Aid Fragmentation and Corruption*

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Abstract

Aid fragmentation—the simultaneous operation of multiple development agencies in one setting—has long raised concerns about coordination challenges and opportunities for corruption. Leveraging unique data on project delivery in Afghanistan, we present the first microlevel empirical analysis of aid fragmentation. We find that aid delivered by a single donor can significantly reduce corruption. Projects delivered under conditions of aid fragmentation, by contrast, can facilitate corruption. We find evidence for a theoretical mechanism linking infrastructure and physical goods with waste and leakage. Our results clarify the policy losses tied to fragmentation, yielding insights for combating misappropriation of aid.

Keywords: aid, corruption, public opinion, Afghanistan

JEL Codes: F35, D73, D74

1 Introduction

The Organization for Economic Cooperation and Development (OECD) has long highlighted the challenges introduced by aid fragmentation—the simultaneous operation of a large number of development agencies in a given setting. In *The Architecture of Development Assistance*—a cornerstone OECD policy document—fragmentation is flagged as a complication that may "seriously impair the effectiveness of aid and is a particular challenge in the poorest countries of Africa and Asia and in fragile, conflict-affected states. Fragmentation puts a strain on governments' administrative capacities, increases donors' costs, duplicates their efforts, and leads to the uneven distribution of aid." One the one hand, fragmentation may reflect the commitment and engagement of numerous donors. On the other, it can also increase transaction costs, create frictions in the allocation of aid, and open up opportunities for graft and corruption. As the volume of aid increases, these opportunities and incentives for corruption may grow, undermining the effectiveness of aid and enhancing the intensity of bureaucratic capture. Despite its clear policy relevance, a significant gap exists in our understanding of how fragmentation moderates the impact of aid. Our study aims to address this gap, yielding valuable insights into how fragmentation can undermine the effectiveness of development assistance by examining its impact on administrative corruption.

Using granular data from Afghanistan, we offer the first micro-level analysis on the effects of aid fragmentation. Our analysis leverages data from two unique sources. Aid data are gleaned from a rare hardcopy of NATO C3 Agency's Afghanistan Country Stability Picture. This source contains over 30,000 development projects from approximately 40 different donors. Subjective measures of institutional quality and public opinion are drawn from the Afghanistan Nationwide Quarterly Assessment Research (ANQAR) surveys sponsored by ISAF HQ and Resolute Support HQ. These data were accessed through a pilot partnership agreement between NATO and the authors.[1] We assemble panel data at the district-quarter level of aggregation, spanning

[1] Additional data from various sources are also incorporated in our extended analysis.

330 districts from July 2008 to September 2009. Aid volumes are measured using the number of ongoing concurrent projects in each district.[2] Aid fragmentation relies on a simple count of donors active in each sector (while results are robust to alternative measures). Our corruption outcome reflects public perceptions of government effectiveness at reducing corruption, which we find are positively associated with self-reported exposure to bribery demands. Using these main measures, we estimate a panel fixed effects model permitting donor fragmentation to moderate aid's effectiveness at reducing corruption.

Our results suggest aid reduces corruption in the absence of fragmentation (i.e., in the presence of a single donor). But as the donor landscape becomes fragmented, those beneficial effects vanish. Consistent with earlier conjectures by theoreticians and practitioners, we discover a moderating force through which donor fragmentation increases corruption. In a reversal of priors, however, our evidence suggests donor fragmentation also reduces corruption when considered at moderate levels of aid. Our micro-level evidence therefore suggests the direction of fragmentation's total effect depends on the volume of aid provision.

Following our main results, we strengthen identification by gathering data on numerous factors potentially confounding the role of fragmentation. We provide evidence to rule out confounding factors related to (i) characteristics of aid programming initiatives; (ii) human and physical geography; (iii) levels of development; and (iv) security conditions. Even when allowing aid's effect to vary by all these criteria simultaneously, our results remain reasonably robust. To bound the potential selection bias arising from the omission of *unobservable* factors, we follow Oster's (2019) implementation of a generalized Altonji, Elder and Taber (2005) method. Unlike prior work, our approach flexibly estimates these bounds under a very large number of alternative selection thresholds, enabling us to visualize how extreme these parameter values must be to nullify the main results. Under the benchmark conditions in Oster (2019), we find that the moderating role of fragmentation remains robustly damaging,

[2] We rely on project *counts* due to an absence of reliable information on project *costs* (i.e. project-level aid flows).

and its direct impact remains mostly beneficial. This exercise therefore provides plausible support for a causal interpretation of our findings.

We supplement the main design and bounding exercises with two additional approaches built on prior work, most notably Dreher and Langlotz (2020) and Kraay (2012), to isolate potential sources of bias in the aid provision process. In one design we leverage cross sectional variation in aid fragmentation prior to the sample period, to directly address the endogeneity of contemporaneous fragmentation. In the other design we offset the start dates of aid projects to address concerns about endogeneous project timing. Under both designs, we find a consistent moderating effect of fragmentation on aid effectiveness in reducing corruption.

Next we explore some channels potentially moderating the impact of fragmentation on aid effectiveness. Based on theory and administrative evidence, we suspect corruption may be most prevalent in aid projects related to infrastructure and material goods. After accounting for this project-level heterogeneity, we find that fragmentation is most problematic when applied to *physical* aid projects (as opposed to training and service-oriented projects). Subsequently we test whether the negative effects of fragmentation are potentially stronger in districts with low levels of government control, or with lower demand for aid. We find neither type of district-level characteristics to be an important source of heterogeneity in our setting.

The position of our study's contribution within the broader aid literature merits careful elaboration. Prior work has proposed various reasons why donor fragmentation may curtail the effectiveness of aid, and limit the quality of institutions. First, greater competition by aid providers restricts spending opportunities, leading donors to select superfluous projects potentially subject to graft.[3] Second, a crowded development field implies fewer high-quality and trustworthy partners for project implementation. Scrutiny by donors is relaxed out of necessity (Djankov, Montalvo and Reynal-Querol, 2009), potentially facilitating rebel and elite capture of development resources (Gibson

[3]This channel was substantiated in a field interview conducted by one of the authors in November 2013. An aid worker in Kabul disclosed their agency spent over $100k on equipment prone to resale by corrupt government officials, because no viable projects were available.

et al., 2005; Acharya, de Lima and Moore, 2006). Third, fragmentation erodes each donor's sense of accountability and responsibility for development outcomes. This further contributes to a (now voluntary) relaxation of scrutiny and quality standards, and potentially undermines local preferences in the pursuit of self-interest (Knack and Rahman, 2007; Knack and Smets, 2013). Finally, all of the above contribute to normalize poor standards of conduct, which then inspire or incentivize poor governance within the burgeoning state apparatus (see, e.g., Isaksson and Kotsadam (2018)).

Notwithstanding the above, the presence of foreign donors may instead foster *exemplary* norms of professional conduct when aid volumes are not intractable. When aid provisions are maintained at relatively moderate rates, competition is not pronounced and coordination is facilitated, thereby attenuating the mechanisms above. Under these conditions, good conduct by donors is more likely to prevail and donor proliferation may actually strengthen institutions. In this case donors may serve to monitor the development sector and public officials (Kimura, Mori and Sawada, 2012; Gibson, Hoffman and Jablonski, 2015). Donors may also bring experience, ideas, and innovation which strengthen development processes and outcomes (Gehring et al., 2017). New licit opportunities for growth (e.g. trade, FDI) may then act as substitutes to displace rent-seeking by opportunistic government agents (Dreher and Michaelowa, 2010). So even though existing theory suggests the *moderating* role of donor fragmentation is largely detrimental, it is nevertheless reasonable to also expect *direct* benefits from fragmentation when aid volumes are relatively contained.

While theoretically compelling, the above arguments have been subject to little empirical scrutiny. Our paper contributes much-needed empirical evidence on the effects of aid fragmentation, thereby informing related theoretical work. Early cross-sectional studies at the country level suggest fragmentation renders aid ineffective (or counterproductive) at boosting the quality of governance and economic growth (Knack and Rahman, 2007; Djankov, Montalvo and Reynal-Querol, 2009; Kimura, Mori and Sawada, 2012). Notably, Gehring et al. (2017) casts doubt on those findings. But coarse country-level variation throughout these studies inhibits the reliability of estimates, and has largely prevented the exploration of mechanisms. We offer unique micro-level evidence on the effects of aid fragmentation. Our results are consistent with theory suggesting fragmentation erodes oversight, accountability, and responsibility over development processes and outcomes, and thereby facilitates corruption (Gibson et al., 2005; Acharya, de Lima and Moore, 2006; Knack and Rahman, 2007; Djankov, Montalvo and Reynal-Querol, 2009; Knack and Smets, 2013). At the same time, we also provide evidence supporting the far less prominent hypothesis that fragmentation may also confer positive effects (Dreher and Michaelowa, 2010; Kimura, Mori and Sawada, 2012; Gehring et al., 2017).

Of equal importance, our paper speaks to literature examining the impact of foreign aid on corruption and governance. Theoretical work suggests aid can improve the quality of institutions in a number of ways. First, aid programs may directly introduce governance reforms, including those related to law enforcement and judicial systems (Jones and Tarp, 2016; Bräutigam and Knack, 2004). Second, aid can alleviate budget constraints otherwise inhibiting (i) the development of well-functioning bureaucracies and legal systems, or (ii) training and salary support for government officials prone to graft (Knack, 2001). Third, aid inflows may defuse distributional conflicts and attenuate the sacrifices of public officials resistant to modernization (see, e.g., Casella and Eichengreen, 1996). Fourth, aid conditionality can prompt improved governance in exchange for continued outlays (Crawford, 1997).

The empirical record on the relationship between aid and corruption is mixed. Widely-cited findings suggest aid increases corruption (Svensson, 2000; Alesina and Weder, 2002; Andersen, Johannesen and Rijkers, 2019) and erodes the quality of institutions (Knack, 2001; Bräutigam and Knack, 2004; Djankov, Montalvo and Reynal-Querol, 2008; Busse and Gröning, 2009; Young and Sheehan, 2014). Yet evidence linking aid to improved governance also exists (Tavares, 2003; Okada and Samreth, 2012; Kersting and Kilby, 2014; Gibson, Hoffman and Jablonski, 2015; Dietrich and Wright, 2015; Jones and Tarp, 2016). Notably, most findings in this vein of inquiry are again based on country-level variation in assistance and corruption. To our knowledge, a single exception is Isaksson and Kotsadam (2018), which finds Chinese aid projects fuel corruption at the local level in Africa. Our paper extends this literature by offering additional results based on granular spatiotemporal data.[4] By explicitly modeling fragmentation as a source of heterogeneity, we are able to reconcile mixed results to date, on both theoretical and empirical grounds.

