serves to benefit from the undoing of foreign-led reconstruction activities. In our model, decisions regarding support and participation are one and the same. The binary indicator, r^i, can be interpreted

either as violent resistance, or as informational assistance towards insurgents (and away from international forces). Practically, a decisive political position must precede any material contribution to the conflict. In our theory, public opinion is the underlying mechanism by which reconstruction efforts translate into peace or violence. As such, we expect public antipathy towards international forces to dictate the strength of the insurgency. Let A be a measure of this antipathy, whereby $A = \int_0^{+\infty} a^i(\alpha_i; G, B) f(\alpha_i) d\alpha_i$, and the individual a^i are as follows:

$$a^i = \begin{cases} 1 & \textit{if} \quad dU^i/dR > 0 \\ 0 & \textit{if} \quad dU^i/dR \leq 0 \end{cases}$$

Under this transparent formulation, we can recharacterize $r^i = a^i$, and by extension $R = A$. The intermediate role of public opinion as the underlying mechanism is now explicit[14], even if the derivation of R has become consequently trivial (redundant). Nevertheless, this one-to-one theoretical correspondence between a^i and r^i enables us to reformulate our three hypotheses in terms of opinion shares, rather than insurgency size. So for completeness, we propose:

Hypothesis Ia: For a fixed level of spending in the good sector, and fixed community member preferences, an increase in outlays to the controversial sector will lead to greater antipathy towards international forces. Ceteris paribus, $\Delta A/\Delta B > 0$.

Hypothesis IIa: For a fixed level of spending in the bad sector, and fixed community member preferences, an increase in outlays to the beneficial sector will lead to a decline in antipathy towards international forces. Ceteris paribus, $\Delta A/\Delta G < 0$.

Hypothesis IIIa: Ceteris paribus, the public opinion response to controversial projects will be larger, the more antagonistic are the underlying ideological preferences of the community. Consider two districts, denoted by subscripts c and m. If the following conditions (i)-(iv) hold, then $(dA/dB)_c > (dA/dB)_m$.

(i) $f_c(\alpha_i) = f_m(\alpha_i + s) \ \forall \ \alpha_i$, where $s > 0$ (so that $F_m(\alpha_i) < F_c(\alpha_i) \ \forall \ \alpha_i$)

(ii) f_m is unimodal

(iii) $R_c > R_m$

(iv) $\alpha_c^* < \arg\max_{\alpha_i} f_c(\alpha_i)$

[14]The distinction between the underlying ideological preference parameter α_i and the decision outcome a^i is important. The individual decision derives from his/her preferences, following a personalized evaluation of the reconstruction effort.

3.2.3 Project Choice

We now turn back to the occupier whose problem, given its preferences and technology, can be summarized as

$$\max_{G,B} \Pi = V(g(G, R(G, B; f(\cdot))), b(B, R(G, B; f(\cdot)))) - C(G, B)$$

This implies the following first-order conditions:

$$V_b b_{_B} = C_B - (V_g g_{_R} + V_b b_{_R}) R_B \tag{3}$$

$$V_g g_{_G} + (V_g g_{_R} + V_b b_{_R}) R_G = C_G \tag{4}$$

The left-hand sides of equations 3 and 4 capture the marginal benefits of increased outlays B and G, respectively; the right-hand side captures the associated marginal costs. The costs of investment in sector b are two-fold, consisting of a direct cost (C_B) and the indirect cost of greater resistance, which dampens output across both sectors. By contrast, the benefits of investment in sector g are two-fold, consisting of the direct benefit ($V_g g_{_G}$), and the indirect growth in output across sectors resulting from improved stability. The occupier therefore accounts for these differences as it allocates spending. Depending on the occupier's preferences and technology, and on community preferences, an equilibrium is reached in which some combination of G^*, B^*, and $R(\alpha^*)$ prevails. The concavity of the occupier's utility function with respect to spending,[15] in combination with the convexity of the cost function, ensures that G offsets cannot endlessly compensate for damages incurred by B.[16] If we impose the Inada conditions on V, the equilibrium is contained within a limited set of feasible allocation bundles.

3.2.4 Parameterization

To visually exemplify our model's results, we now adopt a specific parameterization. For didactic purposes, we choose the following:

$$\begin{aligned} V &= g^{1/4} b^{3/4} \\ U^i &= \alpha_i \sqrt{gb} - b^2; \quad \alpha_i \sim \mathrm{U}(0,1) \\ g &= G(1-R); \qquad b = B(1-R) \\ C &= (G+B)/5 \end{aligned}$$

[15] Because V is concave in g and b, and these latter are concave in their respective spending inputs G and B, V is concave in G and B.

[16] Interestingly, equations 3 and 4 combine to yield the joint condition: $[V_b b_{_B} - C_B] R_G = [V_g g_{_G} - C_G] R_B$. Because $R_G < 0$ and $R_B > 0$, it must be that either $V_b b_{_B} - C_B < 0$, or $V_g g_{_G} - C_G < 0$. In equilibrium, the latter will hold true, demonstrating the occupier overspends on G to leverage against damage arising from B outlays.

From this specification, two items are particularly noteworthy: (i) the occupier has a relatively strong preference for sector b output, and (ii) $U^i_{gb} > 0$. We present a utility function fulfilling the latter to demonstrate our results are not contingent on the potentially controversial condition: $U^i_{gb} \leq 0$.

Given the parameterization above, we can generate the level of resistance for each allocation bundle, and also map the corresponding value function for the occupier. Figure 2a depicts a surface (with level curves) reflecting the level of resistance (R) for various choices of spending (G, B) by the occupier. As expected, violence is increasing in outlays to the bad sector (B), and decreasing in outlays to the good sector (G). There is no violence at all when $B = 0$, and maximal violence when $G = 0$, which are both intuitive results. Next, in Figure 2b we depict the occupier's value function (Π). The function takes a negative slope as spending extends in a single direction from the origin, reflecting the constant cost of outlays. Some combination of outlays does generate positive value, however, and in equilibrium we see greater devotion to G than B, despite the occupier's direct preference for the latter (i). Because spending on B entails a negative externality on the efficiency of both sectors by increasing violence, its output is relatively restricted in the optimum allocation.

4 DATA

Our primary unit of observation is the district-month. We follow the 2005 Afghan Ministry of the Interior administrative designation of 398 districts spanning 34 provinces. Our sample period runs from January 2005 until September 2009. Hence, our sample contains a total of 22,686 observations. Reconstruction volumes for a district-month are calculated as the mean number of projects in progress. Alternatively put, it is the amount of projects completed in that month, with each project weighted by its total duration (measured in fractions of months).[17] Violence levels are obtained by summing up all incidents over the respective period. Reconstruction volumes are lagged one period in order to ensure we measure the impact of recent (not future) development on violence. Both violence and reconstruction variables are expressed in per-capita terms. For descriptive purposes, and for ease of comparison, we scale these measures to the average-sized district (63,000 inhabitants). District population data is for 2011/12, and obtained from the Central Statistics Organization

[17] Other authors (BSF) have previously weighted projects by dollar value rather than project length. We choose the latter for two reasons. Our theory places community perceptions at the heart of resistance. Perceptions are driven by the presence of ongoing projects (e.g. appearance of foreign contractors), and not necessarily their financial value. Technically, cost data is only available for a subset of projects. However, project duration is a strong positive correlate of cost (also when controlling for sector). Replicating our central analysis using dollar-weighted metrics yields no obvious contradictions with the results presented here, but the explanatory power of each statistical model is considerably reduced.

(CSO) of the Islamic Republic of Afghanistan.

4.1 Reconstruction projects

Reconstruction data comes from NATO C3 Agency's Afghanistan Country Stability Picture (ACSP). The ACSP is ostensibly a comprehensive database on reconstruction and development projects across Afghanistan from 2002 to September 2009. It is developed for use by NATO, the Government of the Islamic Republic of Afghanistan, and civilian actors. The database covers all projects funded by the Provincial Reconstruction Teams (PRTs), USAID, the Combined Security Transition Command (CSTC-A), and a host of other foreign donors including the World Bank, the World Health Organization, and numerous United Nations agencies. The ACSP contains detailed project information, including cost, timing, location, and sector classification.

While the ACSP falls short of providing complete coverage of all reconstruction programs, PRT data is particularly well documented. From 2002 to 2009, the ACSP contains data on 22,351 PRT projects accounting for at least $1.8 billion in expenditures (included among these is the CERP, which comprises more than one third of PRT projects in the ACSP). A map of the spatial distribution of mean PRT projects across all districts is presented in Figure 3.[18] The left panel of Figure 4 depicts the level of PRT projects in our sample, across all provinces over time, and scaled by population. Including all donors, the ACSP database contains a total of 118,322 projects, amounting to $28.2 billion, at minimum. A considerable share (73%) of all projects are not coded with accurate dates in the ACSP. Of the PRT-led projects, 54% are missing the start date, the end date, or both. Throughout the analysis, projects with missing dates are dropped from our sample. Accordingly, we are left with 31,486 projects in total, of which 10,357 are PRT-led.[19] We have no reason to believe this measurement error will bias our results, but we address this concern in section 6.3. To foreshadow: our results remain intact when incorporating partial data for an additional 3,969 PRT projects.

Total reconstruction spending is disaggregated according to sector. Sector groups are based on the Afghanistan Standard Industrial Classification of Activities (ASIC) maintained by the Afghanistan Information Management Services (AIMS). Project examples under each ASIC sector are offered in Table 1. Descriptive statistics of reconstruction volumes (as well as violence, district characteristics, and public opinion) are presented in Table 2.

[18] Mean PRT projects for a given district is calculated as the average of the district-month means over the sample period.

[19] Over half the ACSP database consists of projects funded by either Afghanistan's Ministry for Rural Rehabilitation and Development (MRRD), or the Ministry of Finance (MOF). MRRD data do not contain project end dates, while MOF data are not geographically coded at the district level. As such, domestically funded reconstruction projects do not form part of our analysis.

4.2 Violence

Throughout the analysis our dependent variable is violence, which we measure primarily through the Worldwide Incidents Tracking System (WITS).[20] The WITS is a US government database assembled by National Counterterrorism Center analysts. Data are gleaned manually from open media sources, including local media in foreign languages where linguistic capabilities permit. The WITS catalogues all publicly known, premeditated, politically motivated violence directed at police, military, government, and civilians 'outside of war-like settings', but including ambushes, suicide attacks, and IEDs. The data cover incidents in Afghanistan from 2005 until August 2009, and has been geo-coded by the Empirical Studies of Conflict Project at Princeton University. Using the ESRI World Gazetteer and digital mapping software, we district-locate 3,222 incidents included in the WITS.

WITS data are supplemented with violence data from the Global Terrorism Database (GTD) managed by the US Department of Homeland Security's START Center at the University of Maryland. The GTD covers terrorist attacks across Afghanistan from 2001 until 2011. A terrorist attack is defined by the GTD as 'the threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation'. Although the GTD covers a longer time horizon, its coverage is more sparse - we were able to district-locate only 1,428 incidents over our sample period (corresponding to that of the WITS).

Because there is significant overlap between the two sources of violence data, we merge the databases to avoid double counting. Specifically, for any day in which the WITS does not report an attack, we employ GTD data. When both databases report violence on the same day, we draw on the source reporting the larger number of incidents. In line with related research, our measure of violence does not capture actions initiated by the state, such as police raids or counterinsurgency operations. Moreover, in keeping with the previous focus on government-targeted attacks, the vast majority of incidents in the WITS and the GTD involve non-civilian casualties (often exclusively). A monthly time-series of per capita violent incidents by province is offered in the right panel of Figure 4. The spatial distribution of violence, averaged across the sample period, is reflected in Figure 5.[21]

[20] WITS data have previously been used by Krueger and Malecková (2009). See Wigle (2010) for full introduction to the WITS database.

[21] US military SIGACTs (significant activities) data contained within the International Distributed Unified Reporting Environment (INDURE) offers more comprehensive coverage of violent incidents in Afghanistan. But in recent years the SIGACTs data has been made prohibitively difficult to access by unauthorized personnel.

4.3 District characteristics

To understand the spatial distribution of reconstruction spending and violence, we construct district characteristics by invoking National Risk and Vulnerability Assessment (NRVA) national survey data. The NRVA was carried out by the CSO to assess welfare levels across the country, to improve development practices, and to facilitate research efforts by government and international actors. We use two waves of the survey: the first was conducted from June to August of 2005; the second was carried out between August 2007 and July 2008. Both surveys are statistically representative to the provincial level, but district sample sizes are conveniently large, such that the data yield reasonable approximations for district-level inference. NRVA 2005 surveyed 392 districts, 2597 PSUs (villages), 30,822 households, and 385,519 individuals. NRVA 2007/8 surveyed 395 districts, 2572 PSUs, 20,576 households, and 152,284 individuals.

Both waves of the NRVA data consist, for each PSU, of two community-level surveys (filled out by both male and female *shuras*), as well as male and female household questionnaires (completed by household heads and other members). The data cover a wide range of issues including access to services, infrastructure, governance, public opinion, health, education, income, agriculture, housing, women's rights, and more. The amount of time elapsed between survey waves (between two and three years) is likely too large to make dynamic inferences attributing either violence or interim reconstruction activities to changes in community characteristics. As such, we construct district characteristics only to explore the spatial (cross-sectional) distribution of reconstruction programming and violence. Because we want to pool the two periods for cross-sectional analysis,[22] we need comparable indicators across survey waves for each field of interest. Some survey questions are immediately comparable across waves, and others are less comparable. District characteristics for which the NRVA does not provide a consistent measure across waves are instead approximated by way of principal component analysis (PCA).

For each such field of interest, we start by determining all relevant survey questions from the four aforementioned questionnaires. For each district, we calculate the average response to each of these questions, disregarding household sampling weights as they were devised to ensure representativity at the province level. From this collection of district-level responses to all relevant questions, we extract the first principal component and use it to compute a district-level indicator for that field of interest. In particular, we use the percentile rank of a district's first principal component score (vis-a-vis other districts' scores) as the district characteristic indicator. In this way, from NRVA data we are able to obtain district-wave measures regarding

[22] Neither our theory nor qualitative data guides us in making predictions regarding how or whether the logic of project allocation changes over time. We therefore have no reason to analyze our two available time periods separately.

level of education, religiosity, women's rights, and access to health services. From NRVA survey questions which are consistent across waves (upon which PCA is not necessary), we compute district-wave characteristics on development programming preferences, hunger, road access (remoteness), and the presence of government-commissioned community development councils (CDCs) which administer (non-PRT) aid.[23]

4.4 Public opinion

Data on public opinion towards international forces are taken from the Afghanistan Nationwide Quarterly Research (ANQAR) surveys which, as their name implies, were conducted every three months across the country, from March 2008 until the present. The interviews were carried out for NATO by the Afghan Center for Socio-Economic and Opinion Research (ACSOR). The surveys collected information on demographics, and opinions regarding: security, security personnel, government, anti-government elements, foreign forces, and development. For this paper we select a narrow subset of survey questions to best assess the impact of reconstruction projects on public sentiment towards the international forces.

We gained exclusive access to the first six waves of the ANQAR survey, all of which have a sample size of more than 8500 households. Interviews were proportionally distributed across districts according to CSO population data. Within each district, settlements were selected randomly, and 10 households were interviewed per settlement, using random walks and kish grids to select respondents. Where security, transportation, or weather rendered a district inaccessible by survey teams, intercept interviews were conducted instead with residents of the target district travelling in neighbouring districts. Full detail regarding sampling design and methodology of the ANQAR surveys is described in the quarterly methods reports.