In short, our findings suggest locally nonfragmented aid *reduces* corruption, while fragmentation can reverse those effects. Alternatively put, the rent seeking famously associated with aid (e.g. Svensson, 2000; Alesina and Weder, 2002) may be exacerbated once oversight collapses under the weight of donor fragmentation. Foreign aid typically shifts the object of government accountability from the citizenry towards international donors (Rajan and Subramanian, 2007; Kersting and Kilby, 2014; Young and Sheehan, 2014). Under donor fragmentation, however, the commensurate lack of oversight and accountability implies no single donor offers a check on corrupt practices among government or implementing agents (Knack, 2001).

The remainder of our paper is structured as follows. Section 2 introduces the main data and variables used in our analysis. Section 3 examines the relation between aid, donor fragmentation, and corruption, with special attention to identification concerns. Section 4 discusses potential channels underlying the link between aid fragmentation and corruption. Section 5 concludes, with additional robustness in the Appendix.

2 Data

Throughout the analysis, our primary unit of observation is the district-quarter. Our total sample covers 398 districts over 5 quarters (from July 2008 to September 2009), containing 1,990 district-quarter observations.[5] Aid volumes for a district-quarter are calculated as the average number of concurrent projects being implemented. Fragmentation is calculated per day for each sector, then averaged across sectors and over time to obtain a district-quarter average. Perceptions of corruption are calculated using average survey responses within a district-quarter. For ease of interpretation, aid and corruption measures are standardized to zero-mean and unit-variance.

[4] The richness of our data permits us to address a host of observable and unobservable factors potentially confounded with aid provision at the subnational level.

[5] We follow the 2005 Afghan Ministry of Interior administrative designation of 398 districts spanning 34 provinces.

Fragmentation measures are normalized to fall in the range $[0, 1]$. Aid measures are expressed in per-capita terms, and winsorized at the 99.9th percentile. Population data is for 2011/12, and obtained from the Central Statistics Organization of Afghanistan (CSO).

2.1 Aid Projects

Aid data is from NATO C3 Agency's Afghanistan Country Stability Picture (ACSP). The ACSP contains a comprehensive nationwide database of donor-funded development and reconstruction projects between January 2002 and September 2009. These data include detailed information on over 30,000 projects across 38 unique donors, documenting at least $28.2 billion spent.[6] For each project we have information on implementation start/end dates, sector, donor, and location.[7] The ACSP covers projects funded by USAID, World Bank, WHO, UN agencies, military-led Provincial Reconstruction Teams (PRTs), and a host of other donors (including individual countries, national development funds, multilateral agencies, and large international NGOs). Projects span a number of sectors including education, health, security, commerce and industry, agriculture, energy, water and sanitation, environment, transportation, emergency assistance, capacity building, governance, and community development. For each district-quarter we calculate the per-capita number of concurrent projects being implemented on an average day.[8] The spatial distribution of project volumes is presented in Figure 1a.[9] Importantly, because donor fragmentation is undefined in the absence of aid, we restrict our sample to district-quarters with non-zero aid volumes. For the regression analysis, *Aid* is standardized (to zero-mean,

[6]By comparison, according to World Bank and IMF data, Afghanistan's cumulative GDP from 2002–2009 was approximately $60 billion.

[7]Due to inconsistent transliteration of location names in the ACSP database, we invoke the Esri World Gazetteer and digital mapping software to geolocate many projects in our sample.

[8]Reliable cost data is available for only a subset of projects. Accordingly, we use the number of projects as a proxy for overall aid flows.

[9]For descriptive purposes we scale aid measures to the average-sized district (approximately 63,000 inhabitants).

unit-variance) so that the direct effect of fragmentation remains interpretable when *Aid* takes the value of zero.

2.2 Donor Fragmentation

Our main measure of aid fragmentation relies on a simple count of donors simultaneously active in each sector.[10] The more donors that are active, the greater is donor fragmentation (i.e. aid fragmentation). We begin by using the day as our unit of analysis. By this measure, donor fragmentation on day t in sector j is the following:

$$F_{tj} = 1 - 1/N_{tj}$$

where N_{tj} is the number of donors active in sector j on day t. Thus, for all sectors with non-zero aid, $F_{tj} \in [0, 1)$. For sectors *without* donor engagement (i.e. $N_{tj} = 0$), F_{tj} is undefined. To arrive at an overall measure of donor fragmentation across sectors on day t, we take the weighted average:

$$F_t = \sum_{j \in J} \left(\frac{P_{tj}}{P_t} \right) F_{tj}$$

where J is the set of active (i.e. non-zero aid) sectors, P_{tj} is the amount of projects underway in sector j on day t, and P_t is the total amount of projects (across all sectors) on day t. Finally, we compute a quarterly measure, F_q, by taking a simple average of F_t across days in the quarter. Effectively, F_q then reflects the average extent of contemporaneous overlapping development responsibilities within-sector, throughout quarter q. The measure is constructed separately for each district i, such that we have F_{iq} for incorporation into our later regression analysis. Figure 1b reflects a heatmap of average fragmentation across districts in our sample. For our regression analysis we rescale F_{iq} by its maximum, such that $F_{iq} \in [0, 1]$. The distribution of non-zero fragmentation is depicted in Figure A1. Table 1 shows summary statistics of aid and fragmentation for district-quarters in the study sample.

[10] This is akin to a standard market competition metric. See, e.g., Hannan (1997), Kalnins and Lafontaine (2004), and Macher, Miller and Osborne (2021).

2.3 Corruption

Perceptions of corruption are based on the Afghanistan Nationwide Quarterly Assessment Research (ANQAR) surveys sponsored by ISAF HQ and Resolute Support HQ. These data were accessed through a partnership agreement between NATO and the authors. ANQAR collects information on demographics and various aspects of public opinion. Polling was conducted every three months across the country, from September 2008 through 2018. We use the first five waves of the ANQAR survey (beginning September 2008, and ending September 2009). Each wave has a sample size greater than 8500 households, and together they cover 330 districts. During our sample period, interviews were carried out exclusively by the Afghan Center for Socio-Economic and Opinion Research (ACSOR).[11] Interviews were proportionally distributed across districts according to CSO population data. For each survey wave, settlements were selected randomly within each district, and 10 households were interviewed per settlement (using random walks and kish grids to select respondents).[12]

Our main outcome of interest leverages public perceptions of government effectiveness at reducing corruption. The corresponding survey question is asked for varying levels of government authority: national, provincial, and district-level.[13] Accordingly, we use the district-average response for each level of authority, and also compute an index reflecting the average response across *all* levels. It is difficult to disentangle whether shifting perceptions of anti-corruption effectiveness are due to changes in bureaucratic or political effort, or changes in the intensity of corrupt

[11]ACSOR serves as the enumerator for several clients in Afghanistan, including the Asia Foundation and Gallup International. Considerable efforts are made to ensure sponsors of ACSOR surveys (e.g. ISAF) remain anonymous to household respondents. Interviewers are local to the province they work in, having strong familiarity with the area's culture and dialects.

[12]Further detail regarding sampling design and methodology of the ANQAR surveys is available upon request. See also Condra and Wright (2019).

[13]Specifically, the ANQAR survey asks respondents "How well does the [Government of Afghanistan / Provincial Governor / District Governor] do its job reducing corruption in the [Government / administration]?" Responses are provided on a 5-point scale, with larger responses indicating greater perceptions of corruption.

practices (or both). With this in mind we prefer to interpret our outcome as a measure capturing a bundle of perceptions about the presence and severity of local corruption. A heatmap of spatial variation in our *Corruption* index is provided in Figure 1c, with summary statistics in Table 1.

It is important to note that our analysis primarily focuses on civilian perceptions of corruption. As Olken (2009) points out, there may be a meaningful gap between perceived and objective measures of corruption severity, especially when corrupt agents can conceal their behaviors, making it hard for the public to accurately assess misappropriations.[14] To probe these dynamics, we draw on a suggestion in Olken and Pande (2012), and benchmark our main outcomes against a more objective, direct measure of administrative corruption: bribe demands. For this we take advantage of non-overlapping ANQAR data collected one year after our main sample. The later ANQAR questionnaires include our main instruments of interest as well as a battery of questions on administrative bribe taking (not asked during our sample period). We find a robust association between perceptions of corruption and bribe taking. The results are presented in Table A1. A unit shift in the bribery index is associated with a 0.2 standard deviation increase in perceived corruption.

The exercise above also helps to clarify that our outcomes capture a bundle of perceived bureaucratic effort and observed incidence of corruption. More broadly, while these results suggest a link between perceived and actual corruption, it is important to emphasize that public perceptions are, on their own, an important outcome of interest. Public perceptions of institutional effectiveness can meaningfully shape public engagement with the state, mobilizing voters concerned about fiscal responsibility (Carreri and Martinez, 2022), allocation of development assistance (De La O, 2013; Guiteras and Mobarak, 2015), and completion of aid projects (Marx, 2018).

[14]We are grateful to an anonymous reviewer for raising this point.

3 The Effects of Aid Fragmentation

3.1 Estimation

To estimate the effects of aid provision and donor fragmentation on corruption, we use the following baseline model including district and quarter fixed effects:

$$Y_{iq} = \alpha_i + \beta_0 P_{iq} + \beta_1 P_{iq} F_{iq} + \beta_2 F_{iq} + \gamma_q + \epsilon_{iq} \tag{1}$$

In the above model, Y_{iq} captures perceptions of government effectiveness at reducing corruption. In keeping with earlier notation, P_{iq} captures the average number of concurrent aid projects disbursed in district i during quarter q. Our aid measure P_{iq} is standardized (to zero-mean, unit-variance) to facilitate interpretation of β_2.[15] Aid fragmentation, F_{iq}, is exactly as described in Section 2.2.[16] Thus β_0 measures the direct impact of aid on perceptions of corruption, absent of donor fragmentation. The parameter β_2 captures the direct effect of fragmentation on corruption, at average levels of aid provision. Finally, β_1 captures our effect heterogeneity – how aid volumes moderate the impact of donor fragmentation. Alternatively, β_1 may be regarded as estimating the effectiveness of aid in an environment characterized by maximal fragmentation, relative to non-fragmented aid.

Throughout our analysis, in round brackets we report standard errors clustered at the district level to adjust for within-district serial correlation. Additionally, in square brackets we report Conley (1999, 2010) standard errors to account for spatial correlation among districts less than 1000km apart.

[15] Absent of aid provision, fragmentation is theoretically undefined. So without standardizing aid, β_2 would be uninterpretable.

[16] Notably, P_{iq} and F_{iq} are calculated as quarterly averages, whereas Y_{iq} is based on end-of-quarter survey data. In that sense, Equation 1 estimates the accumulated effects of aid and fragmentation on public opinion, rather than strictly contemporaneous effects.

3.2 Results

In Table 2 we estimate Equation 1, with the outcome varying across different measures of *Corruption*. Column 1 uses the corruption index, while columns 2, 3, and 4 use assessments of national, provincial, and district government initiatives, respectively. The first row of Table 2 suggests that aid generally improves perceptions of corruption-reducing initiatives. A standard-deviation increase in non-fragmented aid leads to a nearly 1-standard-deviation decline in mean perceptions of corruption. Estimates for the direct effect of fragmentation suggest that donor proliferation also reduces corruption at moderate levels of aid (i.e., when standardized aid is nil). But when aid volumes become intractably large, the beneficial effects of donor fragmentation are reversed. The interaction term between aid and fragmentation provides evidence for such impact heterogeneity. Fragmented aid is significantly less successful at dampening perceptions of corruption across all specifications.[17] The total (direct plus moderating) effects of fragmentation calculated for different levels of aid are depicted in Figure 2. Under moderate provisions of aid, fragmentation is beneficial to institutional outcomes. But once aid volumes exceed around 0.7 standard deviations above average, the net effect of fragmentation on corruption turns detrimental.

Our baseline measure of fragmentation is supplemented with two additional measures. The first is based on the Herfindahl-Hirschman Index (HHI) of industry concentration (Hirschman, 1945; Herfindahl, 1950), and the second is a concentration index (CI) reflecting the share of projects by all donors *excluding* the largest in each sector (Schmalensee, 1989). Table A2 offers technical details and presents estimates from Equation 1 using these alternative measures of fragmentation. The moderating

[17]It is possible that fragmentation is consistent with strategic collaboration in sectors prone to failure. If actors coordinate the timing of their projects, this may help obfuscate responsibility when aid breaks down. Our results in Sections 3.3.1 and 3.3.2 help guard against this interpretation by accounting for various selection dynamics. Field-based exercises and an exhaustive review of SIGAR documentation also suggest this alternative channel is unlikely. Future research could gainfully explore this possibility, perhaps leveraging internal deliberations about coordination between agencies. We thank an anonymous referee for suggesting this alternative explanation.

effects of both measures are consistent with results of Table 2, while direct effects are not statistically significant.[18]

Overall, our results add nuance to near-consensus views regarding the damaging impact of donor fragmentation on aid effectiveness. Conditional on high levels of aid disbursement, our evidence indeed supports theoretical arguments against fragmentation expounded in Section 1. At moderate levels of aid provision, however, the less-commonly discussed benefits of fragmentation appear to obtain in our setting. Altogether, our evidence therefore suggests both aid and fragmentation can lead to improved governance under the right conditions. But when combined at relatively high levels, the impact of fragmented aid can be deleterious.[19]

3.3 Identification

3.3.1 Selection on Observables

In this study we examine donor fragmentation as both a moderating and direct factor influencing the effectiveness of aid. To this end we exploit rich spatiotemporal variation in fragmentation. Variation in donor fragmentation is the outcome of myriad decision factors spread across the many donors in our study. If our identification were to rely on exogenous variation from a specific donor's policy discontinuity, our LATE would be estimated at the margin of the corresponding donor's engagement (subject to location, sector, or donor specific idiosyncracies). So in the absence of a general shock to donor incentives, we adopt an alternative identification strategy.

We assemble data on a host of observable factors which conceivably confound the

[18] The HHI differs from our baseline measure by emphasizing *competition*, accounting for the 'market share' of each donor. The CI also emphasizes competition by computing the residual market share unaccounted for by the largest donor. In the context of foreign aid, donor competition amounts to a shared sense of responsibility (and commensurate loss of accountability) over development outcomes. From the theoretical vantage point of Section 1, it is therefore understandable if fragmentation measures emphasizing competition reflect more costs and less benefits than our parsimonious measure of donor multiplicity.

[19] In Appendix B we estimate Equation 1 using two related outcomes: (i) public opinion of the development and reconstruction effort, and (ii) perceptions of misuse of power. The corresponding discussion and results are in Section B.1 and Table B1, respectively.

role of donor fragmentation. We then condition our estimates on these factors, identifying our effects of interest from the residual variation in fragmentation. Our main analysis relies on both cross-sectional and panel variation, so we include both time-invariant and time-varying controls. In choosing candidate confounders we seek omitted variables which correlate with fragmentation, moderate aid's effectiveness, and influence outcomes directly. We invoke theoretically motivated confounders across four qualitative domains (elaborated below). We test for the importance of each domain as a source of selection bias by estimating a variant of Equation 1 in which aid's impact is also permitted to vary over the range of confounds in that domain. The corresponding model can be expressed as:

$$Y_{iq} = \alpha_i + \beta_0 P_{iq} + \beta_1 P_{iq} F_{iq} + \beta_2 F_{iq} + \beta_3 P_{iq} C_{iq} + \beta_4 C_{iq} + \gamma_q + \epsilon_{iq} \tag{2}$$

where Y is the *Corruption* index, and C is a column vector containing confounds within a particular domain.[20] In the first column of Table 3 we reproduce the results of column 1 from Table 2. The subsequent four columns of Table 3 control for groups of potential confounders motivated below.

First in column 2 we check whether donor fragmentation is confounded with important characteristics of the aid effort. For example, when total aid volumes are large, they are often delivered by multiple donors. So it is possible our heterogeneous effects thus far reflect decreasing marginal returns to aid. Hence, we include a quadratic aid term as one control in column 2. Additionally, we include indicators for education spending, military-delivered aid (PRT), and USAID-delivered aid, as these have been previously highlighted as relevant characteristics for aid's effectiveness.[21] Control variables (C_{iq}) included in column 2 are defined in Panel A of Table A3, and summary statistics are offered in Panel A of Table A4.

[20]The subscripts of C depend on the dimensions of variation of its components. For time-invariant elements of C, the corresponding term $\beta_4 C_i$ is of course subsumed within the district fixed effect α_i. But even if all elements of C are time-invariant, β_3 can still be identified.

[21]See, e.g., Berman, Shapiro and Felter (2011), Beath, Christia and Enikolopov (2018), and Child (2019).

Next in column 3 we permit aid's effect to vary across the landscape of human and physical geography. The Southern and Eastern regions of Afghanistan are comparatively unstable, and aid's effect has been shown to vary accordingly.[22] Meanwhile, we know from Figure 1b that fragmentation also exhibits spatial concentration. Accordingly, we allow latitudinal and longitudinal coordinates to moderate the impact of aid. We also include ethnicity shares to account for the influence of traditional culture and conservatism on institutional development and aid disbursement. We include measures of population and urban coverage to account for differences between urban and rural environments. And because all aforementioned geographical characteristics are time invariant, we additionally allow for region-specific trends in the form of region-quarter fixed effects. Variable definitions (summary statistics) are again bracketed together in Table A3 (A4), as with potential confounders discussed below.

In column 4 we account for development levels and demand for donor engagement, as these are likely to influence disbursements and institutional quality. To this end we invoke proxies for food shortage, educational attainment, and health services from Child (2019). We also include survey-based measures of job availability, price fluctuations, and financial and physical well-being.[23] Finally, we account for US-military (SIGACTS) reported incidents of displaced persons and natural disasters. Donor engagement is likely to intensify during periods of heightened need, while aid effectiveness may be strained under challenging operational environments.

Finally in column 5 we control for security conditions as an important source of confound. In this respect we include a survey-based measure of local security. We also proxy for government/coalition force prevalence by tallying friendly fire incidents from SIGACTS and include an indicator for military base presence in the district. Each of

[22]See, e.g., Beath, Christia and Enikolopov (2018).

[23]We draw from the Asia Foundation's 2007 survey wave to construct measures of job availability, financial well-being, health, and security (see Table A3). Because the 2007 wave covers approximately 3/4 of the districts in our analysis (due to random sampling within province), we backfill missing values using same-district means from the 2006, 2008, and 2009 waves, respectively.

these measures have clear relevance for aid effectiveness and also for the spatiotemporal selection of donors.

By virtue of the battery of controls assembled, we are able to rule out many alternative interpretations for our results. When examining columns 2-5 of Table 3, we can see the results are generally robust, especially for the interaction term, even when controlling simultaneously for all domains in column 6.[24] These results offer support for a causal interpretation of our main finding that fragmented aid is significantly less successful at reducing corruption than non-fragmented aid. The direct effect of fragmentation, however, becomes imprecisely estimated when including geographical controls in column 3 (and 6).[25]

3.3.2 Selection on Unobservables

In the previous section, we find that our main effects remain robust to accounting for a variety of channels through which observable confounders might bias the quantity of aid fragmentation. Although these are important tests, they leave two issues unresolved. First, in order to determine the size of bias outstanding, one must consider how much outcome variance remains to be explained after the inclusion of observable controls. Second, to understand how much effect sizes are likely to change under the hypothetical inclusion of *unobservable* controls, one must make assumptions regarding the importance of unobservable relative to observable confounds.

Seminal work by Altonji, Elder and Taber (2005) operationalizes the above considerations by calculating bias-adjusted effect sizes. To generate such estimates, they

[24] To simplify exposition, the coefficients β_3 and β_4 (from Equation 2) remain untabulated here. In Table A5 we offer a version of results in which all interaction coefficients (in β_3) are reported.

[25] Readers interested in the cross-sectional determinants of fragmentation may refer to Figure A2. There we regress district average fragmentation on the abovementioned potential confounds (measured prior to the sample period). We standardize the confounding variables to allow comparison of magnitudes across coefficients. Results suggest some of these variables are important determinants of fragmentation. With these factors alone, we are able to explain approximately 40% of the cross-sectional variation in donor fragmentation. Further details are provided in the notes of Figure A2.

assume the degree of confound arising from unobservable factors is equal to that stemming from observables. Under this framework, an estimated effect whose magnitude changes a lot under small changes to R^2 (when adding controls) is unlikely to remain relevant. By contrast, estimated effects which remain stable while observable controls explain a large portion of residual outcome variation are likely to survive the bias adjustment.

Oster (2019) provides a blueprint for implementing a general version of the Altonji, Elder and Taber (2005) method and provides important, empirically derived thresholds for benchmarking models. In particular, the maximal R^2 is typically set at 1.3 (i.e., 30% larger than the R^2 of the researcher's fully controlled model) while the degree of selection on unobservables versus observables (δ in Oster's notation) is often set at 1.[26] Using the Oster coefficient stability test, we are able to estimate bounds for the moderating and direct effects of fragmentation, taking into account potential unobservables. To visualize the results of this test, we vary the maximal R^2 from 1.2 to 1.4 times the within R^2 of our most controlled model in Table 3. We then show the estimates for the moderating and direct effects of fragmentation for different degrees of positive and negative selection on unobservables relative to observables ($\delta = 0.8$, 1, 1.2). The results are shown in Figure 3.

Figure 3a illustrates the various thresholds described above for the moderating effect of fragmentation on aid. At the selection threshold suggested by Oster (i.e. selection on unobservables equally strong as selection on observables), we find that the maximal R^2 needed to attenuate the estimated effect to zero is greater than 1.5. That magnitude of hypothetically explainable outcome variance significantly exceeds the suggested maximal threshold of 1.3. In fact, even if we assume selection on unobservables to be significantly stronger than observables (e.g. $\delta = 1.2$), the scale of maximal R^2 required to neutralize the effect in column 6 of Table 3 exceeds 1.4, still above the maximal bound recommended by Oster. For clarification, the black dot marks the specification in which maximal R^2 is 1.3 times our within R^2 and $\delta = 1$, which is the parameterization recommended by Oster

[26] The latter threshold has the intuitive property that selection on unobservable factors is expected to be just as strong as selection on the observable factors explicitly identified and included in the researcher's fully controlled model.