5 ANALYSIS

5.1 Spatial allocation

To begin our analysis, in Table 3 we investigate the determinants of violence and project outlays, by exploring their spatial distribution with respect to district characteristics (see again Figures 2 and 4). To this effect, we stack two cross-sections corresponding to the NRVA survey waves, yielding 777 district-wave observations. We then estimate the following

[23] Due to censorship, we are unable to access district data on troop movements, which could alleviate potential bias from the omitted variable of hard counterinsurgency. But since we measure the impact of sector-specific projects, rather than total reconstruction, this bias is not of major concern. This is particularly true when comparing service sectors (such as health and education) which require similar levels of security in order to be carried out.

statistical model using OLS:

$$\mathbf{Y}_{iw} = \mathbf{X}_{iw}\beta + \gamma_w + \epsilon_{iw}$$

where the outcome Y_{iw} varies across columns, from (per capita) violence to measures of (per capita) reconstruction projects; and $\mathbf{X}_{iw}$ is a vector capturing a host of characteristics in district i, gleaned from the NRVA wave w, as described in 4.3.

Column 1 of Table 3 indicates that violence is more pronounced in districts with less women's rights; greater food security; greater road access; no CDC; and less population. Column 2 demonstrates that reconstruction projects overall are allocated somewhat similarly. PRT projects (per capita) are less plentiful in remote and populous districts, and in districts with greater food scarcity. PRT projects are, however, positively correlated with the presence of a CDC. In column 3 we see education projects in particular are strongly correlated with CDC presence. In light of the negative correlation between CDCs and violence (found here in column 1, and demonstrated by Beath, Christia, and Enikolopov 2016), and result suggesting education *increases* violence may be understated, subject to confound from this separate realm of development programming. That both violence and reconstruction are targeted at similar districts reflects a need to control for location when attempting to identify causal effects. It could prove problematic for our analysis, however, if violence and reconstruction programming were correlated with third time-varying factors, and if the correlation between those factors and programming *differed across sectors*. Columns 3-5, which examine the spatial allocation of sector-specific projects, suggest this is not the case. In fact, there are very few significant determinants of individual sector programming, and there are none whose direction of correlation significantly changes across sectors. This allays our concerns regarding adverse project selection on omitted local characteristics correlated with violence. The spatial distribution of sector-specific mean PRT projects is mapped in Figure 5. Notice no obvious regional specializations prevail.

5.2 General PRT

Prior to testing our theory, we first follow previous authors by imposing homogeneous effects across reconstruction sectors. In column 1 of Table 4, we start by pooling all observations. But conflict intensity across Afghanistan is highly seasonal, with the Taliban announcing the beginning of the 'spring offensive' around April-May each year. If, for any reason, education projects are carried out in the spring/summer, and health projects in the down-season, this could lead us to erroneously attribute (lack of) violence to education (health) programming, in the absence of seasonal controls. For this we incorporate (57) month-specific dummies into our model to fully condition our effects on nationwide trends. We therefore estimate the cross-sectional relationship between monthly reconstruction work (lagged) and violence,

clustering errors at the province level. Mean projects are significantly positively correlated with violence in this setting. The incidence of greater violence in areas more concentrated with reconstruction spending, however, may simply reflect the spatial selection of projects reflected in Table 3. Furthermore, because reconstruction is viewed as a tool for peace, projects may be set where their benefits are most needed - in volatile regions. To address this concern, we use a first-difference approach in column 2:

$$\Delta \mathrm{V}_{it} = \beta \Delta \mathrm{R}_{it-1} + \gamma_t + \Delta \epsilon_{it} \tag{5}$$

By estimating the above equation, we evaluate the change in violence (ΔV) stemming from a within-district change of PRT outlays (ΔR). Districts are indexed by i, and months are indexed by t. Now the amount of projects becomes an insignificant determinant of violence, suggesting reconstruction programming may be endogenous with respect to the average (expected) level of conflict. But PRT projects are now *negatively* correlated with violence (p-value 0.12), which is broadly in line with BSF (2011). It is therefore possible reconstruction programming does mitigate violence in Afghanistan, although this would be a generous interpretation of our results at this stage. To ascertain whether certain types of projects are successful in that regard (and others less so), we turn to a more disaggregated analysis.

5.3 Sector-wise PRT

Our central aim is to determine whether reconstruction projects in different sectors have differential impacts on violence. Based on field interviews and qualitative evidence, we have classified three ASIC sectors into our theoretical groupings b and g. There are ten other sectors into which PRT projects may fall (see Table 1), but we do not develop clear predictions regarding how programming in those sectors is likely to affect conflict. For ease of reporting, and to avoid attributing economic meaning to potentially spurious correlations, we have refrained from analyzing those sectors individually. We nevertheless control for their combined volume in the analysis that follows, but suppress that coefficient result. Regarding the sectors we do analyze, we consider education and security to comprise the ideologically controversial sector b. Health projects, on the other hand, fall into sector g. This classification may be perceived as results-driven, but importantly - the foregoing predictions were *not* retroactively adjusted for consistency with the empirical results herein. Any doubts may be alleviated with reference to Child and Scoones (2010), which predates the ACSP and ANQAR data release to the author.

In Table 5 we disaggregate PRT projects into three mutually exclusive sectors, plus the catch-all 'residual' sector (suppressed). In this way we allow for heterogeneous effects across the education, health, and security sectors. We report cross-sectional results in column 1, which are purely correlational as noted in the preceding subsection. Once we account for selection on

time invariant unobservable characteristics by first-differencing (see equation 5, with **R** now a vector), the results of column 2 provide compelling evidence that the effect of reconstruction programming varies by sector. As per Hypothesis I, education projects lead to an uptake in subsequent violence. As per Hypothesis II, health projects are indeed effective at improving stability. For an average sized district, one-standard-deviation increase in education (health) programming leads to an escalation (reduction) in expected violence by approximately one-fifth (one-third). Security programming appears to reduce violence, contrary to our first hypothesis. But after all, the direct goal of security projects is to reduce violence, so these projects are likely to have a material impact on security, separate from the indirect effect we postulate here (that which manifests through ideological sentiment). We therefore interpret the effect of security programming as evidence for the success of hard, rather than soft, counterinsurgency.

By removing district effects through first-differencing, we overcome endogeneity from selection based on fixed community characteristics (such as predisposition for violence). A dynamic source of endogeneity may still run through violence though, if decisions regarding project outlays are made on a continual basis, and related to the *contemporaneous* state of instability. To exclude the possibility that our result is a byproduct of dynamic selection on time-varying conflict, we include lagged violence as a control variable in column 3. The magnitudes of the PRT coefficients change very little, suggesting dynamic selection is not a major concern.[24]

One caveat is in order in that the first-difference estimator of column 3 may retain the so-called Nickell bias, as lagged violence correlates with the error term by construction (Nickell 1981). To overcome this difficulty, we adopt the Anderson-Hsiao (1982) 2SLS-IV estimator in Table B1, and demonstrate our results are essentially unchanged under this correction.[25] This is perhaps unsurprising since the Nickell bias is concentrated on the estimated effect of lagged violence, while we are interested in the effects of PRT spending. Simulation findings by Judson and Owen (1999) suggest bias in the latter are relatively small. We include lagged violence in part to reduce variance in the error term, thereby sharpening precision for our coefficients of interest. To the extent that lagged violence is correlated with our reconstruction variables, the Nickell bias would be reflected also in coefficients for the latter. It is therefore reassuring

[24]Including further lags of violence does not reduce the explanatory power of reconstruction variables, nor meaningfully change their effect sizes.

[25]This 2SLS-IV estimator invokes higher-order lags of differenced violence as instruments for the first lagged difference, thereby breaking the structural correspondence between our endogenous variable and the error term. Under this correction, our coefficients of interest (for PRT projects) remain very similar. In columns 2 and 3 we are able to easily reject the hypothesis that our instruments are weak, by comparing the Kleibergen-Paap rk Wald F-stat to critical values (from Stock and Yogo 2005) approximately two orders of magnitude smaller. The highly significant negative coefficient on the lagged difference of violence (in columns 1 and 4) is mechanical. It is an artifact of mean-reversion in a data process characterized by intermittent violence at the district level.

that the contemporaneous correlation coefficient between violence and reconstruction is only -0.002, 0.003, and -0.011, for education, health, and security, respectively. Importantly, none of these correlations are significant - the corresponding p-values are 0.74, 0.71, and 0.11.

Next, in column 4 we additionally allow for district-specific trends in violence (spanning the sample period). Under the scenario in which certain districts are increasingly conflicted over the sample period, whilst undergoing more intensive education programming for other reasons, we might wrongfully attribute the former development to the latter. By including district-specific trend terms, we account for such possibilities. Our results remain practically identical. Because district trends do not add explanatory power, whilst lagged violence does improve model fit, we opt for column 3 as our (parsimonious) full specification:

$$\Delta \mathrm{V}_{it} = \Delta \mathbf{R}_{it-1}\boldsymbol{\beta} + \Delta\gamma_t + \theta\Delta \mathrm{V}_{it-1} + \Delta\epsilon_{it} \tag{6}$$

where i is a district index, t the month index, V is violent incidents, $\mathbf{R}$ is a vector of reconstruction volumes (mean concurrent projects), and Δ is the difference operator. This identification strategy closely follows BSF (2011), except we aggregate observations to the district-month, rather than the district-half year.

In our full specification of column 3, we are able to rule out selection on fixed district-level characteristics, recent district-level violence, and contemporaneous nation-wide violence. Figure B1 presents added variable plots (based on equation 6) to demonstrate our results are not driven by a handful of outliers. Still, a remaining concern is that time *varying* district-level variables could influence both reconstruction outlays and violence. We do control for the overarching volume of reconstruction work, however, so the concern here is restricted to time varying covariates which influence both violent outcomes and the project *mix* (as opposed to its level). In particular, one concern is that education projects are targeted at areas with increasing propensity for violence, and health projects are targeted at districts which are becoming more safe. To the extent that past violence predicts present violence, controlling for lagged violence and district trends should address this concern. We find it unlikely that further sources of endogeneity can explain *differential* effects across programming sectors. Nevertheless, in the subsequent section (and Appendix C) we undertake a host of robustness exercises (including an instrumental variables analysis). Unless otherwise noted, for the remainder of the analysis we employ the full specification expressed in equation 6.

6 ROBUSTNESS

6.1 Reverse causality

One potential concern with the results of Table 5 relates to the direction of causation. Does reconstruction work affect violence, or vice versa? Field interviews conducted by the author,

and previous fieldwork by country-experts (Adams 2014; Sexton 2015) suggest realistic concerns regarding within-district reverse causality at low levels of temporal aggregation are limited, even if we assume projects are selected purely with short-run violence-reduction in mind. A combination of bureaucratic rigidity, idiosyncratic preferences of commanders, logistical limitations, and limited foresight effectively renders project outlays sufficiently random with respect to contemporaneous and imminent violence. This is especially true once results are conditioned on district, month, and trends in recent violence (as in Table 5). Furthermore, the sectoral composition of programming is broadly predetermined (Donor L 2013; Donor D 2013), can be legislatively mandated as the consequence of lobbying/negotation by various government branches (Donor Q 2013), and can altogether exclude security as a selection criterion (Donor L 2013). In effect, the preponderance of evidence in support of our second theoretical assumption from section 2.2 exactly suggests that short-run violence-reduction is unlikely to be either the only, nor the largest, determinant of project selection. Nevertheless, we address concerns related to reverse causality in what follows.

Importantly, it can be shown that reconstruction programming in education, health, and security Granger-causes violence. The converse is not true, which is evident in Panel A of Table 6. In this panel, we effectively re-estimate equation 6, but now with reconstruction projects as the outcome, and (lagged) violence as the predictor. The first column tests the effect of the preceding month's violence on the current volume of PRT projects. Dynamic selection of programming on the basis of recent violence does not seem to be widespread. Next, in columns 2, 3, and 4, we test whether education, health, or security projects (respectively) are targeted differentially according to this principle. None of the sectors exhibit patterns consistent with the notion that recent violence determines project outlays. In fact, the signs of the sector-specific coefficients suggest, if anything, education projects are steered *away* from increasingly violent districts, with health (and security) spending geared *towards* those districts.

It could still be the case, however, that PRTs assess more distant (i.e. historical) patterns of violence when deciding on project allocation, and that these histories also affect the current state of conflict. To address this possibility, we aggregate up to six-month blocks, and rerun our tests in Panel B. Still no evidence suggests reconstruction generally follows violent half-years, as indicated by the null result in column 1. Columns 2 to 4 again provide no evidence for the existence of strategic sector-specific outlays. Violence then (neither recent nor medium-term) does not appear to determine the timing of reconstruction programming.

As a final check on reverse causality, we consider the possibility that sector-specific programs are allocated on the basis of expected (if not recent) violence. To verify this, we extract predicted violence from a simple forecasting model, and test whether next period's expected violence is a determinant of contemporaneous project outlays. For this purpose, we

project violence on the basis of all significant lags (three, in a level equation), the time period, and district fixed effects. The correlation between our predicted violence measure and real outcomes is 0.31. In Panel C, the predicted value for violence is forward-lagged, and included as a regressor to estimate its impact on contemporaneous project outlays. We find the coefficient on expected violence to be insignificant in most cases. In columns 1-3, the coefficient on predicted violence actually points in a direction *opposite* from that which supports a story of selection-driven results. Panel C therefore strengthens our causal interpretation of the results in Table 5. Remarkably, even if we condition the paper's key results (Table 5) additionally on predicted contemporaneous violence, our results still remain significant. We therefore conclude our results are not the consequence of differential sector-specific programming based on trends or expectations of violence.

6.2 Confounding aid

Even if we are able to fully account for the security situation, we are still faced with an important omitted variable which may confound our estimation. Development aid from non-military donors exceeds reconstruction aid in Afghanistan by a factor of nearly five-to-one (by project count, see Table 2). Insofar as civil aid programming is selective on the basis of local security (or some related characteristic), and PRTs coordinate with civil donors, then a selection problem persists. Related work examining the impact of single reconstruction or development programming efforts has failed to account for the slew of development agents active in conflict areas (BSF 2011; Crost, Felter, & Johnston 2014; Iyengar, Monten, & Hanson, 2011; Berman et al. 2011; Nunn & Qian 2013; Beath, Christia, & Enikolopov 2016). We contend this is an extremely important potential source of confounding bias, and therefore control for non-PRT programming in Table 7. Column 1 controls for projects funded by USAID - the largest donor in Afghanistan. Column 2 includes all other civil donors, including various UN agencies, development banks, IFIs, international NGOs, and so on. Column 3, for completeness, includes the Combined Security Transition Command - a multinational effort to train Afghan security forces. All our sector-specific results on PRT programming from Table 5 are robust to the inclusion of development aid controls. Interestingly, civil aid concentrated in our sectors of interest does not have a significant effect on violent outcomes. Education projects funded and administered by non-military development actors are not destabilizing, nor do health and security projects appear to alleviate conflict. This finding suggests military programming has a unique relationship with violence, which supports our theoretical contention that ideological perceptions are important when development is seen to be carried out by an occupying force. The finding was also anticipated by interview respondents who suggested that aid projects funded or implemented by established civil society actors are unlikely to elicit adverse security responses (Foreign Company P 2013; Donor N 2013; Donor

G 2013).