(2019). Under this specification, the bias-adjusted moderating effect of fragmentation is still substantial. Figure 3b reproduces these results for the direct effect of fragmentation, and we find that the direct effect is similarly robust under the suggested thresholds as well as more extreme parameter values. Taken together, these results should give readers additional confidence in the main results.

3.3.3 Endogeneity of fragmentation and aid

We supplement the main design and bounding exercises with two additional approaches. These alternative designs allow us to address two potential concerns more directly: endogenous aid fragmentation and timing of aid allocation. In particular, we implement approaches building on prior work, most notably Dreher and Langlotz (2020) and Kraay (2012), to isolate potential sources of bias in the aid provision process.

We start by leveraging cross-sectional variation in aid fragmentation akin to a Bartik-style design. This aligns closely with the concerns raised in Dreher and Langlotz (2020) regarding donor-government fractionalization. Rather than allowing the intensity of fragmentation to vary over time across districts, we calculate the extent of fragmentation using a presample period (2007 – the last complete year before our study sample begins). We then interact this cross-sectional (by district) measure with aid volume, following the main approach. Note that our fixed effects absorb the baseline aid fragmentation measure, which is now constant. Column 2 of Table 4 shows the results. We find results consistent with our main effects (reproduced in column 1), suggesting that endogenous changes to the presence and activities of aid providers (e.g., entry, exit, increased activity) are unlikely to explain the moderating effect of fragmentation on aid effectiveness in reducing corruption.

We then consider whether endogenous timing of aid projects might be a meaningful type of bias. To this end, we borrow intuition from Kraay (2012), which focuses primarily on project-based lending by the World Bank. Kraay (2012) leverages the approval cycle of projects, lagging the start date of transfers, to address the association between simultaneous aid and economic growth. By exploiting variation in assistance observed after the period when allocation occurs, Kraay (2012) attempts to isolate the causal effect of aid on growth from the period-specific conditions that may have motivated the transfer. We implement an analogous design, using a variety of district-by-time window offsets and estimate results across various window sizes (see Column 3-5 of Table 4). Overall we find consistent effects throughout, with fragmentation significantly enhancing perceived corruption in the presence of large aid transfers.[27]

4 Channels of Influence

4.1 Infrastructure and material goods

Aid projects of all types are susceptible to (deliberate or inadvertent) implementation shortcomings, ultimately contributing to programmatic failurs. In Section 1 we identify several channels through which fragmentation may facilitate undesirable outcomes in this regard. Some channels are related to capacity constraints naturally arising in a crowded field of development (e.g., coordination failures leading to redundancies; limited availability of high-quality projects and implementation partners). Other channels describe outright corruption facilitated by a loss of accountability and responsibility among donors. In the latter case, self-serving development stakeholders exploit the fragmented landscape in pursuit of economic gain. This particular mechanism is most likely to emerge in projects involving construction or goods provision, where implementing agents are profit-oriented enterprises (as opposed to non-profit NGOs specialized in training or support services). In fact, the US government's watchdog agency—the Special Inspector General for Afghanistan Reconstruction (SIGAR)—appears largely focused on stamping out corruption in projects of a *physical* nature (i.e. relating to infrastructure or provision of material goods). This point is exemplified in Figure A3—a widely distributed advertisement by

[27]Two additional identification concerns are addressed in Appendix B. In particular, we demonstrate: (i) our results are not driven by special circumstances characterizing any single period, and (ii) our findings are not spurious byproducts of changes to sample composition in ANQAR. Corresponding discussions and results are provided in Sections B.2 and B.3, respectively.

SIGAR appealing for information on fraud, waste, and abuse of US reconstruction money.[28]

From 2008 through 2019, SIGAR released quarterly reports offering investigation details into projects involving misappropriation of funds. For example, the Provincial Reconstruction Team (PRT) in Kunar subcontracted the construction of a $1.2 million truck bridge in 2011. SIGAR found the contractor used inferior construction materials jeopardizing the bridge's integrity, requiring several hundred thousand dollars in repairs (SIGAR, 2011). As another example, circa 2013 PAE Inc. received a contract from the US State Department to provide uniforms and training to Afghan correctional officers. The supply of uniforms was subcontracted to Aminzian Logistics Services, which ultimately submitted fraudulent invoices for over $120,000 in uniforms never actually provided (SIGAR, 2014). These are just two examples among 176 projects investigated by SIGAR for corruption between 2008 and 2019. Through careful reading of these cases, we manually identified 137 *physical* aid projects. We cross-check our manual classification using a list of keywords related to infrastructure and material goods.[29] Among those 176 projects investigated by SIGAR for corruption, 135 are described in the SIGAR quarterly reports using at least one keyword on our list. Accordingly, a large majority of projects meriting SIGAR investigation are those of a physical nature.

Motivated by the (theoretical, administrative, empirical) reasoning above, we suspect the deleterious impact of fragmentation may be more concentrated in projects involving infrastructure or material goods provision. We therefore parse development projects in our data by applying the abovementioned list of keywords to ACSP project descriptions. Figure 4 provides a word cloud for project descriptions across the two resulting categories: (a) physical projects containing at least one keyword in the short (1-2 sentence) project description, and (b) other (non-physical) projects constituting the remainder. Evidently,

[28]Note the three examples provided in Figure A3 all relate to physical infrastructure.

[29]The keywords are based on our close reading of project descriptions provided in the ACSP. The list includes: build, bridge, construct, equip, furni, install, new, procure, purchase, refurb, renovate, repair, repar, replace, replenish, restor, road, suppl, wall, water, and well.

non-physical projects also comprise a reasonably homogeneous group corresponding to training, vocational, and rehabilitation services (in the areas of education, agriculture, and health, for example). Importantly for our subsequent analysis, non-physical projects outnumber physical projects by a ratio greater than 3:1 (see Table 1).

Next we formally test whether the impact of fragmentation is disproportionately concentrated in projects related to infrastructure and material goods. For this we recalculate fragmentation separately for the subsets of physical and non-physical projects. In Table 5 we estimate our model from Equation 1, allowing aid and fragmentation to vary across the physical and non-physical categories.[30] We find the beneficial impact of aid on corruption to be robust across both types of projects, and compute similar effect sizes. The moderating impact of fragmentation, however, appears concentrated in the domain of physical aid.[31] That is, the deleterious impact of fragmentation is found only within projects related to infrastructure or material goods. It is possible that physical projects are more susceptible to inadvertent implementation shortcomings due to capacity constraints in a crowded development field. But theoretical reasoning and SIGAR evidence suggests physical projects are relatively more prone to deliberate acts of rent-seeking. As such, we cautiously interpret the findings of Table 5 as suggestive evidence that fragmentation primarily facilitates outright corruption, rather than complicating project delivery in a more benign fashion.

4.2 Baseline government control

The above project-level distinction between physical and non-physical aid is motivated from existing theoretical and policymaking perspectives on fragmentation. Through

[30]We standardize the two measures of aid using the mean and standard deviation of total aid. We also rescale the two measures of fragmentation by the maximal of overall fragmentation F_{iq} calculated in Section 2.2. We keep only district-quarters with both non-zero physical and non-zero non-physical projects because fragmentation cannot be computed when aid is zero. However, our results do not change qualitatively if we do not impose such sample restrictions.

[31]Importantly, the mean and variance of non-physical aid is much greater than that of physical aid. It is thus even more theoretically compelling that our moderating effect is identified from the comparatively restricted source of variation.

additional reasoning, readers may suspect the degree of baseline government control constitutes a district-level factor moderating the impact of fragmentation.[32] Where the central government, district authorities, or international forces exercise a higher degree of control, the operating environment for aid providers may be characterized by stronger rule-of-law and greater political oversight. In such areas, fragmentation may introduce fewer possibilities for shirking and corruption among donors and implementation partners. To explore this possibility, we gather information on several proxies of baseline government control. We then test whether these district-level factors influence the direct and indirect effects of fragmentation.

In particular, we invoke the following measures related to government control: (1) security conditions; (2) conflict activity; (3) military base presence; (4) urban settings; (5) President Karzai's vote share; (6) Pashtun population; and (7) opium cultivation. The columns of Table A6 examine each of the aforementioned as a potential moderator in our analysis. For each test we bifurcate the sample according to some threshold value of the corresponding moderator (typically the median). We then estimate our model of Equation 1 on each subsample and compare results. Although coefficient magnitudes and significance levels often vary across subsamples (for fragmentation, and its interaction with aid), subsequent Wald tests generally fail to reject the null hypothesis of equal effect sizes. Accordingly, we do not find strong evidence that government control is an important moderator for the impact of fragmentation in our setting.

4.3 Demand for aid

Another district-level condition potentially moderating the effects of fragmentation is the demand for aid itself.[33] Where economic conditions are especially dire, a plethora of aid providers may introduce more benefits than challenges for aid delivery. This same logic could apply to areas having undergone recent natural or human-inflicted hardship. Accordingly, we construct various proxies of the demand for aid, and test whether they moderate the impact of fragmentation. In particular, we invoke measures of (1)

[32] We are grateful to an anonymous reviewer for identifying this potential mechanism.
[33] We are grateful to an anonymous reviewer for recognizing this additional channel.

reported hunger within households; (2) job opportunities; (3) employment opportunities; (4) income levels; and (5) income growth. We test for heterogeneity in these dimensions using the same approach as in Section 4.2 above, and Table A7 reports the results. Although coefficient magnitudes and/or significance levels occasionally differ across subsamples, Wald tests again fail to reject the null hypothesis of equal effect sizes (for fragmentation, and its interaction with aid). Therefore we do not find compelling evidence that demand for aid moderates the effects of fragmentation in our setting.

5 Conclusion

Aid fragmentation remains a global policy challenge, and it has grown significantly as foreign assistance has surged. By impeding coordination of development support, creating frictions in the allocation of aid, and opening up opportunities for the misuse of assistance, fragmentation can undermine the effectiveness of aid. Although these policy concerns have attracted significant debate among aid agencies and assistance organizations, little scholarly attention has focused on the potential unintended consequences of fragmentation on recipient institutions, including opportunities for graft and corruption. This paper takes an important first step towards credibly estimating these policy impacts using microlevel data from Afghanistan.

Our findings suggest that non-fragmented aid in Afghanistan curtails corruption. In the presence of donor fragmentation, however, the beneficial impact of aid is obstructed. Fragmentation enhances corruption when aid volumes are high, and mitigates corruption when aid is relatively contained. This effect heterogeneity survives a strict bias-adjustment to account for selection on both observable and unobservable confounding factors, as well as alternative identification strategies that account for the endogeneity of fragmentation and project timing. The robustness of our findings suggests a causal interpretation is credible.

We consider a series of potential mechanisms, finding consistent evidence that fragmentation moderates the positive impacts of aid when it is tied to infrastructure projects and material goods. These results are in-line with prior efforts by aid agencies to monitor graft, waste, and leakage in public works in Afghanistan and beyond.

This study of aid allocation in Afghanistan sheds light on fragmentation in a highly important policy context. The characteristics of the Afghan case—dependence on international assistance, persistent political violence, stymied economic growth, and social cleavages—also raise natural questions about the generalizability of our main results. How likely are the policy losses we document to bind in other contexts? The mechanism we highlight, in particular the role of assistance via infrastructure development and physical goods allocation, builds on a deeper intuition about the political and economic conditions that create opportunities for misappropriation of public resources. This dynamic could also be present in other settings where high profile infrastructure projects have been captured by corrupt bureaucrats and aligned private actors. More broadly, although Afghanistan is a context where violence and engagement in illicit activities remains high, our supplemental results suggest that accounting for local variation in these factors (using a battery of measures) does not significantly alter our core findings. While aid agencies will continue to confront unique challenges in each country of operation, well-grounded theoretical arguments and our microlevel evidence suggest that aid fragmentation may well be a policy complication encountered across a variety of settings. Ultimately, however, generalizability remains an open question best addressed by future research. With more nuanced theory development and broader geographical analyses, additional insights can be uncovered to guide decision makers at various levels of aid provision.

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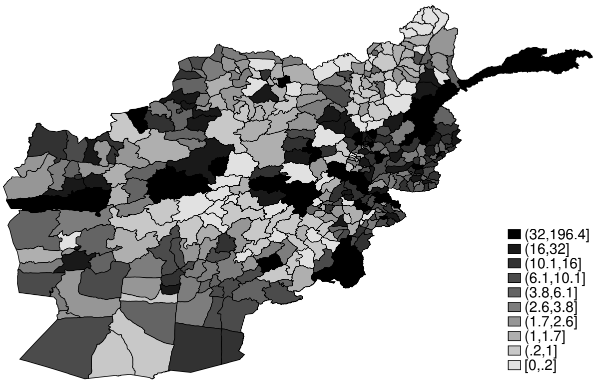
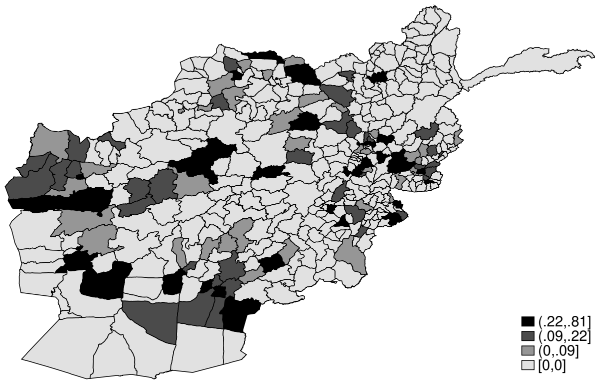
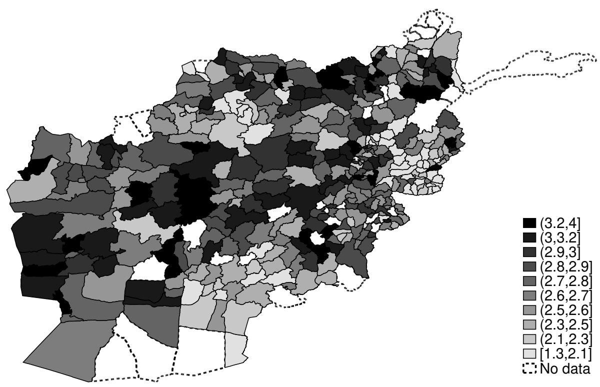
Figure 1: Spatial distribution of aid, fragmentation, and corruption



(a) Aid



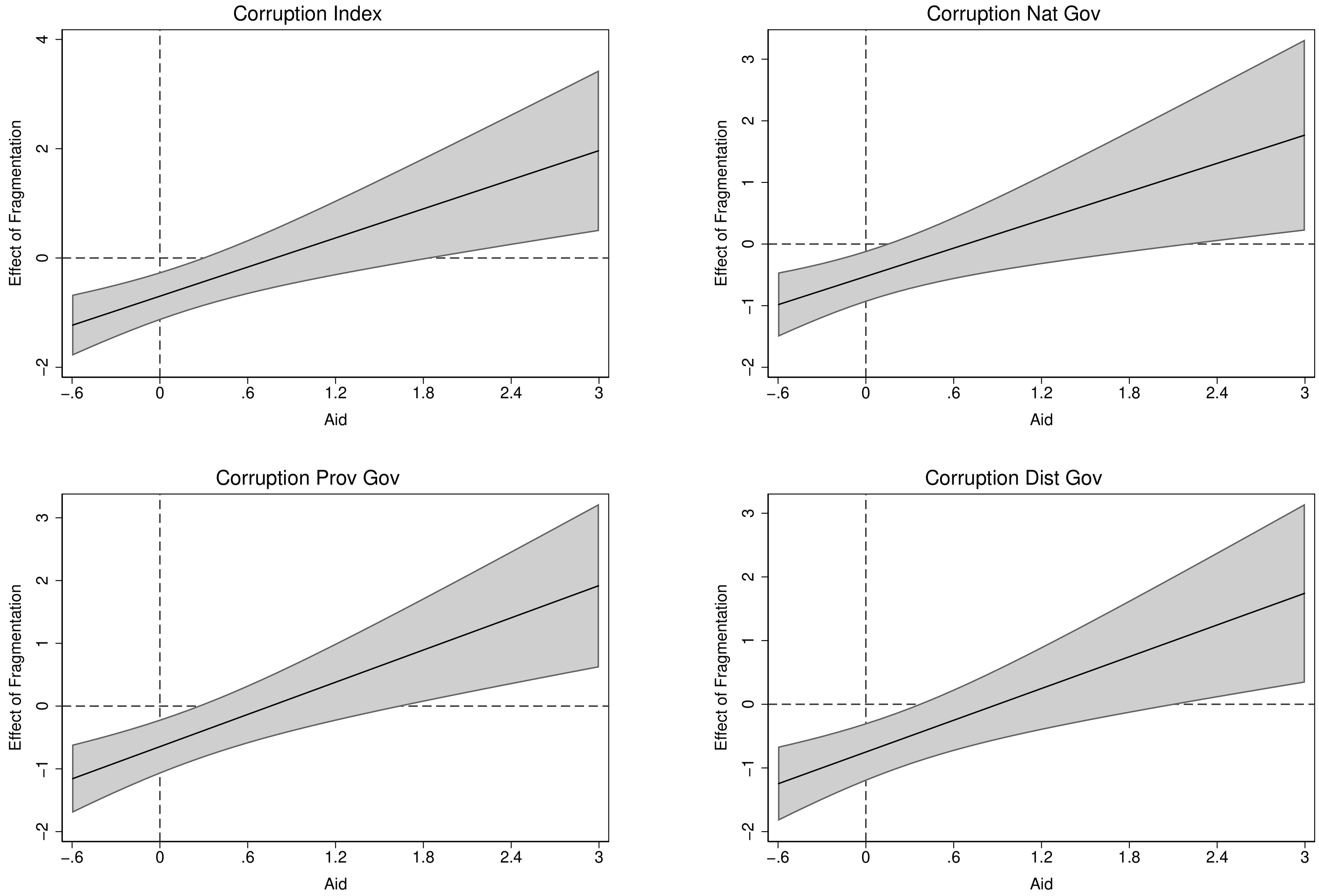
(b) Fragmentation



(c) Corruption

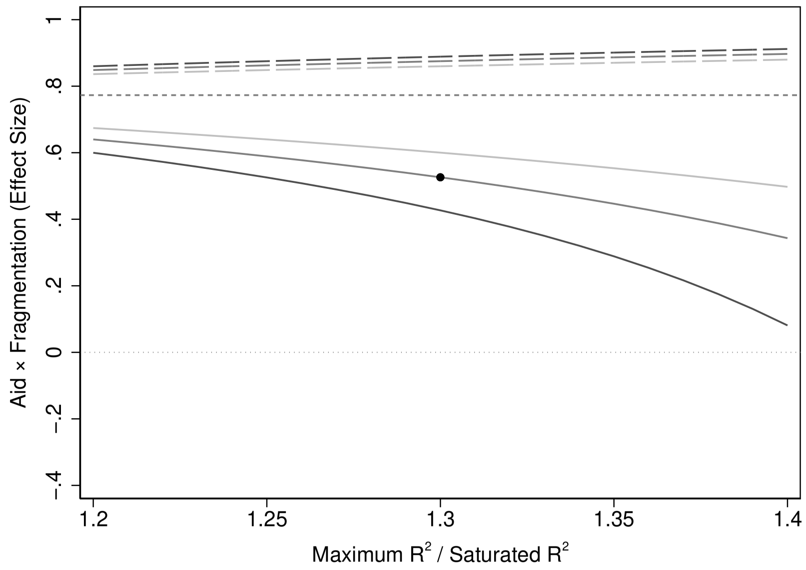
Notes: Subfigures map spatial distributions of sample-wide district averages of aid, fragmentation, and the index of corruption. Subfigure (a) depicts our measure of aid volumes, reflecting the number of concurrent aid projects on an average day, as defined in Section 2.1. Subfigure (b) depicts our measure of donor fragmentation, relecting the average number of active donors within a sector as defined in Section 2.2. Subfigure (c) depicts the index of corruption, reflecting public perceptions about government effectiveness in reducing corruption, as defined in Section 2.3. Aid data to construct the measures of aid volumes and donor fragmentation are from NATO C3 Agency's Afghanistan Country Stability Picture (ACSP). Survey data to construct the *Corruption* index are from the Afghanistan Nationwide Quarterly Assessment Research (ANQAR) surveys sponsored by ISAF HQ and Resolute Support HQ. Each shade corresponds to one decile. Darker shades indicates higher deciles. All subfigures depict district-level averages of corresponding measures spanning from July 2008 to September 2009.