6.3 Missing data

Admittedly, there are concerns regarding reconstruction project data accuracy. Although the ACSP self-identifies as an exhaustive list of all reconstruction and development activities in Afghanistan from 2002 to 2009, it is doubtful all projects were individually coded into the database by the responsible agents. That said, we have no reason to suspect miscoding is systematically related to violence and reconstruction programming in a way that would bias our results. In particular, it would be required that education projects are more likely to be included in the database when (unanticipated) conflict is on the immediate horizon, and that health projects are more likely to be included prior to sudden improvements in stability. However unlikely such miscoding practices must be to explain the differential effects we observe across programming sectors, in what follows we address missing data issues. At any rate, we feel this research question is too important to remain unexplored, so we elect to undertake the most rigorous analysis possible with the best data available (notwithstanding its limitations).

As mentioned in section 4.1, the majority of projects in the ACSP are missing data on either the start date, the end date, or both. But because the bulk of our analysis is based on first differences in project volumes, it is still possible to partially incorporate much of the project data we have thus far excluded. That is, our identification has been leveraged off the timing and location of project commencements and project completions. Missing data for the start (end) date of a project does not preclude us from incorporating the end (start) date of that project into our analysis. Of course, these partial data may be less reliable than complete project data, and including data subject to classical measurement error can attenuate our coefficient estimates. On the other hand, excluding these data amounts to systematic underreporting of project volumes at best, leading to overstated effect sizes. At worst, this could result in directional bias if data-coding errors are systematically associated with imminent violence, and differentially-so across sectors. We thus re-run our main analysis including all available partial project data.

When we incorporate projects for which we have only the start date or the end date, our database coverage expands considerably. The amount of projects increases from 31,486 to 36,947; PRT projects in particular increase from 10,357 to 14,326. Impressively (given the difference in sample size), the results obtained from this expanded database qualitatively match those presented in the main analysis. In Tables B2, B3, and B4, we reproduce Tables 2, 5, and 7, respectively. The descriptive statistics in Table B2 closely resemble the corresponding figures in Table 2. In Tables B3 and B4, the coefficients on PRT projects are smaller than in Tables 5 and 7, respectively. This potentially reflects attenuation bias from (classical) measurement error

in the revised sample, systematic under-representation of projects in the main sample, or both. In fact, one might treat the two corresponding estimates as bounds on the true parameter values. Because all coefficients shrink in absolute value, there is little reason to believe directional bias could explain our differential results across sectors.

7 MECHANISM

7.1 Community perceptions theory

7.1.1 Local conservatism

So far we have presented evidence supporting Hypotheses I and II of our theory, which are premised on the notion that reconstruction work impacts violence through popular perceptions. In particular we have demonstrated that education programming leads to uptakes in violence, while health programming improves stability (security-sector effects do not correspond to our expectation). Hypothesis III suggests the adverse impact of education-sector spending will be greater in areas where controversial projects are most highly contested. Next, we test this hypothesis, offering further support for our favoured mechanism linking reconstruction to conflict.

To the extent that education programming by a foreign military is perceived negatively on ideological grounds, we expect this sentiment to be strongest in conservative areas. Reconstruction stakeholders have expressed that the geographical breadth of certain projects is limited, and this may be due to heightened controversy associated with those projects in insecure areas (Foreign Company M 2013; Donor G 2013; Foreign Company P 2013). With reference to the Southern provinces in particular, one local NGO acknowledged education can actually be the cause of violence (Afghan NGO J 2013). To operationalize an empirical test for Hypothesis III, we must first arrive at a local measure of underlying conservatism. The South of Afghanistan is the birthplace of the Taliban, and is understood to be the most conservative part of the country. However, geographical location alone is not the only proxy for conservatism. As discussed earlier, we build measures of religiosity and women's rights, based on responses to the NRVA surveys. By combining responses across both survey waves, we generate two additional district-level measures of conservatism (beyond the regional indicator). A fourth measure comes from ethnicity data collected over the universe of ANQAR surveys. We use the district-share of Pashtun, due to that group's historical ties to the Taliban, and to their well-known conservative norms with respect to women's rights and Islam.

Table 8 tests whether the unintended consequences of education programming are stronger in conservative districts. Across columns, we alternately interact all reconstruction measures with our various proxies for conservatism. Column 1 of Table 8 reports the effects on violence

of sector-specific PRT programming in the South (in the provinces of Helmand, Kandahar, Uruzgan, and Zabul), and for all areas outside the South. The coefficient magnitude and statistical significance for education projects in the South suggests they are much more destabilizing than in the rest of the country. That is, education and health projects have the expected effect across the country generally, but in the South education is even more inciteful than elsewhere. This result is expected from our third hypothesis. Admittedly, security programming again does not comply to expectations. It appears security projects are more effective in the South (consistent with our earlier reference to hard, rather than soft, counterinsurgency).

In column 2 we test the difference between effect sizes in areas with high religiosity, and those with low religiosity. We are not able to provide evidence for heterogeneous effects of education programming across this measure of conservatism. The results of column 2 may suggest, however, the peace-inducing effects of health programming are concentrated in conservative areas. Column 3 tests for heterogeneity across the level of women's rights. While there are no statistical differences to report, coefficient signs and magnitudes suggest effects are stronger in conservative districts. Lastly, we test for differences based on the population share of Pashtun. Our interpretation of column 4 is the same as that for column 3. In sum, we can suggest the effects of education programming are stronger in conservative areas (albeit the same is true of security projects). While the evidence is not overwhelming, the heterogeneity is most strongly captured by a simple Southern region indicator, rather than our more nuanced (and continuous) measures of cultural conservatism. But the concept of conservatism is, after all, complex and multidimensional. Strict adherence to traditional norms of education can be pervasive across the South, and yet need not be captured by other notions of conservatism. Of course there exist potential confounds with the Southern indicator, which are not easily incorporated into our study, and lack theoretical basis for inclusion. These include, for example, differences in the organizational structure of non-governmental powerbrokers (Giustozzi & Ullah 2006; Thruelsen 2010), and in PRT development models (Abbaszadeh et al. 2008; Eronen 2008).

7.1.2 Popular antipathy

Thus far, we have conducted reduced form tests of the impact of reconstruction on violence, but without a direct empirical test of the causal mechanism. Our theory suggests the effect runs through public opinion, which plays an intermediary role in our model (see 3.2.2). Specifically, we have contended that controversial projects will generate unfavourable views towards the reconstruction effort and occupation at large; and projects deemed acceptable will generate goodwill. Balancing these offsets, each community member in our model arrives at an overall assessment which determines his/her level of support for the insurgency. So to test this causal

pathway of our theory, we next invoke public opinion data from the ANQAR surveys.

In particular, we analyze community responses to the four questions capturing individual assessment of the international forces. These include: (1) '*How would you rate your opinion of ISAF in Afghanistan?*'; (2) '*Should ISAF/international forces deal less with, or implement more, reconstruction and development in Afghanistan?*'; (3) '*Do foreign forces respect the religion and traditions of Afghans?*'; and (4) '*Even if you haven't seen or heard any information or video, audio and print materials communicated by the foreign forces, how trustworthy do you think their messaging is?*'. We code the responses to each of these as ordered categorical variables, increasing in antipathy towards the international forces. We then analyze the impact of sector-specific reconstruction on these measures of antipathy, to ascertain whether our reduced form results are ultimately borne of (or at least consistent with) this intermediate causal pathway. In effect, we are testing Hypotheses Ia, IIa, and IIIa. Due to our formal theoretical equivalence between antipathy and insurgency, we now estimate the public opinion analogue to our earlier specification, with observations necessarily aggregated to the 3-month quarter (due to survey frequency). We also use fixed effects instead of first-differencing, because the public opinion data constitute a broken panel (from inconsistent inclusion of both survey questions and sampled districts). The model we estimate is thus:

$$\mathrm{A}_{it} = \alpha_i + \mathbf{R}_{it-1}\boldsymbol{\beta} + \gamma_t + \epsilon_{it}$$

where A_{it} is the average antipathy towards international forces in district i for quarter t. Included in the vector $\mathbf{R}$ are the project sectors of interest, together with their interactions with a conservative indicator, and also the residual level of projects. Results from the restricted model in which projects carry homogeneous effects across all districts are not significant, but arguably less theoretically compelling in light of findings from the preceding subsection. As such, we focus our discussion on the results of tests permitting heterogeneous effects in the South - our measure of conservatism with clearest relevance.

The columns of Table 9 are numbered in accordance with the above-mentioned questions whose answers serve as the corresponding outcome variables. Regarding Hypothesis Ia, we find some evidence that controversial spending breeds antipathy in general (in districts outside of the South). The coefficients on education and security projects are generally positive, but the corresponding p-values are typically above acceptable thresholds. By contrast, our data reject Hypothesis IIa (there is little evidence to suggest health projects boost approval ratings of international forces, measured in this way). Focusing on columns 1 and 2, we see that education projects lead to significant reductions in approval ratings for international forces in the South, offering convincing evidence in support of Hypothesis IIIa. Following a one-standard-deviation increase in education projects, average opinions of ISAF deteriorate by a half-point out of four (equivalent to half the district population changing from an assessment of 'fair' to 'bad').

The same increase in education spending would push a quarter of the population to suggest ISAF should deal less with (rather than implement more) reconstruction and development. By contrast, our results suggest opinions regarding the respectfulness and trustworthiness of ISAF may be unchanged following reconstruction activity. Perhaps those measures (in columns 3 and 4) are best thought of as fixed underlying ideological preferences, whereas the overall assessments (in columns 1 and 2) may be fluid, tending towards antipathy in the presence of controversial reconstruction spending.

7.1.3 Homegrown insurgency

We argue resistance is community-based, and popular antipathy is a necessary condition for violence. We characterize communities as the source of their own insurgency (regardless of whether the latter involves local Taliban). Though less appealing, our theory also accommodates an interpretation suggesting local communities simply permit the entrance of outside Taliban activities, when those communities are displeased. Our theory is *not* consistent with the notion that outside Taliban selectively attack districts with education projects, regardless of community preferences. To gauge the importance of imported violence to our results, we adopt a spatial approach to examine patterns of violence displacement.

Under a scenario in which education projects attract outside Taliban, we should detect some displacement of insurgent activity around our attacks of interest. Specifically, resources must be sourced from the surrounding area if outside Taliban wish to selectively target a project. As such, a project-fuelled incident of violence should be met with a commensurate decline in violence elsewhere. Given the regional nature of Taliban control structures, and given the quick timing of incidents under study (within a month of project inception/completion), we expect resources to be sourced nearby. We therefore examine whether a spike in local reconstruction-fuelled violence is accompanied by a lull in insurgent activity in neighbouring districts.

To conduct this test, we first isolate violence predicted by reconstruction spending, district and time effects, and recent trends in violence (from equation 6). We then net out all variation driven by the latter three determinants, leaving only variation in violence predicted by reconstruction spending. If outside Taliban are the source of these particular incidents, their occurence should negatively correlate with violence in the neighbouring districts. We therefore estimate

$$\widehat{\mathrm{V}_t} = \alpha + \beta \mathbf{M} \mathrm{V}_t + \gamma_t + \theta \mathrm{V}_{t-1} + \epsilon_t$$

where all variables are vectors with an element for each district, and $\mathbf{M}$ is the adjacency matrix reflecting district borders.[26] The above is a fixed effects specification, with all violence

[26]Notice the reflection problem would arise if the left- and right-hand side violence vectors were equivalent. Using actual (rather than project-predicted) violence as the outcome would test the spatial correlation of all types of violence, which is much less revealing of our mechanism. But unsurprisingly, such a test indicates significant

expressed in gross (not per-capita) terms, to ease interpretation. Likewise, the binary matrix **M** is not row-standardized. Strictly in terms of resources, one may therefore expect $\beta = -1$, for instance, if one project-fuelled attack at home requires the resources of exactly one foregone attack next door (in any adjacent district). In column 1 of Table 10, however, we are unable to detect a statistically or economically significant effect (though the coefficient estimate is negative). This result does not suggest education-fuelled violence is sourced from outside the district-proper. But of course, for many reasons we typically expect conflict to positively cluster in space. So in an effort to filter out this tendency, in column 2 we re-conduct our test including region-month dummies. We thus check whether reconstruction-fuelled conflict is enabled by neighbourhood displacement of attacks, fixing the region-month average.[27] Again, the data do not suggest education projects are simply displacing insurgent activity, rather than fomenting new sources of resistance. Our preferred interpretation of a homegrown insurgency appears to hold sway against those espousing Taliban outsiders as the source of all violence.

7.2 Competing theories

This paper argues the relationship between reconstruction and conflict is largely influenced by how foreign-led programming is ideologically perceived by recipient communities. Competing theories would suggest that relationship is instead characterized by whether reconstruction generates economic opportunities, or increases the attractiveness of economic control. In this section we test whether our data supports such extant theories linking conflict to development. We show the data in Afghanistan is inconsistent with alternative explanations. Furthermore, our results are robust to accounting for these alternative explanations. Lastly, in response to numerous comments/requests, in Appendix D we explore two additional interpretations which neither support nor refute our theory, but nevertheless elucidate underlying mechanisms.

As previously discussed, opportunity cost models of conflict suggest rebellion is essentially a career choice. As outside economic options become more attractive, the opportunity cost of resistance increases, and insurgents are inclined to stop conducting violence in favour of more fruitful economic pursuits. Should this characterization of insurgency hold sway in Afghanistan, general economic development should be accompanied by a decline in the level of violence (under the assumption that reconstruction and development translates into local economic opportunities). In the first column of Table 10 we test the impact of all development and reconstruction projects on violence, since all sources

positive spatial clustering of violence.

[27] If we include contemporaneous spatial effects at a lower level of aggregation (the province, for example), a significant negative β will eventually result mechanically. Conditional on the within-group average, an above average value for one subgroup necessarily implies below average values for the other.

and sectors of programming could imply improvements to local economic conditions. The effect of general development on violence is actually positive, while our sector-specific results remain intact. Next, in column 2, we restrict our focus to projects designed explicitly to improve economic opportunities within the community. As described in Table 1, 'commerce and industry' type projects include job training programs, development of bazaar infrastructure, skills workshops, and other similar efforts. These projects enhance local career options in the licit sector, thereby increasing the opportunity cost of rebellion. Still, development and reconstruction programming of this type does not significantly reduce the prevailing level of violence, and our earlier results are maintained.

A second theoretical camp in the economics of conflict literature equates violence with rent-seeking. In this framework, rebels conduct violence in an effort to gain control over resources. Therefore, reconstruction and development could exacerbate or initiate conflict insofar as the 'prize' of victory is enhanced. In the context of post-conflict reconstruction, large infrastructure works are high-value projects. Investments in agriculture, energy, and water infrastructure all increase the productive capacity of a region. Such projects are therefore likely to yield higher rents to those in control, than would otherwise be the case in the absence of those developments. Columns 3 through 5 test the response of conflict to investments in high-value projects. In line with a resource competition model, we do not differentiate between military reconstruction and civil aid. Only agriculture (neither energy, nor water) projects increase the incidence of violence as a rent-seeking explanation would predict. At the same time, these results consistently support our own explanation of violence.

In sum, neither opportunity cost nor resource competition explanations for violence are strongly supported by our data. However, those competing theories may be perceived to explain the relationship between development and conflict over a time horizon longer than a few months. As such, we also test the theories when aggregating data to 6-month intervals. With longer temporal units, the results provide even less evidence in support of either opportunity cost or resource competition theories. To conserve space, the outcomes of these tests are stored in Table B5 of the appendix.

Finally, the information-centric theory of BSF (2011) suggests reconstruction can reduce violence insofar as it is conditional. Desirable projects are used as a carrot to induce community members to share information about insurgents, thereby enabling the government authority to capture or kill them. Empirical tests in BSF (2011) have focused on projects in the Commander's Emergency Response Program (CERP). Funding under this program is doled out by U.S. commanders on the ground, and is therefore thought to fulfill the conditionality requirement critical to this theory. Small projects are expected to be most effective at leveraging community support, because their financing is less constrained by bureaucratic oversight. Three replication studies have empirically examined the impact of the CERP in

Afghanistan (Chou 2013; Child 2014; Adams 2015). Using the approach of BSF (2011), none of the studies were able to convincingly support the information-centric theory. Taken as a whole, the evidence does not suggest the CERP (neither small nor large projects) has been effective in Afghanistan. To conserve space and avoid repetition, we do not re-present those findings here.

8 CONCLUSION

Employing unique data on reconstruction, development, public opinion, and violence across Afghanistan from 2005 to 2009, we evaluate the success of reconstruction programming. Motivated by the author's own theoretical work and field interviews conducted in Kabul, we explore the possibility that certain types of reconstruction projects are controversial on ideological grounds, and can therefore exacerbate conflict. To test this hypothesis, we adopt a first-differences framework in which we control for contemporary trends in violence, civil sector development, and time-invariant district characteristics. Our findings suggest military-led education projects exacerbate local conflict, whereas health projects attenuate violence. The adverse effects of education programming are most pronounced in the conservative South. Strengthening our theoretical interpretation, those projects are also found to fuel antipathy towards international forces. Moreover, reconstruction-borne insurgency appears to be homegrown, rather than sourced externally. Importantly, our data do not support alternative theories linking conflict to development.

Skeptics of this work express identification-related grievances. We have addressed the possibility of reverse causation, and we have also dealt with selection on time-invariant unobservables down to the district level. Any remaining (time-varying) omitted factor must, at once, drive violence and *differentially* influence reconstruction programming across sectors. It is worth repeating that because we are interested in the *composition* rather than the amount of projects, most intuitive concerns regarding endogeneity are not applicable once we control for the overall level of reconstruction activity. To enhance identification, our central analysis could have exploited a policy discontinuity or natural experiment, akin to our IV approach in Appendix C.2. But we feel the practical case for endogeneity is limited, given our existing identification strategy, and given realities on the ground. As such, we feel it is not worth sacrificing general results (across 398 districts over 57 months) in favour of marginally more convincing identification based on a highly local subsample. To us the choice is obvious; especially since reservations regarding external validity are enhanced in our application, given the idiosyncrasies of conflict and development across the highly volatile landscape of Afghanistan over the past decade of insurgency.

Throughout the analysis we have attempted to practice the utmost transparency. We do not

explore nor report results for many sectors of reconstruction because we have no theoretical prior regarding their effects. We acknowledge that significance levels are merely probabilistic statements, and so we refrain from specification searching across development sectors to avoid being subsequently compelled to retroactively attribute economic meaning to potentially spurious correlations. Our theoretical priors regarding projects in health, education, and security were established in earlier work (Child & Scoones 2010). Because of this, we report results on security projects, even though they do not conform to our theoretical expectations.[28] Given data availability and resource constraints, we undertake the analysis best suited to our research question. So although we provide our own interpretation of the results herein, we leave it to readers to ultimately decide on the strength of our evidence (by openly acknowledging the limitations of our results).

An open question left mostly unexplored here (for lack of theoretical guidance) is whether the effects we measure are heterogeneous. In section 7.1.1 we explore heterogeneity along various dimensions of conservatism, but presumably there are many other covariates which could conceivably bear on the effectiveness of reconstruction programming. If heterogeneity implies a complete *reversal* of the effect for certain subpopulations, and if heterogeneity derives from a characteristic upon which sector-specific programming is differentially selected, then our results are less general than thought. However, from Table 3 we would argue this is not a major empirical concern. But although we suggest heterogeneity is unlikely to unravel our sector-based results, it remains nevertheless an important and outstanding empirical issue. Our paper has demonstrated heterogeneous impacts of projects across sectors, and across regions. An alternative analysis could embrace heterogeneity more generally (and atheoretically), by employing a machine-learning algorithm for model selection (e.g. lasso or ridge regression; random forests).

Lastly, this paper explores one possible connection between reconstruction work and violence. We by no means suggest ideological perceptions are the only factor bearing on the success of programming. To the contrary, field interviews by the author suggest there are plenty of reasons why reconstruction, and development more generally, can fail to produce peace, and even inflame local tensions. These include, but are not limited to: the level of corruption/leakage associated with development programming; relative programming levels in comparison to neighboring districts; and elite capture of reconstruction contracts in communities with fractionalized power distributions. It is important for our identification that these local conditions are orthogonal to the sector-mix (but not necessarily the overall level) of projects. Based on our reading and field experience, we have no reason to believe otherwise. Going forward, however, these alternative channels through which reconstruction and

[28] We neither explore nor report on a fourth sector discussed by Child and Scoones (2010) - *emergency assistance*, because it is obviously wrought with confounding bias.

development can affect conflict remain unexplored. There is a rich body of anecdotal evidence contained within our field interviews, which will motivate exciting new empirical work in this area.

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Table 1: **Sector descriptions**

Sector	Typical projects
Education	boys/girls schools; supplies; teacher training; vocational courses
Health	clinics; hospitals; supplies; medical training
Security	police stations; army barracks; checkpoints; fortification of civilian targets; prison repair
Commerce & Industry	market/bazaar infrastructure; training workshops; enterprise development
Agriculture	irrigation; livestock treatment; seed & fertilizer distribution
Energy	generators; wells; hydroplants
Water & Sanitation	wells; waterpumps
Environment	floodwalls; environmental protection; snow removal
Transportation	roads; bridges; highways
Emergency Assistance	refugee camps; humanitarian relief; compensation
Capacity Building	town hall; civic center; post office; district office
Governance	court facilities; district offices; governor's compounds
Community Development	clothes; food; blankets; sports facilities; mosques; radio
Unknown	other

Sector groups are from Afghanistan Standard Industrial Classification of Activities (ASIC) maintained by the Afghanistan Management Information Services (AIMS). 'Typical project' describe the most common projects falling under each sector classification.

Table 2: **Descriptive statistics**

	Levels					Differences			
	N	Mean	SD	Min	Max	Mean	SD	Min	Max
Violence	22686	0.20	0.8	0	34	0.0015	1.06	-26	34
Reconstruction & Development:									
PRT projects	22686	2.22	6.9	0	342	0.0225	2.58	-118	143
Education (PRT)	22686	0.37	1.4	0	62	0.0028	0.84	-41	56
Health (PRT)	22686	0.19	1.6	0	96	0.0020	0.65	-39	41
Security (PRT)	22686	0.07	0.5	0	13	0.0002	0.24	-9	7
Aid projects	22686	11.75	30.6	0	1303	-0.2297	11.50	-1122	665
Education (Aid)	22686	5.60	18.8	0	228	0.0073	2.35	-107	85
Health (Aid)	22686	7.66	5.2	0	65	-0.0552	1.50	-42	53
Security (Aid)	22686	0.76	1.9	0	32	0.0180	0.51	-17	31
Commerce (All)	22686	0.33	1.0	0	42	-0.0076	0.47	-27	30
Agriculture (All)	22686	2.49	21.0	0	1288	-0.0488	10.29	-1120	665
Energy (All)	22686	0.46	3.0	0	145	-0.0002	1.30	-67	77
Water (All)	22686	0.61	8.3	0	383	-0.1129	4.03	-313	16

[Table 2 continues on next page...]

[...Table 2 continued from previous page]

	N	Mean	SD	Min	Max
District Characteristics:					
Education preference	777	0.39	0.34	0	1
Health preference	777	0.40	0.35	0	1
Security preference	777	0.07	0.20	0	1
Hunger	777	1.86	0.86	0	4.37
Road access	777	0.84	0.94	0	4.97
CDC presence	777	0.51	0.43	0	1
Population (thousands)	777	63.0	170.3	2	3289
Public Opinion:					
Opinion	1435	3.11	0.68	1.0	5.0
R&D	498	1.19	0.17	1.0	2.0
Respect	957	2.90	0.58	1.0	4.0
Trust	1204	2.76	0.57	1.1	4.0

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, GTD, NRVA, and ANQAR. Violence data are measured as incidents per average district population (per 63,000 inhabitants). Reconstruction and development (R&D) data are measured in terms of mean concurrent projects per average district population. Unit of observation for violence and R&D data is the district-month. Projects in unmentioned sectors are tallied in the appropriate total project subcategories (either 'PRT projects' or 'Aid projects'). Unit of observation for district characteristics and public opinion data is the district-survey wave.

Table 3: **Spatial allocation of reconstruction and violence**

	(1) Violence	(2) PRT	(3) Education	(4) Health	(5) Security
Preference			1.818*	0.895	1.803
			(0.0667)	(0.161)	(0.367)
Schooling	-1.01*	1.93	1.16	1.25	0.18
	(0.054)	(0.699)	(0.240)	(0.114)	(0.733)
Healthiness	-0.459	2.89	0.165	-0.788	-0.471
	(0.375)	(0.574)	(0.884)	(0.305)	(0.453)
Religiosity	0.467	8.31	1.33	1.87	1.02**
	(0.437)	(0.267)	(0.342)	(0.145)	(0.023)
Women	-1.75***	-5.73	-0.867	-0.309	0.557
	(0.000254)	(0.330)	(0.474)	(0.738)	(0.218)
Hunger	-0.876***	-5.384***	-0.679*	-0.368	-0.333
	(1.49e-06)	(0.00613)	(0.0848)	(0.104)	(0.118)
Roads	-0.406**	-3.405**	-0.337	-0.408*	-0.0966
	(0.0150)	(0.0117)	(0.289)	(0.0660)	(0.465)
CDC	-0.932**	5.513*	1.836***	-0.405	-0.121
	(0.0103)	(0.0995)	(0.00875)	(0.451)	(0.696)
Population	-0.515***	-4.48**	-0.634*	-0.733***	-0.339*
	(0.000)	(0.013)	(0.077)	(0.006)	(0.052)
Observations	777	777	777	777	777
R-squared	0.139	0.085	0.067	0.035	0.057

Sample includes 398 districts across Afghanistan, and covers two NRVA survey periods (2005 and 2007/8). Data are gleaned from the ACSP, WITS, GTD, and NRVA. Dependent variable is either violent incidents or reconstruction projects, per average-sized district (63,000 inhabitants). $Schooling$, $Healthiness$, $Religiosity$, and $Women$ are expressed as percentile ranks, normalized between 0 and 1. Population is expressed in millions. Regressions are weighted by district population, and survey period effects are included. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4: **Impact of reconstruction**

	(1)	(2)
Time controls	Y	Y
First differences		Y
PRT	0.0133**	-0.00500
	(0.025)	(0.118)
Observations	22,288	21,890
R-squared	0.033	0.012

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is violent incidents per capita. Reconstruction variable is lagged one period. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 5: **Sector-specific impact of reconstruction**

	(1)	(2)	(3)	(4)
First differences		Y	Y	Y
Pre-existing trend			Y	Y
District-specific trend				Y
Education	0.0179	0.0243**	0.0286***	0.0286***
	(0.234)	(0.012)	(0.008)	(0.008)
Health	0.0560	-0.0585**	-0.0416*	-0.0419*
	(0.100)	(0.024)	(0.070)	(0.071)
Security	0.0509	-0.0295*	-0.0433*	-0.0433*
	(0.328)	(0.077)	(0.066)	(0.069)
Observations	22,288	21,890	21,890	21,890
R-squared	0.036	0.012	0.262	0.263

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. Reconstruction variables are lagged one period. All specifications include controls for time period and residual PRT (reconstruction projects in sectors not explicitly reported in table). Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 6: **Reverse causality**

	(1) PRT	(2) Education	(3) Health	(4) Security
Panel A: 1 month intervals				
Violence	0.00646	-0.00830	0.00563	0.00282
	(0.641)	(0.173)	(0.132)	(0.251)
Observations	21,890	21,890	21,890	21,890
R-squared	0.017	0.008	0.006	0.006
Panel B: 6 month intervals				
Violence	0.0201	-0.0156	-0.00185	0.00688
	(0.641)	(0.309)	(0.797)	(0.124)
Observations	1,617	1,617	1,617	1,617
R-squared	0.117	0.053	0.032	0.036
Panel C: predicted violence				
Violence	-0.389	-0.0939	0.0929**	0.0113
	(0.214)	(0.386)	(0.016)	(0.653)
Observations	21,094	21,094	21,094	21,094
R-squared	0.017	0.009	0.006	0.006

Sample includes 398 districts across Afghanistan, and spans 57 months (9 half-years). Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in mean concurrent daily projects per capita. All specifications are first-differenced. Violence variable is lagged one period. Time controls, and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 7: **Civil aid donors**

	(1) USAID	(2) Other	(3) CSTCA	(4) Aid
Education (PRT)	0.0287***	0.0286***	0.0285***	0.0286***
	(0.007)	(0.007)	(0.008)	(0.007)
Health (PRT)	-0.0417*	-0.0420*	-0.0423*	-0.0425*
	(0.069)	(0.068)	(0.066)	(0.066)
Security (PRT)	-0.0454*	-0.0432*	-0.0431*	-0.0451*
	(0.067)	(0.068)	(0.066)	(0.069)
Education (Aid)	-0.00152	-0.0111		-0.00186
	(0.141)	(0.346)		(0.110)
Health (Aid)	0.00650	0.00320		0.00260
	(0.416)	(0.198)		(0.153)
Security (Aid)	-0.0216	-0.0108	-0.0138	-0.0124
	(0.488)	(0.451)	(0.343)	(0.144)
Observations	21,890	21,890	21,890	21,890
R-squared	0.262	0.262	0.262	0.262

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, GTD. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Reconstruction and aid variables are lagged one period. Time controls, pre-existing trends, civil aid project volumes, and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 8: **Local conservatism**

	(1) South	(2) Religion	(3) Women	(4) Pashtun
Education	0.0209**	0.0278	0.00563	0.0174
	(0.033)	(0.242)	(0.825)	(0.126)
Health	-0.0259*	0.0428	-0.0249	-0.0154
	(0.095)	(0.287)	(0.658)	(0.494)
Security	-0.00826	-0.000228	0.0447	0.00224
	(0.699)	(0.994)	(0.185)	(0.916)
Conservatism*Education	0.0912***	-0.00187	0.0370	0.0220
	(0.006)	(0.965)	(0.357)	(0.344)
Conservatism*Health	-0.111	-0.163*	-0.0413	-0.0444
	(0.268)	(0.099)	(0.711)	(0.387)
Conservatism*Security	-0.0800***	-0.0728	-0.191***	-0.0805**
	(0.010)	(0.156)	(0.005)	(0.026)
Observations	21,890	20,955	20,955	21,890
R-squared	0.263	0.262	0.262	0.263

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, GTD, NRVA, and ANQAR. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Reconstruction variables are lagged one period. Time controls, pre-existing trends, civil aid project volumes, and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 9: **Popular antipathy**