Figure 2: Heterogeneous effects of fragmentation on corruption

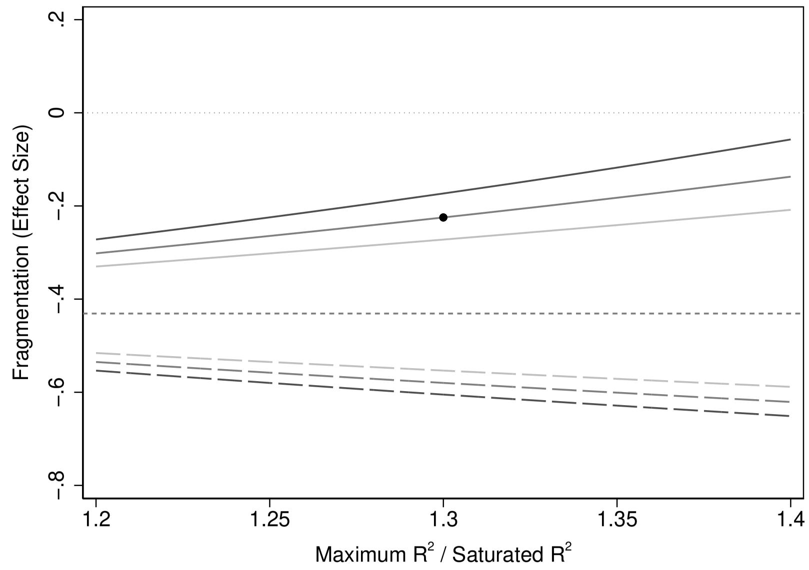


Notes: Subfigures plot effect sizes with 90% confidence intervals for the heterogeneous impact of fragmentation on corruption. The range of the x-axis $[-0.6, 3]$ captures most of the density of standardized aid (total range $[-0.57, 8.08]$). Subfigures report total effects of fragmentation on four measures of corruption, with the top left subfigure corresponding to the index of corruption. Outcomes are described in Section 2.3. Total effects are calculated as $\beta_1 P_{iq} + \beta_2$, where coefficients are estimated from Equation 1, and aid volumes (P_{iq}) read off the x-axis.

Figure 3: Coefficient stability



(a) Moderating effect of fragmentation



(b) Direct effect of fragmentation

Notes: Subfigures display the bounds for the moderating and direct effects of fragmentation on corruption estimated using the Oster coefficient stability test (Oster, 2019). The relative degree of selection on unobservables (compared to observables), δ, is allowed to vary in the most saturated model specification of Table 3: 0.8 (lightest gray), 1, 1.2 (darkest gray). The dashed lines display the coefficients when we allow negative selection, where δ equals to -0.8 (lightest gray), -1, -1.2 (darkest gray), respectively. The corresponding value of maximum R^2 is allowed to vary continuously from 1.2 to 1.4 times 0.236, the share of within-district variation explained by our most saturated model in column 6 of Table 3. The black dot marks the specification where $\delta = 1$ and Max R^2 is 1.3 times 0.236. The dashed gray line in subfigure (a) corresponds to 0.773, the coefficient of Aid $\times$ Fragmentation in the fully controlled model. The dashed gray line in subfigure (b) corresponds to -0.431, the coefficient of Fragmentation in the fully controlled model.

Figure 4: Word clouds describing physical and non-physical projects

(a) Physical projects

(b) Other projects

Notes: Aid project data are from NATO C3 Agency's Afghanistan Country Stability Picture (ACSP). Subfigure (a) depicts the most frequent words used in the ACSP descriptions of *physical* projects. Subfigure (b) depicts frequent words for other (non-physical) projects. We identify physical projects through the presence of (root) keywords in the ACSP project descriptions: build, bridge, construct, equip, furni, install, new, procure, purchase, refurb, renovate, repair, repar, replace, replenish, restor, road, suppl, wall, water, and well.

Table 1: Summary statistics

	N	mean	s.d	min	max
Aid	1,686	14.30	25.26	0.01	218.47
Physical projects	1,686	3.23	6.95	0	80.77
Other (non-physical) projects	1,686	11.05	23.89	0	218.47
Fragmentation	1,686	0.07	0.19	0	1
Physical projects	1,686	0.01	0.07	0	0.73
Other (non-physical) projects	1,686	0.03	0.13	0	0.88
Corruption (Index)	1,083	3.67	0.60	1.49	5.00
Nat Gov	1,083	3.78	0.61	1.39	5.00
Prov Gov	1,083	3.63	0.68	1.50	5.00
Dist Gov	1,083	3.61	0.67	1.30	5.00

Notes: The sample spans 5 quarters from July 2008 to September 2009. Each observation correspond to a district-quarter. Only district-quarters that received positive aid are included. *Aid* refers to the number of concurrent aid projects on an average day within a district-quarter as defined in Section 2.1. *Fragmentation* reflects the average number of active donors within-sector as defined in Section 2.2. Aid project data to construct the measures of aid volumes and fragmentation are from NATO C3 Agency's Afghanistan Country Stability Picture (ACSP). *Physical projects* are those related to infrastructure and material goods as defined in Section 4.1. Aid and fragmentation measures are constructed for all projects, and for physical and non-physical projects separately. *Corruption* outcomes are from Afghanistan Nationwide Quarterly Assessment Research (ANQAR) surveys sponsored by ISAF HQ and Resolute Support HQ. *Nat Gov*, *Prov Gov*, and *Dist Gov* are district-quarter average responses to the question "How well does the [Government of Afghanistan / Provincial Governor / District Governor] do its job reducing corruption in the [Government / administration]?" Individual responses are on a 5-point scale, with larger responses indicating greater perceptions of corruption. *Corruption (Index)* takes the average of the three government-level measures.

Table 2: Aid fragmentation and corruption

	(1) Corruption	(2) Nat Gov	(3) Prov Gov	(4) Dist Gov
Aid	-0.903***	-0.990***	-0.809***	-0.715***
	(0.262)	(0.272)	(0.250)	(0.247)
	[0.220]	[0.245]	[0.176]	[0.213]
Aid × Fragmentation	0.888***	0.765**	0.855***	0.831***
	(0.296)	(0.306)	(0.266)	(0.289)
	[0.233]	[0.231]	[0.234]	[0.192]
Fragmentation	-0.699***	-0.525**	-0.646**	-0.750***
	(0.267)	(0.252)	(0.263)	(0.276)
	[0.272]	[0.317]	[0.228]	[0.234]
R^2	0.086	0.078	0.071	0.083
Observations	1,083	1,083	1,083	1,083
Districts	330	330	330	330

Notes: Dependent variables are measures of corruption perceptions described in Section 2.3. Each column represents a separate regression based on Equation 1. The sample spans 5 quarters from July 2008 to September 2009. District fixed effects and year-quarter fixed effects are included in all specifications. *Nat Gov*, *Prov Gov*, and *Dist Gov* refer to the perceived effectiveness in reducing corruption of government authorities at the national, provincial, and district level, respectively. *Corruption* is the index that averages the three government-level measures. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Table 3: Selection on observable factors

	(1)	(2)	(3)	(4)	(5)	(6)
Aid	-0.903***	-0.327	-13.006	1.318	-1.301	-1.268
	(0.262)	(0.952)	(29.973)	(2.005)	(1.203)	(36.180)
	[0.220]	[1.106]	[23.298]	[1.831]	[1.207]	[18.943]
Aid × Fragmentation	0.888***	0.721**	0.711**	0.781**	0.949***	0.773**
	(0.296)	(0.335)	(0.288)	(0.311)	(0.317)	(0.372)
	[0.233]	[0.298]	[0.233]	[0.218]	[0.246]	[0.269]
Fragmentation	-0.699***	-0.702**	-0.442	-0.663**	-0.695***	-0.431
	(0.267)	(0.278)	(0.291)	(0.265)	(0.264)	(0.302)
	[0.272]	[0.237]	[0.207]	[0.250]	[0.261]	[0.238]
Aid characteristics		Yes				Yes
Geography			Yes			Yes
Development				Yes		Yes
Security					Yes	Yes
R^2	0.086	0.090	0.193	0.141	0.094	0.252
Observations	1,083	1,083	1,083	1,009	1,013	1,009
Districts	330	330	330	300	302	300

Notes: Dependent variable is the *Corruption* index. Each column represents a separate regression based on Equation 2. District fixed effects and year-quarter fixed effects are included in all specifications. We include four sets of potentially confounding factors (in both levels and interactions with *Aid*). Variable definitions, sources, and summary statistics for these variables are reported in Tables A3 and A4. Notice that we include *Aid* as a potential confounding moderator in columns 2 and 6. Interacting *Aid* with itself generates the quadratic term Aid^2. Variables from SIGACTS and ANQAR are time-variant, whereas variables from other data sources are measured cross-sectionally prior to the first wave of ANQAR. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Table 4: Endogeneity of fragmentation and aid timing

	(1) Baseline	(2) 2007 Average	(3) 1 Month	(4) 2 Month	(5) 3 Month
Aid	-0.903***	-1.059***	-0.900***	-0.876***	-0.895***
	(0.262)	(0.349)	(0.253)	(0.259)	(0.252)
	[0.220]	[0.295]	[0.260]	[0.271]	[0.294]
Aid × Fragmentation	0.888***	0.935*	0.793***	0.674***	0.555***
	(0.296)	(0.544)	(0.215)	(0.183)	(0.177)
	[0.233]	[0.887]	[0.164]	[0.135]	[0.156]
Fragmentation	-0.699***		-0.514**	-0.453	-0.244
	(0.267)		(0.255)	(0.276)	(0.249)
	[0.272]		[0.222]	[0.211]	[0.173]
R^2	0.086	0.069	0.081	0.082	0.079
Observations	1,083	1,052	1,068	1,047	1,038
Districts	330	318	326	324	323

Notes: Dependent variable is the *Corruption* index. District fixed effects and year-quarter fixed effects are included in all specifications. Column 1 reproduces the results in column 1 of Table 2. In column 2, we replace the time-variant measure of current fragmentation with the time-invariant district-level average fragmentation in 2007. In columns 3, 4, and 5, we reconstruct the measures of aid and fragmentation following the procedures listed in Sections 2.1 and 2.2, but assuming the start dates of aid projects are one, two, and three months later than officially reported. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Table 5: Heterogeneity by project type

	(1) Corruption	(2) Nat Gov	(3) Prov Gov	(4) Dist Gov
Panel A: Physical projects				
Aid	-1.337**	-1.631***	-1.143**	-0.964*
	(0.574)	(0.586)	(0.579)	(0.524)
	[0.538]	[0.613]	[0.475]	[0.509]
Aid × Fragmentation	4.296**	4.923***	3.785**	3.271*
	(1.829)	(1.848)	(1.619)	(1.889)
	[0.632]	[0.241]	[0.418]	[1.122]
Fragmentation	1.286	1.882*	0.923	0.821
	(0.971)	(0.986)	(0.844)	(1.015)
	[0.345]	[0.362]	[0.341]	[0.434]
Panel B: Other (non-physical) projects				
Aid	-1.661***	-1.656***	-1.513***	-1.438***
	(0.535)	(0.563)	(0.463)	(0.541)
	[0.402]	[0.468]	[0.325]	[0.398]
Aid × Fragmentation	1.103	1.082	0.845	1.132
	(0.826)	(0.796)	(0.847)	(0.715)
	[0.515]	[0.232]	[0.661]	[0.557]
Fragmentation	0.070	0.239	0.130	-0.160
	(0.420)	(0.430)	(0.424)	(0.372)
	[0.328]	[0.281]	[0.366]	[0.272]
R^2	0.110	0.104	0.097	0.102
Observations	651	651	651	651
Districts	224	224	224	224