	(1) Opinion	(2) R&D	(3) Respect	(4) Trust
Education	0.0253	0.0274*	0.00960	0.0245
	(0.253)	(0.065)	(0.725)	(0.364)
Health	0.00616	0.0417	0.0146	-0.0377
	(0.893)	(0.390)	(0.784)	(0.355)
Security	0.202	-0.123	0.188*	0.00520
	(0.162)	(0.142)	(0.055)	(0.949)
South*Education	0.330**	0.181**	0.0467	-0.0365
	(0.011)	(0.025)	(0.601)	(0.668)
South*Health	0.288	-0.262	0.126	0.176
	(0.135)	(0.218)	(0.422)	(0.269)
South*Security	-0.221	0.217*	-0.445**	-0.00271
	(0.332)	(0.071)	(0.010)	(0.987)
Observations	1,435	498	957	1,204
R-squared	0.080	0.033	0.016	0.040
Number of district	365	322	343	353

Sample includes 398 districts across Afghanistan, and spans 6 quarters. Data are gleaned from the ANQAR, ACSP, WITS, and GTD. Dependent variable is antipathy towards international forces. All specifications include district fixed effects. Reconstruction variables are lagged one period. Time controls and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 10: **Displacement of violence**

	(1)	(2)
District effects	Y	Y
Pre-existing trend	Y	Y
Time effects	Y	
Region $\times$ Time effects		Y
Neighbours	-0.192	-0.105
	(0.230)	(0.268)
Observations	22,288	22,288
R-squared	0.700	0.825

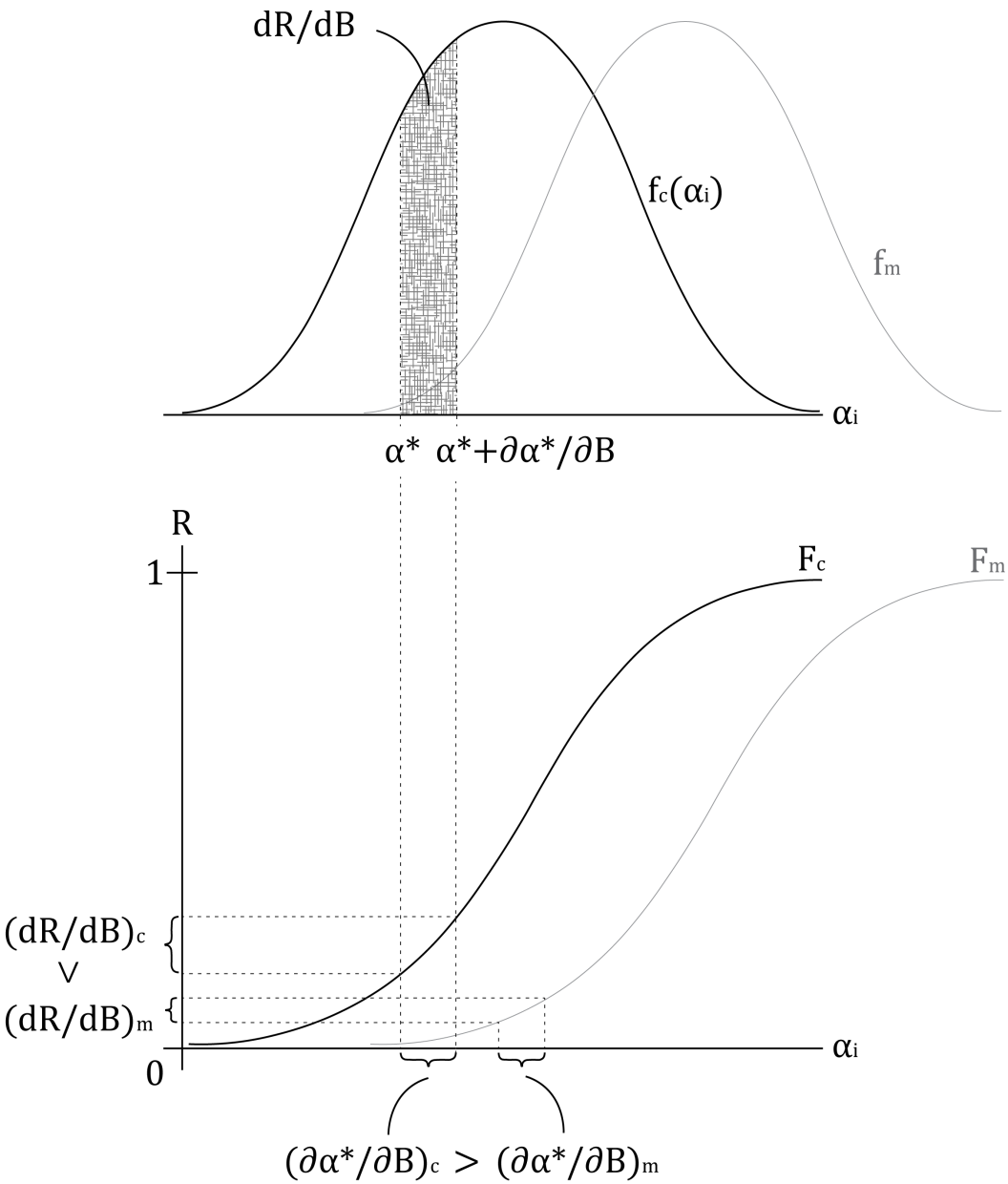
Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is predicted number of attacks. *Neighbours* is the total number of attacks in surrounding districts. All specifications include fixed effects, time controls, and pre-existing trends. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 11: **Competing explanations**

	(1) Opp Cost	(2) Opp Cost	(3) Rent	(4) Rent	(5) Rent
Aid+PRT	0.000508***				
	(0.001)				
Commerce		-0.0174			
		(0.472)			
Agriculture			0.00277***		
			(0.010)		
Energy				0.00364	
				(0.253)	
Water					-0.00355**
					(0.0210)
Education	0.0281***	0.0287***	0.0286***	0.0286***	0.0285***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Health	-0.0424*	-0.0413*	-0.0416*	-0.0416*	-0.0416*
	(0.066)	(0.074)	(0.069)	(0.069)	(0.070)
Security	-0.0458*	-0.0451*	-0.0457*	-0.0453*	-0.0460*
	(0.066)	(0.070)	(0.065)	(0.069)	(0.064)
Observations	21,890	21,890	21,890	21,890	21,890
R-squared	0.262	0.262	0.263	0.262	0.263

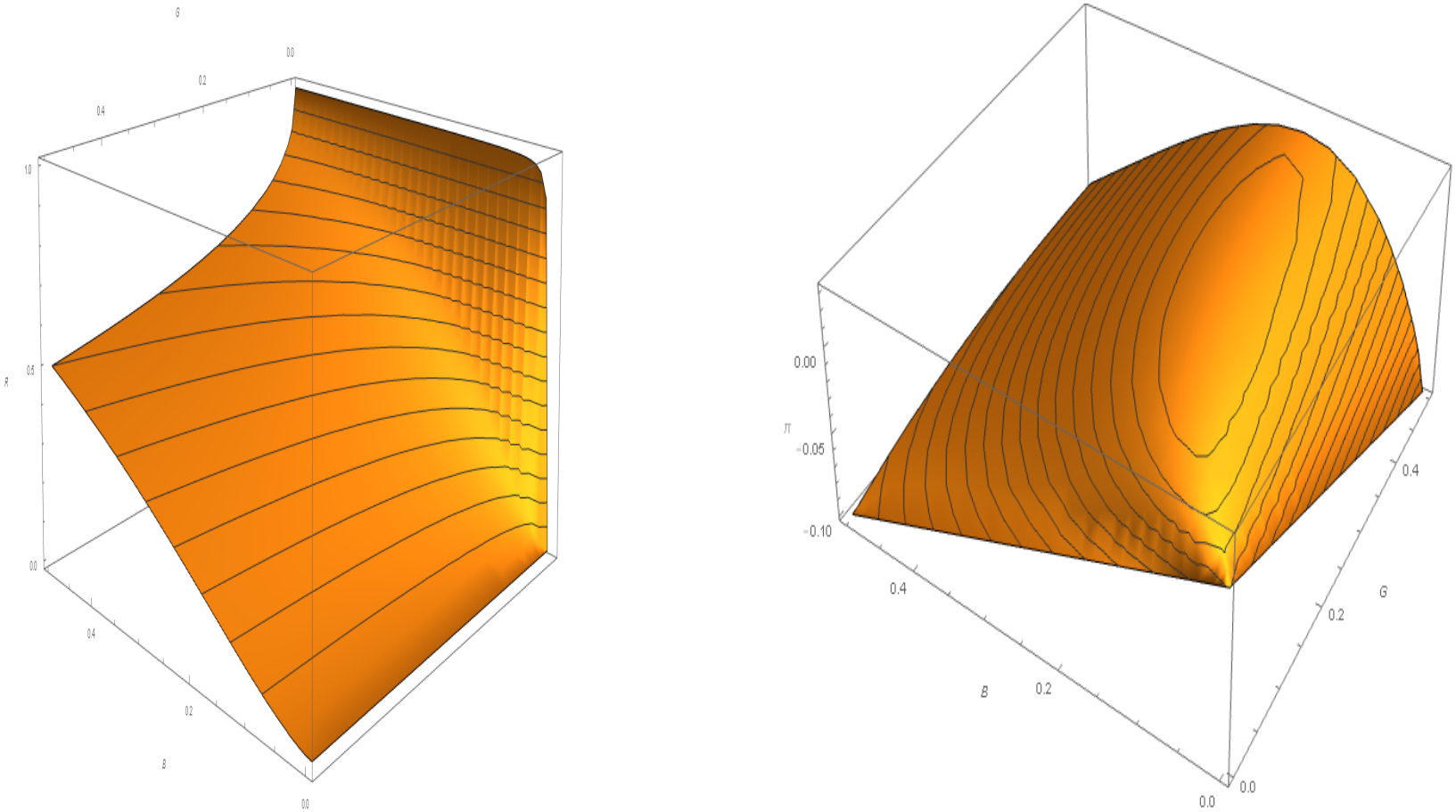
Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Reconstruction and aid variables are lagged one period. Time controls, pre-existing trends, civil aid project volumes, and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Figure 1: **Community preferences and the impact of controversial reconstruction**



Upper panel of figure depicts a probability density function for ideological preferences (α_i) of a conservative community (denoted by c, in black), and of a moderate community (denoted by m, in grey). Bottom panel depicts corresponding cumulative density functions, whose heights indicate the overall level of insurgency (R). An injection of controversial reconstruction B shifts the marginal insurgent (α^*) to the right, leading to an expansion of the insurgency. The size of the effect is larger for conservative communities than for moderate ones.

Figure 2: **Size of insurgency and occupier payoffs**

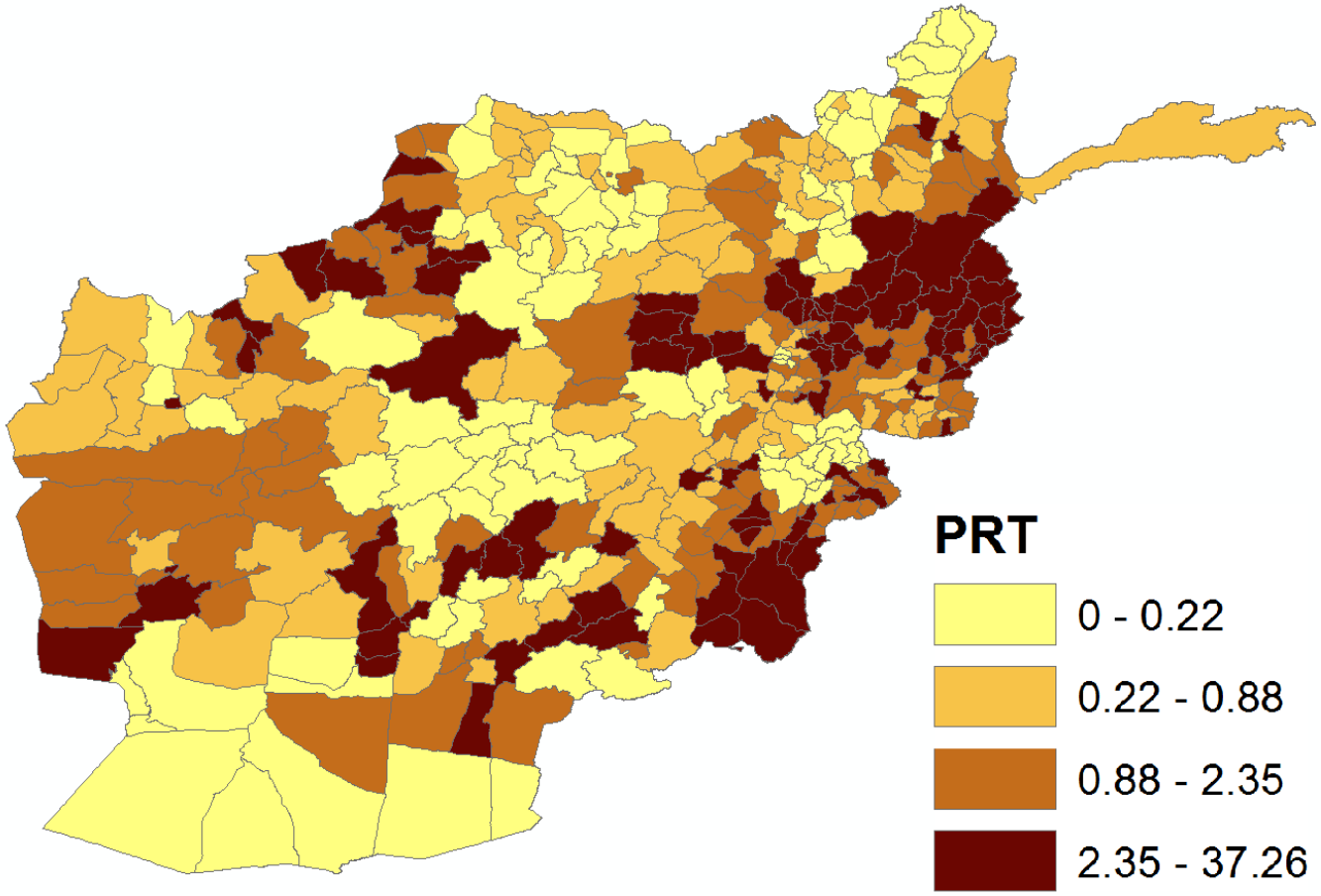


(a) Resistance

(b) Occupier payoffs

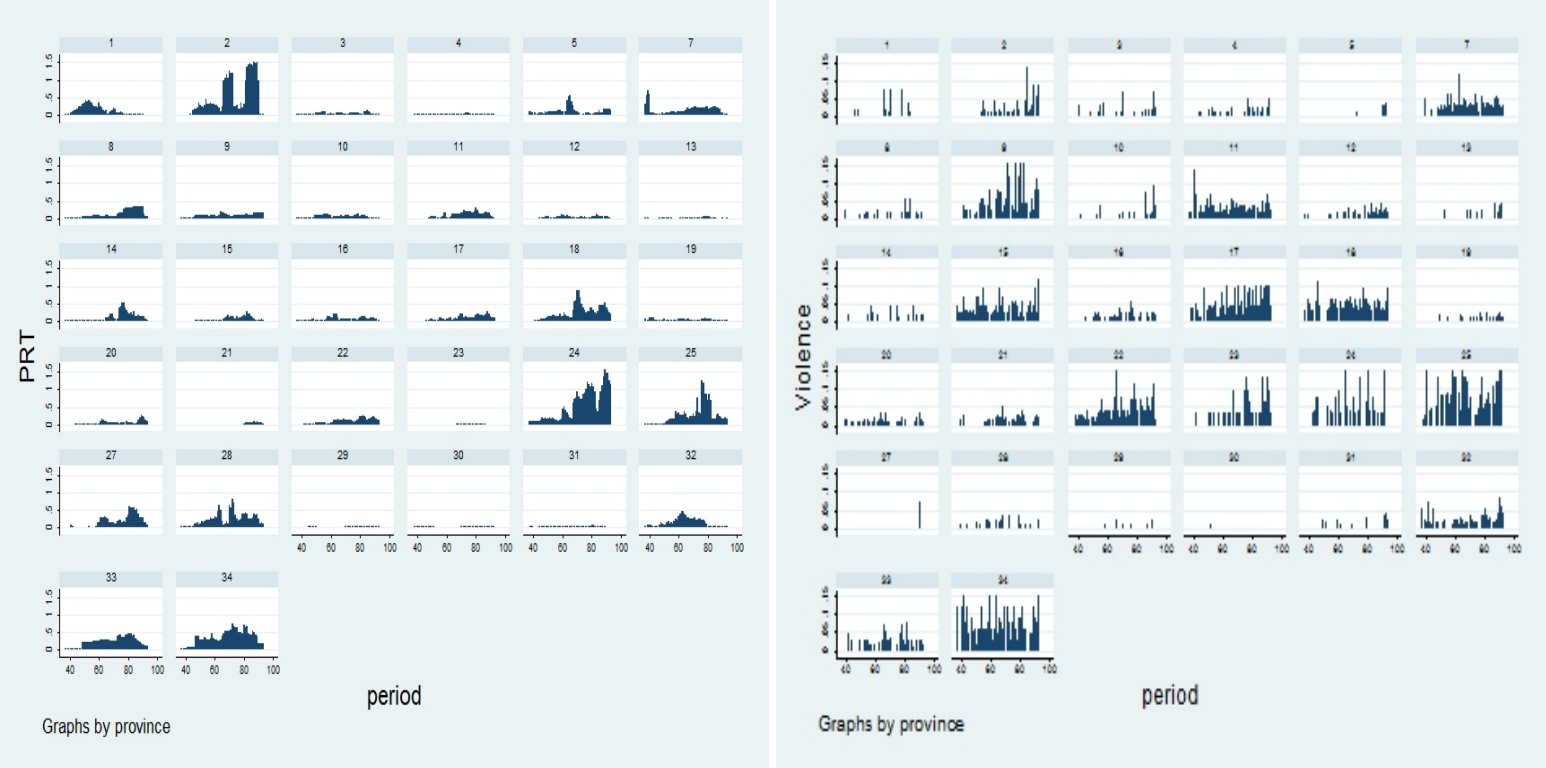
Left panel of figure depicts level curves of insurgency size (R) for various allocations of spending. Right panel depicts level curves of occupier utility (V) for the same allocations. Outcomes are based on parameterization of model given in section 3.2.4.

Figure 3: **Spatial distribution of PRT projects**



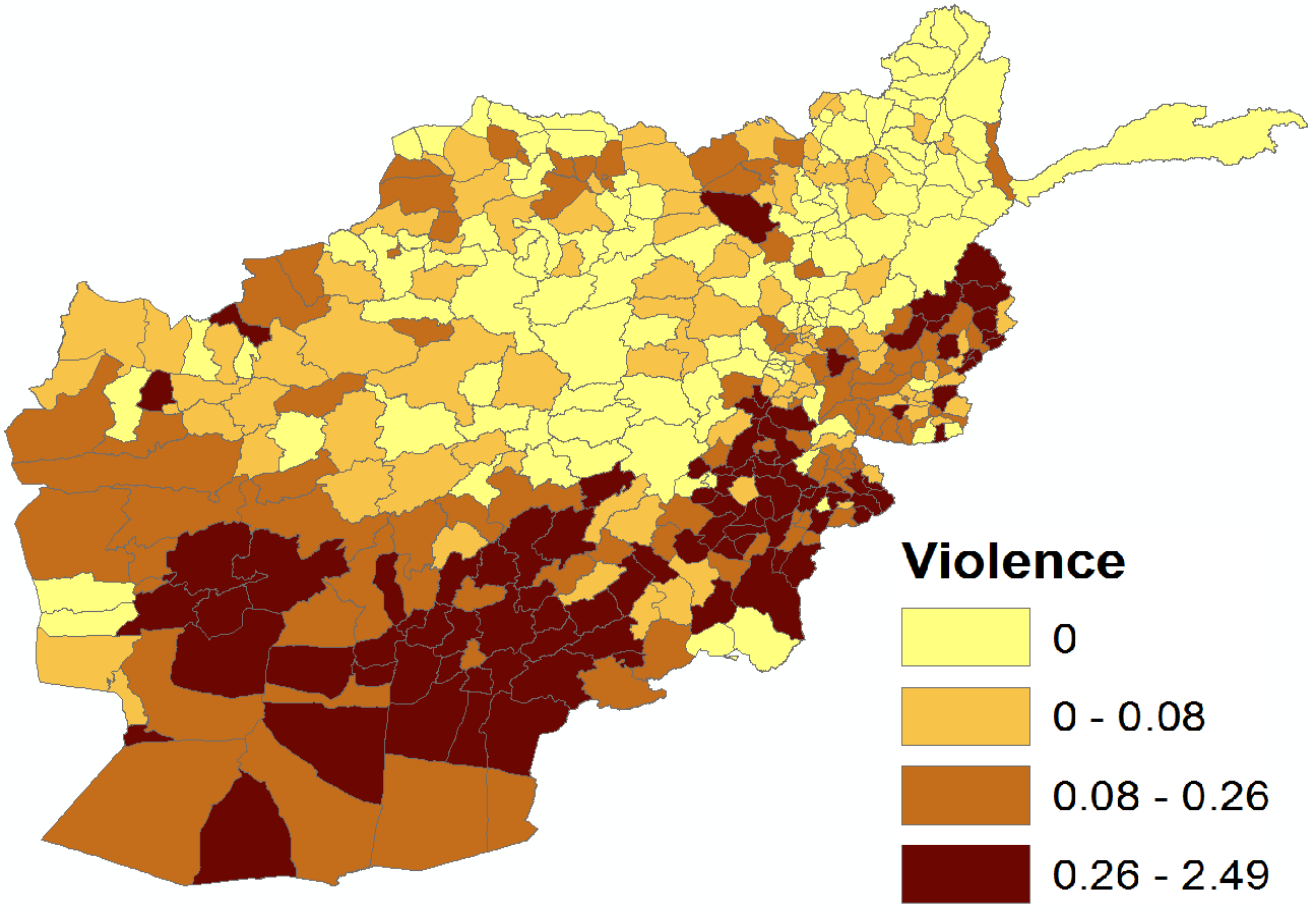
Map reflects average rate of Provincial Reconstruction Team (PRT) projects underway, per month, calculated across 57 months for 398 districts. The measure is expressed in per capita terms, and scaled to the average district population. For comparison, an average size district is expected to witness 2.22 PRT projects per month. The ranges provided in the legend are based on quartiles. Data are gleaned from the ACSP.

Figure 4: **Monthly variation in reconstruction and violence**



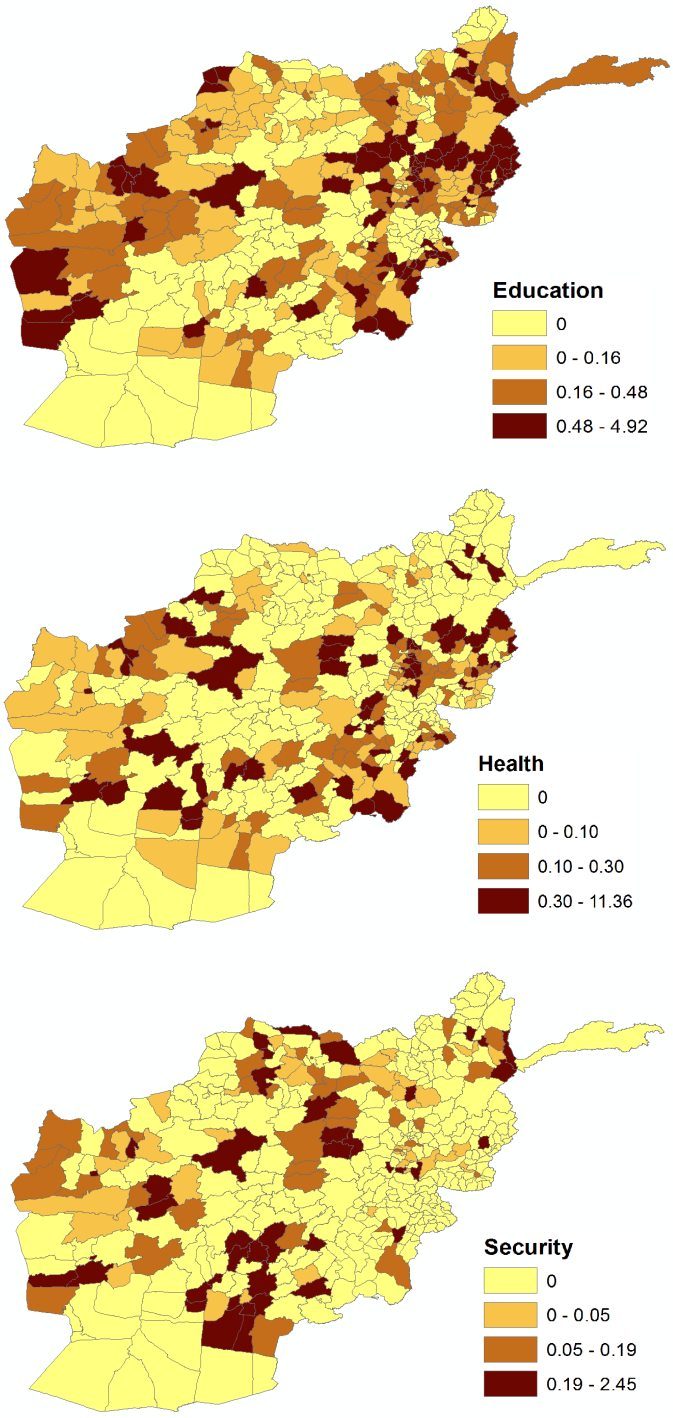
Left panel of figure depicts monthly volumes of per-capita PRT projects across 34 provinces. Right panel reflects the incidence of violence, at the same level of aggregation. Data are gleaned from the ACSP, WITS, and GTD.

Figure 5: **Spatial distribution of Violence**



Map reflects average rate of violent incidents per month, calculated across 57 months for 398 districts. The measure is expressed in per capita terms, and scaled to the average district population. For comparison, an average size district is expected to incur 0.20 incidents per month. The ranges provided in the legend are based on quartiles. Data are gleaned from the WITS and GTD.

Figure 6: **Spatial distribution of PRT sectors**



Map reflects average rate of Provincial Reconstruction Team (PRT) projects underway, per month, calculated across 57 months for 398 districts. The measure is expressed in per capita terms, and scaled to the average district population. For comparison, an average size district is expected to witness, per month: 0.37 education projects, 0.19 health projects, and 0.07 security projects. The ranges provided in the legend are based on quartiles. Data are gleaned from the ACSP.

APPENDIX A: FORMAL SOLUTIONS

In this mathematical appendix, we impose additional properties to prove uniqueness and existence of the equilibrium, and formally derive Hypotheses I through III.

Properties

Property 1: Separability and symmetry of the production functions.

$$g(G,R) = g(G,0)h(R) \equiv \widetilde{g}(G)h(R)$$
$$b(B,R) = b(B,0)h(R) \equiv \widetilde{b}(B)h(R)$$
$$\text{where } \; h'(R) < 0$$

Property 2: Linear homogeneity of the community member utility function.

$$U^i(\lambda g, \lambda b; \alpha_i) = \lambda U^i(g,b;\alpha_i) \Longrightarrow \begin{cases} \frac{\partial U^i}{\partial g}(\lambda g, \lambda b; \alpha_i) = \frac{\partial U^i}{\partial g}(g,b;\alpha_i) \\ \frac{\partial U^i}{\partial b}(\lambda g, \lambda b; \alpha_i) = \frac{\partial U^i}{\partial b}(g,b;\alpha_i) \end{cases}$$

Property 3: Limit conditions on marginal utilities of extreme community members.[29]

$$\lim_{\alpha_i \to -\infty} U^i_b \to -\infty \qquad \lim_{\alpha_i \to +\infty} U^i_b \to 0$$
$$\lim_{\alpha_i \to -\infty} U^i_g \to C_1 > 0 \qquad \lim_{\alpha_i \to +\infty} U^i_g \to C_2 > 0$$

Uniqueness and existence

Given the properties above, we can now proceed with our proofs. Take the first-order condition (FOC) of $U^i(g,b;\alpha_i) = U^i(\widetilde{g}(G)h(R), \widetilde{b}(B)h(R);\alpha_i)$ with respect to R for individual i.

$$\begin{aligned}
\frac{dU^i}{dR} =& \frac{\partial U^i}{\partial g}(\widetilde{g}(G)h(R), \widetilde{b}(B)h(R);\alpha_i)\widetilde{g}h' + \frac{\partial U^i}{\partial b}(\widetilde{g}(G)h(R), \widetilde{b}(B)h(R);\alpha_i)\widetilde{b}h' = 0 && \text{(FOC)} \\
\Longrightarrow& \frac{\partial U^i}{\partial g}(\widetilde{g}(G)h(R), \widetilde{b}(B)h(R);\alpha_i)\widetilde{g} + \frac{\partial U^i}{\partial b}(\widetilde{g}(G)h(R), \widetilde{b}(B)h(R);\alpha_i)\widetilde{b} = 0 && \text{(from Property 1)} \\
\Longrightarrow& \frac{\partial U^i}{\partial g}(\widetilde{g}(G), \widetilde{b}(B);\alpha_i)\widetilde{g} + \frac{\partial U^i}{\partial b}(\widetilde{g}(G), \widetilde{b}(B);\alpha_i)\widetilde{b} = 0 && \text{(from Property 2)} \\
\Longrightarrow& H(G,B;\alpha^*) = 0 && \text{(implicit function)}
\end{aligned}$$

Now for uniqueness, we differentiate H with respect to α_i: $H_{\alpha_i} = U^i_{g\alpha_i}\widetilde{g} + U^i_{b\alpha_i}\widetilde{b}$. Recall $U_{g\alpha_i} \geq 0$ and $U_{b\alpha_i} > 0$, by assumption. Then it is clear that $H_{\alpha_i} > 0$. Since $H_{\alpha_i} = \frac{d}{d\alpha_i}\frac{dU^i}{dR}$, then $\frac{d}{d\alpha_i}\frac{dU^i}{dR} > 0$, implying there is *at most* one α^* fulfilling the FOC for a given expenditure bundle (G,B). Hence, $R^*(\alpha^*(G,B))$ is unique.

[29] We could also substitute $\lim_{\alpha_i \to +\infty} U^i_g \to +\infty$.