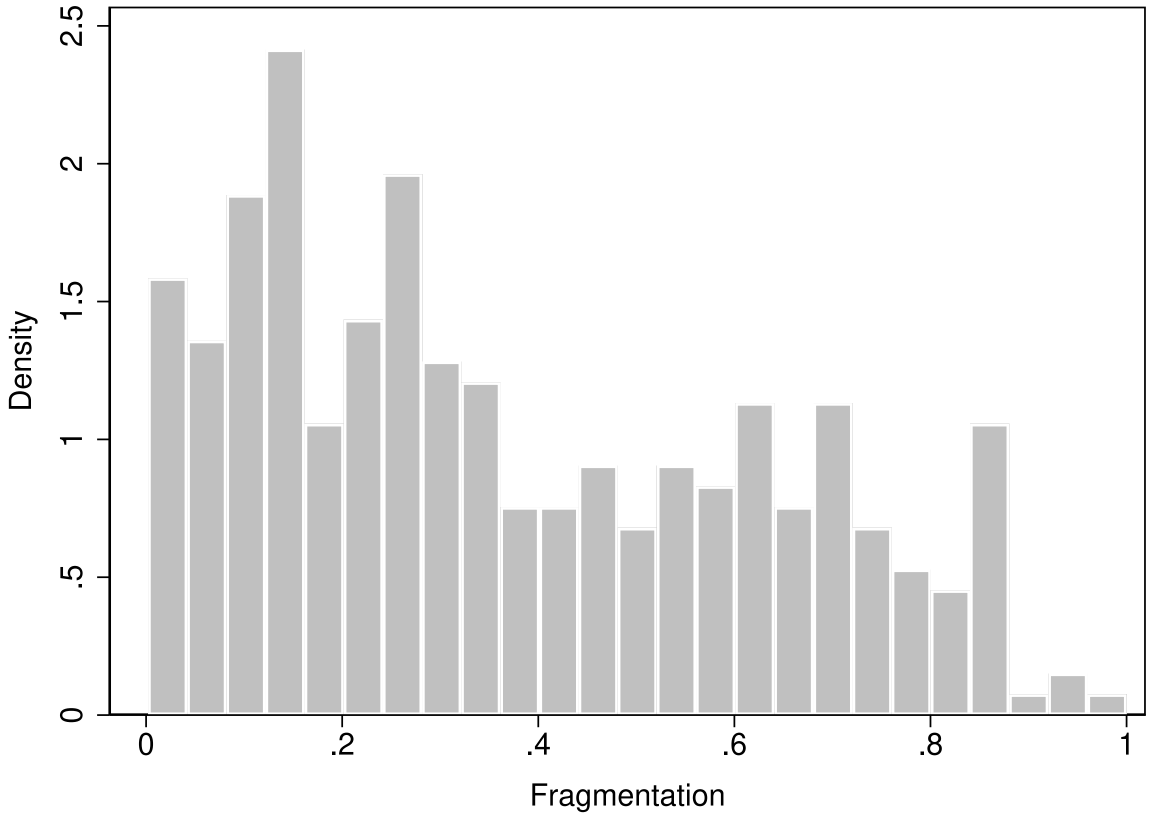
Notes: Dependent variables are measures of corruption perceptions described in Section 2.3. Each column represents a separate regression adapted from Equation 1. District fixed effects and year-quarter fixed effects are included in all specifications. *Nat Gov*, *Prov Gov*, and *Dist Gov* refer to the perceived effectiveness in reducing corruption of government authorities at the national, provincial, and district level, respectively. *Corruption* is the index that averages the three government-level measures. Aid in the upper (lower) panel measures the number of *physical* (non-*physical*) projects. Both measures are standardized by the mean and standard deviations of total aid volumes. Fragmentation in the upper (lower) panel measures the level of fragmentation among *physical* (non-*physical*) projects. Both measures are scaled by the maximum of fragmentation among all projects. Sample includes only district-quarters with a positive number of both physical and non-physical projects to obtain meaningful measures of fragmentation. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Appendix to *Aid Fragmentation and Corruption*

For Online Publication

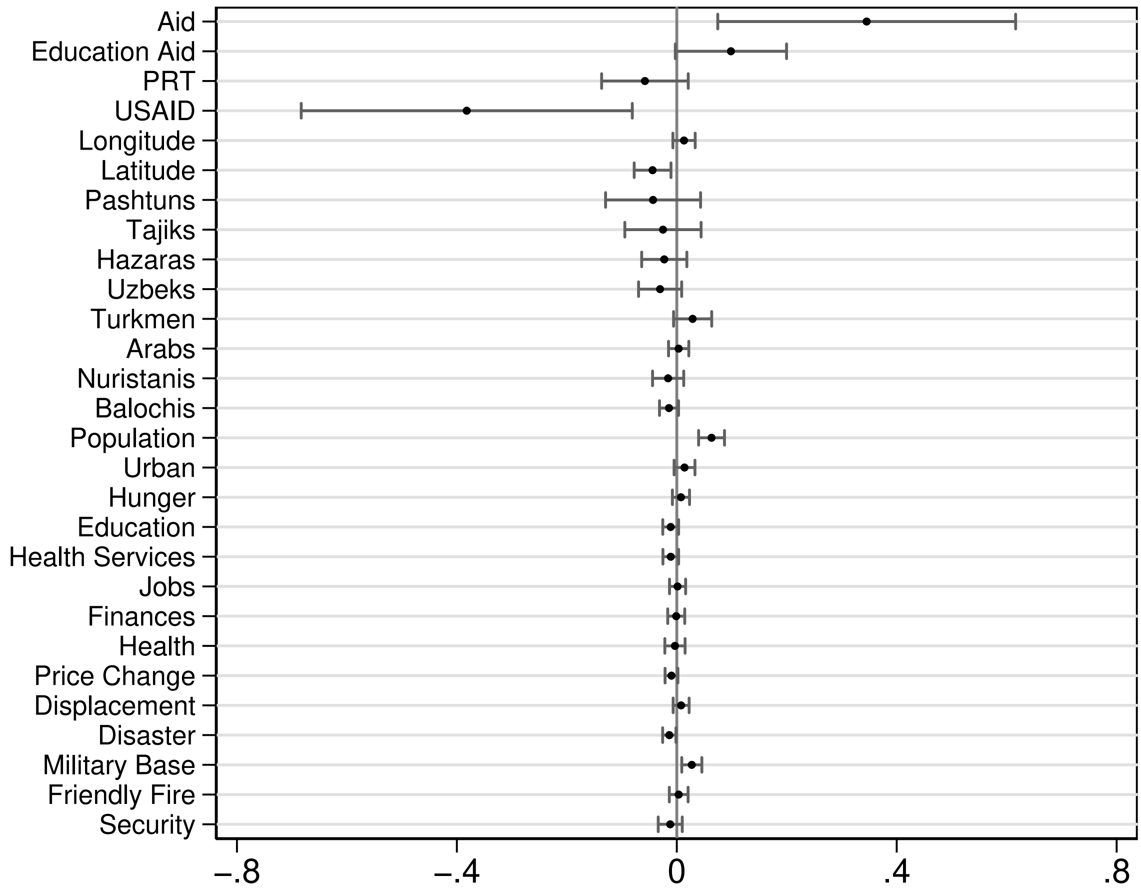
Appendix A Additional Exhibits

Figure A1: Distribution of non-zero aid fragmentation



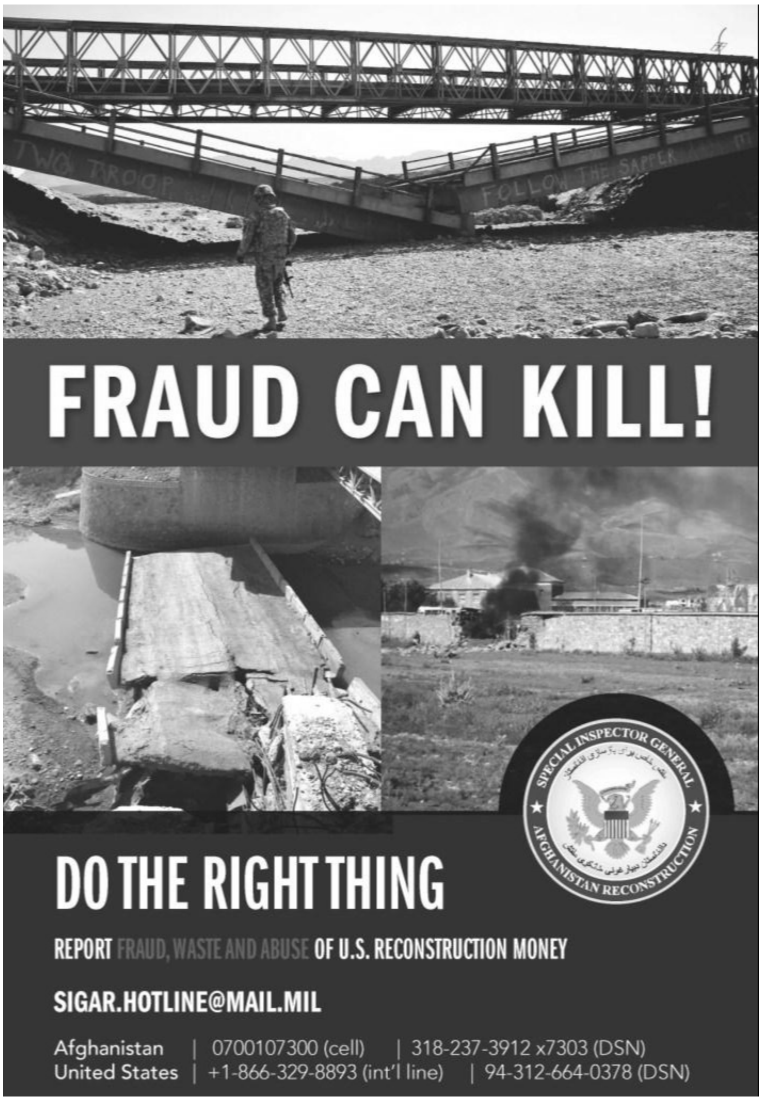
Notes: Figure depicts empirical distribution of non-zero donor fragmentation. Variable construction is detailed in Section 2.2. Sample includes 367 districts across Afghanistan, and spans from July 2008 to September 2009. Only districts having received positive amounts aid during the sample period are included. Data is from NATO C3 Agency's Afghanistan Country Stability Picture (ACSP).

Figure A2: Cross-sectional determinants of fragmentation



Notes: Figure plots the coefficients and 90% confidence intervals (using robust standard errors) from estimating the cross-sectional model: $F_i = \alpha + \beta C_i + \epsilon_i$. Fragmentation, F_i, is calculated as the average of F_{iq} (see Section 2.2) over the sample period July 2008 – September 2009. Explanatory variables, C_i, are taken from the list of confounding factors discussed in Section 4.1 and defined in Table A3. The items of C_i are measured as static prior to July 2008, or calculated as an average of values during the four quarters preceding July 2008. These control variables are standardized to facilitate comparison of coefficient magnitudes. Sample includes 367 districts having received a positive amount of aid between July 2008 and September 2009.