But does α^* exist?

$$\lim_{\alpha_i \to 0} dU^i/dR = \lim_{\alpha_i \to 0} U^i_g \widetilde{g} + U^i_b \widetilde{b} \longrightarrow -\infty$$
$$\lim_{\alpha_i \to +\infty} dU^i/dR = \lim_{\alpha_i \to +\infty} U^i_g \widetilde{g} + U^i_b \widetilde{b} \longrightarrow C_3 > 0$$

Since dU^i/dR spans the interval $(-\infty, C_3)$, there exists an α^* for which the FOC is satisfied, conditional on H being continuous and differentiable with respect to α_i.

Hypotheses

Our first hypothesis is $\Delta R/\Delta B > 0$, which follows directly from $\alpha^*_B > 0$. In order to establish the latter, we make use of the implicit function theorem (i.e. $\partial\alpha^*/\partial B = -H_B/H_{\alpha^*}$).

$$H_{\alpha^*} = U^*_{g\alpha^*}\widetilde{g} + U^*_{b\alpha^*}\widetilde{b}$$
$$H_B = U^*_{gb}\widetilde{b}'\widetilde{g} + U^*_{bb}\widetilde{b}'\widetilde{b} + U^*_b\widetilde{b}' = \widetilde{b}'(U^*_{gb}\widetilde{g} + U^*_{bb}\widetilde{b}) + U^*_b\widetilde{b}'$$

Note: By the property of homotheticity, $U^*_g g + U^*_b b = U^*$. So the following obtains:

$$\frac{d}{db}(U^*_g g + U^*_b b) = \frac{d}{db}(U^*) \Longrightarrow U^*_{gb} g + U^*_{bb} b + U^*_b = U^*_b$$
$$\Longrightarrow \; U^*_{gb} g + U^*_{bb} b = 0 \Longrightarrow U^*_{gb}\widetilde{g}h + U^*_{bb}\widetilde{b}h = 0$$
$$\Longrightarrow \; U^*_{gb}\widetilde{g} + U^*_{bb}\widetilde{b} = 0$$

So, $H_B = U^*_b\widetilde{b}'$, and we can express

$$\alpha^*_B = \frac{-H_B}{H_{\alpha^*}} = \frac{-U^*_b\widetilde{b}'}{U^*_{g\alpha}\widetilde{g} + U^*_{b\alpha}\widetilde{b}} > 0 \tag{A1}$$

Following analogous logical steps, we can also derive Hypotheis II ($\Delta R/\Delta G < 0$) under Properties 1-3.

$$H_G = U^*_{gg}\widetilde{g}'\widetilde{g} + U^*_{bg}\widetilde{g}'\widetilde{b} + U^*_g\widetilde{g}' = U^*_g\widetilde{g}'$$
$$\alpha^*_G = \frac{-U^*_g\widetilde{g}'}{U^*_{g\alpha}\widetilde{g} + U^*_{b\alpha}\widetilde{b}} < 0$$

Our third hypothesis requires further elaboration. Consider two communities (denoted by subscripts c and m) where the preference distributions differ by a constant, such that $f_c(\alpha_i) = f_m(\alpha_i + s) \;\forall\; \alpha_i$, where $s > 0$ (so that $F_m(\alpha_i) < F_c(\alpha_i) \;\forall\; \alpha_i$). A given (G_0, B_0) bundle yields α^*_c and α^*_m. If the following conditions (i)-(iii) hold, then $f_c(\alpha^*_c) > f_m(\alpha^*_m)$.

(i) f_m is unimodal

(ii) $R_c > R_m$

(iii) $\alpha^*_c < \arg\max_{\alpha_i} f_c(\alpha_i)$

(iv) $\alpha^*_c < \alpha^*_m$

Since $dR/dB \approx f(\alpha^*)(\partial\alpha^*/\partial B)$, we now compare α_B^* across communities. To clarify notation we substitute the asterisk for the community index, to reflect that (G_0, B_0) will generate different MIs in each community. We begin by comparing denominators from equation A1. Given (G_0, B_0), under $R_c > R_m$ (condition (ii)), it follows that $g_c < g_m$ and $b_c < b_m$. By Property 1, $g_c = Dg_m$ and $b_c = Db_m$, where $0 < D < 1$. By Property 2, $U_g^i(g_c, b_c) = U_g^i(Dg_c, Db_c) = U_g^i(g_m, b_m)$; likewise $U_b^i(g_c, b_c) = U_b^i(g_m, b_m)$. If we impose $U_{g\alpha\alpha} = 0$, then $U_{g\alpha}^i = U_{g\alpha}^j \ \ \forall \ i, j$. So under the constraint $U_{g\alpha\alpha} = U_{b\alpha\alpha} = 0$, the following is true: $U_{g\alpha}^c = U_{g\alpha}^m$ and $U_{b\alpha}^c = U_{b\alpha}^m$. Because $\widetilde{g}$ and $\widetilde{b}$ are independent of R, $\widetilde{g_c} = \widetilde{g_m}$ and $\widetilde{b_c} = \widetilde{b_m}$. We thus confirm under these conditions: $U_{g\alpha}^c\widetilde{g} + U_{b\alpha}^c\widetilde{b} = U_{g\alpha}^m\widetilde{g} + U_{b\alpha}^m\widetilde{b}$.

We now turn to the numerator of equation A1. Since $\widetilde{b_c} = \widetilde{b_m}$, it is clear that $\widetilde{b}_c' = \widetilde{b}_m'$. Finally, given $U_{b\alpha}^i > 0$, under condition (iv), it follows that $U_b^c < U_b^m$. Thus, under Properties 1-3, conditions (i)-(iv), and $U_{g\alpha\alpha} = U_{b\alpha\alpha} = 0$, the following holds true: $\alpha_B^c > \alpha_B^m$, and $(dR/dB)_c > (dR/dB)_m$.

APPENDIX B: ADDITIONAL TABLES AND FIGURES

Table B1: **Anderson-Hsiao 2SLS-IV**

	(1) OLS	(2) IV (L2)	(3) IV (L2,L3)	(4) IV (L3,L4)
Education	0.0286***	0.0240***	0.0247***	0.0285***
	(0.008)	(0.008)	(0.007)	(0.005)
Health	-0.0416*	-0.0585**	-0.0575**	-0.0419*
	(0.070)	(0.015)	(0.016)	(0.050)
Security	-0.0433*	-0.0328**	-0.0349**	-0.0490**
	(0.066)	(0.047)	(0.041)	(0.021)
Violence (Lag)	-0.515***	0.007	-0.025	-0.498**
	(0.000)	(0.766)	(0.242)	(0.043)
Observations	21,890	21,492	21,094	20,696
Kleibergen-Paap rk Wald F-stat		4941	1637	3.97

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Reconstruction variables are lagged one period. Column 1 replicates column 3 of Table 5. In columns 2, 3, and 4, we instrument for lagged violence with, respectively: the second lag; the second and third lags; and, the third and fourth lags of violence. Time controls and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table B2: **Descriptive statistics (extended sample)**

	N	Mean	SD	Min	Max
PRT projects	22288	0.0275	2.97	-118	143
Education (PRT)	22288	0.0060	0.93	-41	56
Health (PRT)	22288	-0.0018	0.68	-39	41
Security (PRT)	22288	0.0070	0.42	-9	24
Aid projects	22288	-0.1580	11.65	-1122	665
Education (Aid)	22288	0.0078	2.36	-107	85
Health (Aid)	22288	-0.0552	1.50	-42	53
Security (Aid)	22288	0.0353	0.66	-17	31
Commerce (All)	22288	-0.0065	0.48	-27	30
Agriculture (All)	22288	-0.0285	10.43	-1120	665
Energy (All)	22288	-0.0048	1.32	-67	77
Water (All)	22288	-0.1071	4.04	-313	16

All values are expressed in terms of first-differences. Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, GTD, NRVA, and ANQAR. Violence data are measured as incidents per average district population (63,000 inhabitants). Reconstruction and development (R&D) data are measured in terms of mean concurrent projects per average district population. Unit of observation for violence and R&D data is the district-month. Projects in unmentioned sectors are tallied in the appropriate total project subcategories (either 'PRT projects' or 'Aid projects'). Unit of observation for district characteristics and public opinion data is the district-survey wave.

Table B3: **Sector-specific impact of reconstruction (extended sample)**

	(1)	(2)	(3)
First differences	Y	Y	Y
Pre-existing trend		Y	Y
District-specific trend			Y
Education	0.019**	0.020**	0.020**
	(0.020)	(0.037)	(0.040)
Health	-0.051**	-0.038**	-0.038**
	(0.022)	(0.037)	(0.040)
Security	-0.018	-0.023*	-0.024*
	(0.138)	(0.082)	(0.079)
Observations	21,890	21,890	21,890
R-squared	0.012	0.262	0.263

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Reconstruction variables are lagged one period. All specifications include controls for time period and residual PRT (reconstruction projects in sectors not explicitly reported in table). Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table B4: **Civil aid donors (extended sample)**

	(1) USAID	(2) Other	(3) CSTCA	(4) Aid
Education (PRT)	0.0195**	0.0196**	0.0194**	0.0195**
	(0.0366)	(0.0356)	(0.0388)	(0.0373)
Health (PRT)	-0.0377**	-0.0379**	-0.0374**	-0.0378**
	(0.0361)	(0.0355)	(0.0381)	(0.0361)
Security (PRT)	-0.0240*	-0.0233*	-0.0235*	-0.0240*
	(0.0814)	(0.0840)	(0.0808)	(0.0825)
Education (Aid)	-0.00154	-0.0107		-0.00185
	(0.128)	(0.355)		(0.104)
Health (Aid)	0.00567	0.00317		0.00207
	(0.477)	(0.176)		(0.226)
Security (Aid)	-0.0207	-0.00991	0.00801	0.000109
	(0.498)	(0.522)	(0.678)	(0.991)
Observations	21,890	21,890	21,890	21,890
R-squared	0.262	0.262	0.262	0.262

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Reconstruction and aid variables are lagged one period. Time controls, pre-existing trends, civil aid project volumes, and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table B5: **Competing explanations (half-year units)**

	(1) Opp Cost	(2) Opp Cost	(3) Rent	(4) Rent	(5) Rent
Aid+PRT	0.00102				
	(0.402)				
Commerce		-0.176			
		(0.155)			
Agriculture			0.00110		
			(0.392)		
Energy				-0.00777	
				(0.726)	
Water					-0.0109
					(0.252)
Education	-0.0395	-0.0353	-0.0382	-0.0373	-0.0373
	(0.710)	(0.739)	(0.719)	(0.726)	(0.726)
Health	-0.0775	-0.0762	-0.0760	-0.0707	-0.0701
	(0.640)	(0.645)	(0.647)	(0.676)	(0.675)
Security	-0.215	-0.188	-0.214	-0.205	-0.205
	(0.369)	(0.426)	(0.370)	(0.389)	(0.389)
Observations	1,617	1,617	1,617	1,617	1,617
R-squared	0.251	0.252	0.251	0.251	0.252

Sample includes 398 districts across Afghanistan, and spans 54 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Reconstruction and aid variables are lagged one period. Time controls, pre-existing trends, civil aid project volumes, and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Figure B1: **Partial regression plots**

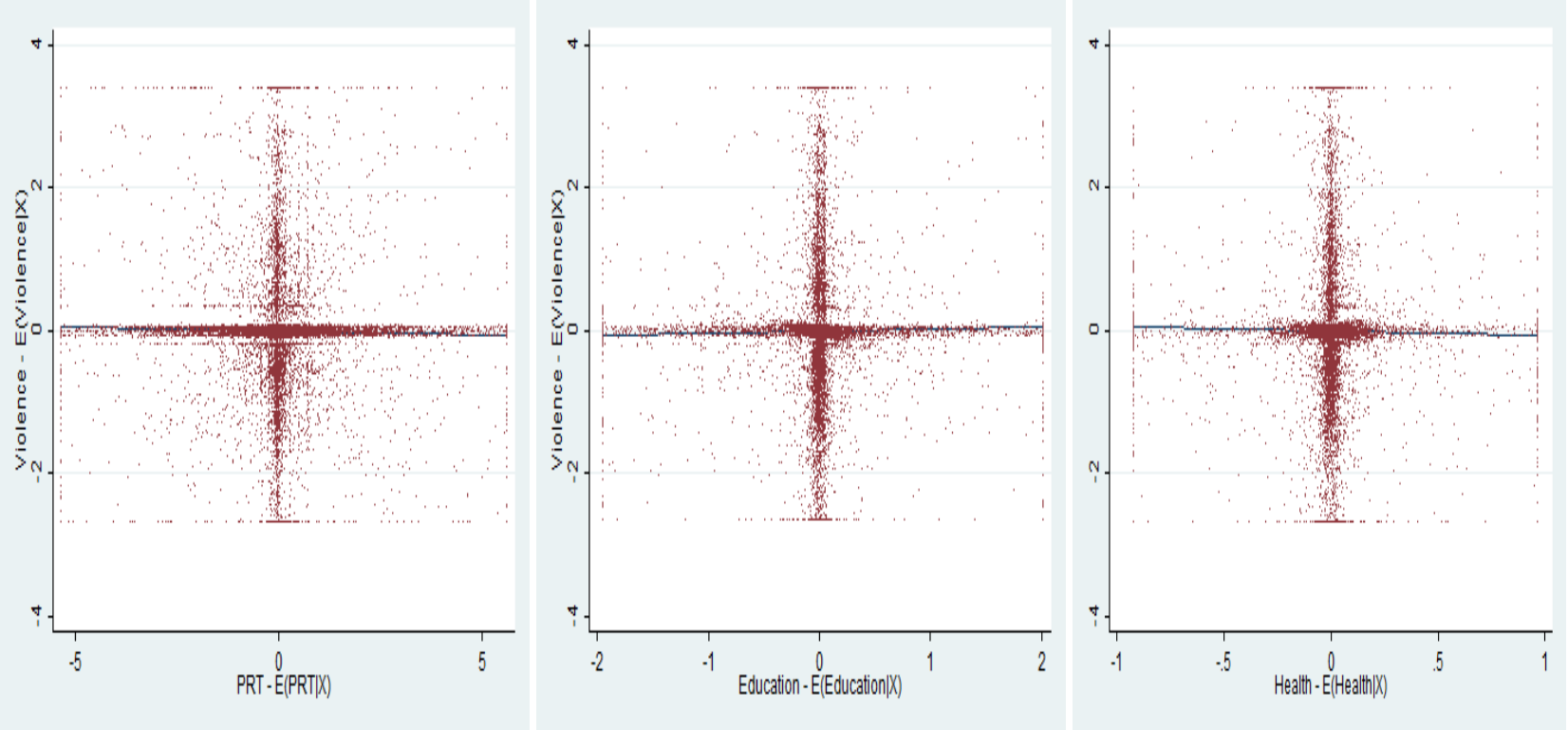


Figure depicts added-variable plots for partial regressions based on equation 5. Unexplained residuals (along both axes) are winsorized at the 0.1% level in this graph, to magnify the core relationship of interest. Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD.

APPENDIX C: ADDITIONAL ROBUSTNESS CHECKS

C.1 Regional political drivers

The dynamics of power vary immensely across Afghanistan. The central government enjoys relative strength and stability in Kabul and other urban areas, whereas the distribution of power is more diffuse in the Afghan hinterland (particularly in contested areas, which comprise at least one third of the country). In Southern Afghanistan, the central government holds the least authority. Across much of the country, in fact, government authority is effectively inexistent outside of city centers. Given this political heterogeneity, one obvious question is whether the effects we observe are driven by differential power structures. If health projects are disproportionately channeled to areas falling under strict government control, whereas education programming is carried out in areas increasingly isolated from the state, then this could explain our results. From Table 3, however, there is no indication that either type of programming is disproportionately channeled towards more or less populated areas. Still, we do not have precise spatial data on effective government control (population is merely a proxy). So in order to better ensure our results are not driven by regional particularities (i.e. disparities in wealth, governmental control, etc.), we alternately exclude various ISAF Regional Command regions and urban centers from our tests. When doing so, we yield similar results.[30] It is apparent our general findings are not driven by particularities of urban areas, the South, or any other region. Results are stored in Table C1.

C.2 PRT command shifts

In total, there have been 26 PRTs established across Afghanistan. Among these, transfers of command have taken place on 30 separate occasions. The Americans are responsible for initially operating most PRT bases in the country, particularly at the beginning of the occupation. As early as June 2003, however, the command of some PRTs was handed over to coalition partner countries (as NATO took the military lead from the smaller US-led coalition Operation Enduring Freedom in Kabul).

We consider the establishment of PRT bases and handover periods as a source of project variation which is not driven by local conflict. Decisions regarding PRT command are negotiated at the highest level of authority (Eronen 2008; Stapleton 2003), months or years in advance of changes on the ground (NATO-ISAF 2006; Maloney 2005).[31] Conveniently for our analysis, experts have noted the style of PRT management is country specific. The

[30] We consider urban centers to compromise the 5% most populated districts. For robustness, we alternate our urban indicator to denote the 10% and 20% most populated districts, and find similar results.

[31] Maloney (2005) even states the NATO expansion plan entailed the construction of (or replacement of OEF PRTs with) NATO ISAF PRTs *in a counterclockwise fashion* around the country. See ISAF (2009) for post-rollout confirmation.

organizational structure, development focus, and funding sources can vary across models (Eronen 2008). Because coordination between PRTs was limited, handovers of control implied real changes to operational focus (Stapleton 2003). The sectoral shifts in programming which accompany handovers therefore reflect individual nation proclivities, rather than real-time adjustments to future security. Even if project selection is normally tailored to local conditions, such nuanced expertise is unlikely to obtain at the beginning of a PRT command.

Consequent to the above, the handover of a PRT implies a structural break in the level and composition of reconstruction programming. That break is arguably exogenous with respect to contemporaneous local conflict, which implies its validity for use as an instrument. Throughout our sample period there are 19 instances of PRT establishment or handover, enabling us to define 16 instruments corresponding to the entry/exit of various coalition members into/from PRT management. Selective targeting of management teams by insurgents would constitute a violation of the exclusion restriction. It is therefore worth noting PRT bases are distinct from combat-tasked military outposts, and rarely bear the burden of attack in our data.

The breakpoints associated with command shifts are evident through (unreported) graphical inspection. Their timing, however, does not perfectly coincide with dates reported in official documents or media. Therefore, we define 6-month transition windows centered around the publicly reported date of transition. So each of our 16 dummy variables indicates (for each observation) whether that district-month is subject to the corresponding transition type. These transition windows capture immediate shifts during the month of handover, wind-down effects in the months preceding the handover, and scale-ups (or further scale-downs) which occurred in the months subsequent to handover.[32]

Before reporting 2SLS-IV results, we present OLS counterparts for comparison. We adopt a parsimonious specification here, so as not to limit the residual variation available for identifying our LATE. Relative to the full specification of equation 6, we drop the following controls: time period effects; lagged violence; and total (residual) PRT projects. Because our instrument is aggregated to the province (sometimes broader) 6-month level, we feel this parsimony is justified to retain sufficient variation in predicted PRT programming. At any rate, the OLS results in Panel A of Table C2 are practically equivalent to those reported earlier (in Table 5).

In Panel B we instrument for the number of projects with the incidence of transition in or out of PRT management for various countries. When doing so, the estimated impact of PRT programming remains qualitatively intact for education and health (columns 1, 2, and 4), but not for security (columns 3 and 4). The results strengthen our causal interpretation offered

[32] Around dates of establishment, the window enables comparison between programming inception, and the immediately preceding period which is void of PRT programming, but often replete with other civic aid projects. By exploiting both PRT handovers and the establishment of bases, we use (arguably) exogenous variation in sector programming along both the intensive and extensive margins.

thus far, but it should be noted we cannot exclude the possibility our instruments are weak. In Panel C we report small Cragg-Donald Wald F statistics, which fall far short of the appropriate critical values reported in Stock and Yogo (2005). On the other hand, Hansen J statistic p-values indicate we cannot reject that the overidentifying restrictions, and by implication–our instruments, are valid. Moreover, the Hausman test (p-value) results indicate we cannot reject that PRT spending is exogenous, since the estimated effects are not systematically different, whether measured using the instrumented or unfiltered variation. As such, we may revert back to Table 3 for (arguably) causal estimates of the impact of PRT programming.

Table C1: **Regional drivers**

	(1) /Kabul	(2) /Urban	(3) /South	(4) /East	(5) /North	(6) /West
Education	0.0275**	0.0287***	0.0203**	0.0340**	0.0347***	0.0298**
	(0.013)	(0.008)	(0.042)	(0.029)	(0.006)	(0.013)
Health	-0.0395	-0.0406*	-0.0261*	-0.0876*	-0.0473*	-0.0319
	(0.104)	(0.084)	(0.090)	(0.055)	(0.061)	(0.188)
Security	-0.0465*	-0.0538**	-0.00846	-0.0384	-0.0541*	-0.0665***
	(0.078)	(0.025)	(0.695)	(0.184)	(0.057)	(0.003)
Observations	21,065	20,845	18,645	13,145	15,235	19,470
R-squared	0.264	0.267	0.246	0.285	0.264	0.263

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. All specifications are first-differenced. Each column *excludes* observations pertaining to the region listed in the corresponding header. Reconstruction variables are lagged one period. Time controls, pre-existing trends, civil aid project volumes, and residual PRT (reconstruction projects in sectors not explicitly reported in table) are controlled for in all specifications. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table C2: **PRT command shifts**

	(1)	(2)	(3)	(4)
Panel A: OLS				
Education	0.0170			0.0217**
	(0.110)			(0.029)
Health		-0.0600**		-0.0613**
		(0.027)		(0.021)
Security			-0.0371**	-0.0347**
			(0.033)	(0.037)
Observations	21,890	21,890	21,890	21,890
Panel B: 2SLS-IV				
Education	0.114*			0.147**
	(0.071)			(0.011)
Health		-0.302*		-0.415***
		(0.097)		(0.003)
Security			0.172	0.122**
			(0.203)	(0.038)
Observations	21,890	21,890	21,890	21,890
Panel C: Diagnostics				
Cragg-Donald Wald F statistic	0.71	0.30	0.86	0.27
Hansen J statistic (p-value)	0.36	0.40	0.42	0.36
Hausman test (p-value)	0.71	0.96	0.74	0.98

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, GTD, and media. Dependent variable is change in violent incidents per capita. Reconstruction variables are lagged one period, and instrumented in Panel B with PRT command shifts. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

APPENDIX D: EXTENSIONS

D.1 Hardware vs. software

It is worth distinguishing between the quantity of institutions, and their quality. Some projects (the 'hardware') bolster the stock of physical infrastructure, whereas others (the 'software') refine the associated human capital inputs. One may conjure reasons for why either hardware or software should disproportionately affect violence if the channel is public opinion. Regarding hardware, building a clinic or a school achieves a tangible, visual impression of progress. Public recognition of software in the form of medical or educational training could be slower, even if those projects carry greater real impact (Foreign NGO K 2013; Donor B 2013). Security problems associated with reconstruction typically arise in the construction phase (Foreign NGO I 2013), suggesting the material presence of foreign-led development may elicit more adversity than affinity for hardware projects irrespective of sector. Both education and health projects (relative to security, transportation, or energy, for example) consist largely of human capital improvements. As such, it is very unlikely that human capital is confounded with health, for instance, and physical capital with education. That is, our differential findings across sectors are unlikely to be driven by differences in human/physical capital inputs. Nevertheless, the distinction is interesting to explore, particularly if it sheds light on which type of programming affects conflict within the education and health sectors.[33]

To distinguish between 'hardware' and 'software'-oriented programming, we adopt a basic automated content analysis method. In particular, we use a *dictionary* method to classify projects based on keyword detection.[34] Within each project description stored in the ACSP, our algorithm identifies designated keywords associated with either hardware or software-oriented programming, and scores the project by running a tally. Our decision rule for classification is simply the following: If a project description contains more keywords associated with hardware than with software, then the project is deemed hardware (and vice versa).[35] In the case of a tie, no category is assigned and the project is grouped in a third residual category. This algorithm is then manually verified to the satisfaction of the author. Of the 22,351 PRT projects in total, 5,135 are classified as software, and 11,447 are classified as

[33]This appendix constitutes deeper explorative analysis of our findings. The empirical tests conducted herein are not motivated by qualitative evidence or formal theory, so for brevity and parsimony we refrain from discussing security-sector projects.

[34]More sophisticated classification schemes such as the nonparametric approach of Hopkins and King (2010), or various supervised learning methods, are neither necessary nor appropriate for this particular application. This is partly because project descriptions are very brief, and so 'training' would be somewhat futile in this setting (while it is straightforward to simply select keywords directly).

[35]Our hardware-associated (root) keywords are the following: 'construct', 'repair', 'refurb', 'restor', 'replace', 'replenish', 'renovate', 'procure', 'equip', 'suppl', 'furni', 'install', 'purchase', 'water', 'well', 'wall', 'build', and 'new'. Our software-associated (root) keywords are comprised of: 'service', 'train', 'support', 'program', 'develop', 'workshop', 'skill', 'teach', 'assist', and 'course'.

hardware. Of all 4,009 education-oriented PRT projects, 732 are classified as software, and 2,221 as hardware. Among 1,877 PRT health projects, 618 are deemed software, and 855 as hardware. The remaining projects generally lack sufficient detail to be classified even by manual coders. But of course, some project descriptions are just sufficiently unique that our keywords do not identify them with either of our dichotomous (and somewhat exhaustive) categories.

Column 1 of Table D1 estimates a parsimonious specification, examining the impact of hardware and software-linked projects within each sector, without accounting for the broader picture of reconstruction and development. Column 2 additionally controls for all remaining (and mutually exclusive) PRT project categories, as well as aid more generally. In full, the results demonstrate the impact of both education and health programming is more precisely estimated for the subset of hardware-oriented projects. Also reported are Wald tests for equality of coefficients between hardware and software within each sector. The estimated effect sizes do not significantly differ between hardware and software programming for either sector. It is thus difficult to attribute our findings to hardware alone. Nevertheless, we feel such an interpretation would not be inconsistent with our theory which places perceptions at the heart of community response to foreign-led development. Particularly since we examine month-on-month changes, from our theoretical perspective it would be surprising if software carried the stronger immediate impact.

D.2 Gender sensitivity

Our theory is premised on the notion that certain reconstruction projects are ill-perceived through a local (read, traditional) lens, whereas others are relatively innocuous or even welcomed. Gender-oriented programming is a common point of controversy cited by media and laypersons alike. According to Jackson and Giustozzi (2012), certain segments of Afghan society strongly oppose female education, for instance. Training workshops for integration of females into the local labour market, or women's rights seminars may also elicit local opposition, particularly in conservative areas.

We therefore want to ascertain whether the positive effect of education programming on violence is actually driven by the introduction of girls' schools, as some readers might imagine. A number of major stakeholders have, after all, asserted that local problems surrounding education programming are likely to be gender-related (Donor E 2013; Foreign NGO I 2013; Research Organization C 2013). If this assertion is true, then our findings are driven less by the abrasiveness of one sector over another on ideological grounds, and more by one specific traditional friction. While the adverse effects of reconstruction programming in that case would still ultimately derive from public opinion, the explanation would perhaps be less compelling as a more narrow subset of the community may be responsible for violent

resistance. In such a case, one would expect gender-specific programming in general (particularly programming aimed at the empowerment of women) to positively affect the incidence of conflict.

To test whether this alternative explanation for our results has merit, we test whether female-oriented projects have a positive impact on violence. But first, to identify such projects, we apply the automated content analysis method described in the foregoing section. Through project descriptions in the ACSP, we search for any of the following keywords: 'female', 'girl', 'woman', 'women', 'maternal', and 'gender'. All projects containing any such keywords are classified as being female-oriented. Manual inspection verifies the accuracy of this algorithm. Of the 22,351 PRT projects in total, 1,084 contain this explicit gender-focus (630 of which fall into either the education or health sectors). Given this new variable, we simply construct a project volume measure for female-oriented projects, in the same manner as we constructed sector-specific flows.

In column 1 of Table D2 we run a parsimonious specification, examining the impact of female-oriented programming (across all sectors) on violence. While the point estimate is positive, it is not statistically significant. Next, in column 2 we control for all residual (and mutually exclusive) PRT spending categories, as well as civic aid projects. Although the precision of the estimate improves, it remains insignificant. In the following two columns we focus on female-oriented projects within the education and health sectors, to ascertain whether these drive our previous results. While it does not appear that female-oriented programming in education incites violence, the evidence rather (albeit, weakly) suggests that female-oriented health projects may elicit popular resistance. In sum, however, we cannot make strong claims regarding any special role of gender sensitivity in the link between reconstruction and conflict.

Table D1: **Hardware vs. software**

	(1)	(2)
Residual PRT		Y
Aid		Y
Education (Hardware)	0.0253***	0.0276***
	(0.008)	(0.004)
Education (Software)	0.0362	0.0389
	(0.141)	(0.106)
Health (Hardware)	-0.0567*	-0.0521*
	(0.073)	(0.092)
Health (Software)	-0.0734	-0.0699
	(0.111)	(0.131)
Education		0.0231
		(0.509)
Health		0.00926
		(0.758)
Security		-0.0454*
		(0.066)
Observations	21,890	21,890
R-squared	0.262	0.262
Wald test p-values ($H_0 : Hardware = Software$)		
Education	(0.685)	(0.677)
Health	(0.703)	(0.679)

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. Reconstruction variables are lagged one period. Time controls and pre-existing trends are controlled for in both specifications. Civil aid project volumes, and residual PRT (reconstruction projects in categories not explicitly reported in table) are controlled for in column 2. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table D2: **Female-oriented programming**

	(1)	(2)	(3)	(4)
Residual PRT		Y		Y
Aid		Y		Y
Female	0.0295	0.0334		
	(0.223)	(0.172)		
Female (Education)			0.00330	-0.00299
			(0.911)	(0.920)
Female (Health)			0.140	0.154*
			(0.123)	(0.093)
Education				0.0350***
				(0.003)
Health				-0.0484**
				(0.043)
Observations	21,890	21,890	21,890	21,890
R-squared	0.262	0.262	0.262	0.263

Sample includes 398 districts across Afghanistan, and spans 57 months. Data are gleaned from the ACSP, WITS, and GTD. Dependent variable is change in violent incidents per capita. Reconstruction variables are lagged one period. Time controls and pre-existing trends are controlled for in all specifications. Civil aid project volumes, and residual PRT (reconstruction projects in categories not explicitly reported in table) are controlled for in columns 2 and 4. Regressions are weighted by district population, and standard errors are clustered by province. P-values are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).