Figure A3: Example of SIGAR Advertisement



Notes: Figure presents an advertisement from the Special Inspector General for Afghanistan Reconstruction (SIGAR). For this campaign, advertisements were circulated in military bases, Afghan ministries, job sites, and even the in-flight magazine of Safi Airways.

Table A1: Perceived corruption and administrative bribe taking

	(1) Corruption	(2) Nat Gov	(3) Prov Gov	(4) Dist Gov
Administrative bribe taking	0.049**	0.050*	0.044**	0.061**
	(0.024)	(0.028)	(0.022)	(0.027)
R^2	0.224	0.182	0.206	0.166
Observations	9,781	9,974	9,937	9,949
Districts	241	241	241	241

Notes: Dependent variables are measures of corruption perceptions described in Section 2.3. Each column represents a separate respondent-level regression using district fixed effects. Bribe taking is measured as an index of bribe demands for various administrative activities including law enforcement, court judgements, and document processing in the past year. The outcome is rescaled to the unit interval for comparability. The sample (enumeration period) spans August–September 2010. The sample unit is an individual. *Nat Gov*, *Prov Gov*, and *Dist Gov* refer to the perceived effectiveness in reducing corruption of government authorities at the national, provincial, and district level, respectively. *Corruption* is the index that averages the three government-level measures. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level.

Table A2: Alternative measures of fragmentation

	(1) Corruption	(2) Nat Gov	(3) Prov Gov	(4) Dist Gov
Panel A: Herfindahl-Hirschman Index				
Aid	-1.064***	-1.257***	-0.935***	-0.778**
	(0.336)	(0.336)	(0.322)	(0.316)
	[0.240]	[0.263]	[0.190]	[0.230]
Aid × Fragmentation	1.380**	1.605***	1.233**	1.013*
	(0.589)	(0.598)	(0.544)	(0.559)
	[0.421]	[0.465]	[0.438]	[0.322]
Fragmentation	-0.366	-0.074	-0.337	-0.576*
	(0.355)	(0.348)	(0.348)	(0.349)
	[0.328]	[0.410]	[0.261]	[0.266]
R^2	0.082	0.079	0.066	0.078
Observations	1,083	1,083	1,083	1,083
Districts	330	330	330	330
Panel B: Concentration Index				
Aid	-1.063***	-1.273***	-0.931***	-0.767**
	(0.340)	(0.342)	(0.324)	(0.319)
	[0.249]	[0.274]	[0.200]	[0.232]
Aid × Fragmentation	1.643**	2.096***	1.446**	1.059
	(0.790)	(0.807)	(0.721)	(0.755)
	[0.525]	[0.585]	[0.539]	[0.414]
Fragmentation	-0.261	0.079	-0.245	-0.526
	(0.488)	(0.477)	(0.472)	(0.474)
	[0.422]	[0.506]	[0.361]	[0.334]
R^2	0.080	0.079	0.063	0.074
Observations	1,083	1,083	1,083	1,083
Districts	330	330	330	330

Notes: Dependent variables are corruption measures described in Section 2.3. Each column of Panels A and B represents a separate regression based on Equation 1. District fixed effects and year-quarter fixed effects are included in all specifications. Panel A (B) invokes the *Herfindahl-Hirschman Index* (*Concentration Index*) measure of fragmentation. Under the HHI, donor fragmentation on day t in sector j is: $F^H_{tj} = 1 - \sum_{d \in N} \left(\frac{P_{dtj}}{P_{tj}}\right)^2$. Here P_{dtj} is the number of projects being undertaken by donor d (in set N) on day t in sector j. As in Section 2.2, we take a weighted average across active sectors to obtain a development-wide measure F^H_t. Then, we again average over time to obtain a quarterly measure, F^H_q (all constructed at the district level, yielding F^H_{iq}). Under the CI, donor fragmentation on day t in sector j is: $F^C_{tj} = 1 - \max\{\frac{P_{dtj}}{P_{tj}} : d \in N\}$. We take a weighted average across active sectors to obtain a development-wide measure F^C_t, then average over time to obtain a quarterly measure at the district level (F^C_{iq}). For our regression analysis, we again normalize both measures to fall in the $[0, 1]$ range. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Table A3: Variable definitions for potential confounds

Name	Source	Description
Panel A: Aid		
Aid	ACSP	Mean concurrent projects (see Section 2.1)*
Education Aid	ACSP	Number of ongoing education project(s)*
PRT	ACSP	Number of projects from military-led PRT donor*
USAID	ACSP	Number of projects from USAID donor*
Panel B: Geography		
Longitude	Esri	Longitudinal coordinates of district center
Latitude	Esri	Latitudinal coordinates of district center
Ethnic group	ANQAR	Vector of variables expressing population share of Pashtuns, Tajiks, Hazaras, Uzbeks, Turkmen, Arabs, Nuristanis, and Balochis
Population	CSO	log of district population (1000s)
Urban	NRVA	Urban share of district population
Region	ACSP	Categorical indicators for North, East, South, West, and Central regions
Panel C: Development		
Hunger	Child (2019), NRVA	Unable to satisfy food needs of household (times/year)
Education	Child (2019), NRVA	Measure of educational attainment; percentile rank of 1st principal component score
Health services	Child (2019), NRVA	Measure of access to health services; percentile rank of 1st principal component score
Jobs	AF	Availability of jobs? [1=very good, ..., 4=very bad]
Finances	AF	Financial wellbeing better? [1=better, ..., 3=worse]
Health	AF	Health wellbeing of your family members
Opium	UNODC	Opium cultivation estimates (hectares)
Price Change	ANQAR	Have you noticed any changes in price of goods in the last 3 months that are not based on the season?
Displacement	SIGACTS	Event where persons have been internally displaced as a result of armed conflict, generalized violence, violations of human rights, or natural disasters*
Disaster	SIGACTS	Events where a natural event has caused significant loss of life or damage to property and infrastructure (e.g. severe weather, rock fall, and flooding)*
Karzai vote	IEC	Voting share of President Karzai
Panel D: Security		
Military base	Gehring, Langlotz and Kienberger (2019)	Indicator for any military base in the district
Friendly fire	SIGACTS	Conflict event occurring accidentally between friendly forces (e.g. National Army fires upon National Police)*
Security	AF	Good security situation? [1=good, ..., 4=bad]

Notes: Variables denoted with an asterisk are scaled to per-capita values and winsorized above the 99.9% level. ACSP: Afghanistan Country Stability Picture. Esri: GIS mapping software. ANQAR: Afghanistan Nationwide Quarterly Assessment Research. CSO: Central Statistics Organization of Afghanistan. NRVA: National Risk and Vulnerability Assessment survey, 2007-2008. AF: Asia Foundation survey, 2007 (missing values are backfilled using district-specific information from proximate survey waves; see text for more details). SIGACTS: Conflict microdata provided by US Central Command. UNODC: United Nations Office on Drugs and Crime. IEC: Afghanistan Independent Election Commission.

Table A4: Summary statistics for potential confounds

	N	mean	s.d	min	max
Panel A: Aid					
Aid	367	9.07	15.85	0.05	196.43
Education Aid	367	4.95	14.59	0	196.43
PRT	367	2.44	4.91	0	66.97
USAID	367	5.70	14.79	0	196.43
Panel B: Geography					
Longitude	367	67.53	2.58	61.01	73.30
Latitude	367	34.61	1.54	29.90	37.66
Pashtuns	367	0.42	0.38	0	1
Tajiks	367	0.34	0.32	0	1
Hazaras	367	0.09	0.21	0	0.98
Uzbeks	367	0.08	0.19	0	0.92
Turkmen	367	0.02	0.09	0	0.91
Arabs	367	0.01	0.03	0	0.27
Nuristanis	367	0.01	0.07	0	0.99
Balochis	367	0.01	0.05	0	0.80
Population	367	4.86	1.49	0.69	8.10
Urban	365	0.25	0.40	0	1
Panel C: Development					
Hunger	365	2.28	0.64	0	4.04
Education	365	61.38	30.26	1	100
Health Services	365	43.90	28.19	1	100
Jobs	317	2.89	0.40	1.85	4.00
Finances	317	1.74	0.29	1	2.93
Health	317	1.70	0.30	1.05	2.79
Price Change	330	0.72	0.10	0.32	1
Displacement	367	0.01	0.03	0	0.34
Disaster	367	0.01	0.06	0	1.50
Panel D: Security					
Security	317	2.19	0.61	1	4.00
Friendly Fire	367	0.02	0.07	0	0.94
Military Base	367	0.24	0.43	0	1

Notes: *Aid, Education, PRT, USAID, Displacement, Disaster,* and *Friendly Fire* are district averages between July 2007 and June 2008. Remaining variables are either cross-sectional or static. See Table A3 for variable descriptions and sources.

Table A5: Selection on observable factors (interactions reported)

	(1)	(2)	(3)	(4)	(5)	(6)
Aid	-0.903***	-0.327	-13.006	1.318	-1.301	-1.268
	(0.262)	(0.952)	(29.973)	(2.005)	(1.203)	(36.180)
Aid × Fragmentation	0.888***	0.721**	0.711**	0.781**	0.949***	0.773**
	(0.296)	(0.335)	(0.288)	(0.311)	(0.317)	(0.372)
Fragmentation	-0.699***	-0.702**	-0.442	-0.663**	-0.695***	-0.431
	(0.267)	(0.278)	(0.291)	(0.265)	(0.264)	(0.302)
Aid × Aid		-0.092				-2.368**
		(0.341)				(1.174)
Aid × Education Aid		-0.009				-0.010
		(0.016)				(0.019)
Aid × USAID		0.021				0.097*
		(0.021)				(0.055)
Aid × PRT		0.007				0.096**
		(0.016)				(0.047)
Aid × Longitude			0.459			0.405
			(0.301)			(0.332)
Aid × Latitude			-0.471			-0.413
			(0.327)			(0.736)
Aid × Pashtuns			6.785			7.897
			(5.270)			(5.076)
Aid × Tajiks			8.056*			8.334*
			(4.791)			(4.809)
Aid × Hazaras			10.027*			11.440**
			(5.230)			(5.066)
Aid × Uzbeks			9.826			14.930**
			(6.143)			(6.482)
Aid × Turkmen			11.124**			21.073*
			(5.545)			(11.122)
Aid × Arabs			7.088			19.537
			(14.296)			(12.511)
Aid × Nuristanis			7.655			8.412*
			(4.988)			(4.977)
Aid × Balochis			8.398			3.243
			(7.669)			(7.822)
Aid × Urban			-0.675			-1.977
			(1.647)			(1.951)
Aid × Population			-0.499			-1.024*
			(0.402)			(0.548)
Aid × Hunger				0.190		-0.222
				(0.304)		(0.720)
Aid × Education				-0.015		-0.032**
				(0.012)		(0.015)
Aid × Health Services				-0.015		-0.033**
				(0.010)		(0.016)
Aid × Jobs				0.813		-0.557
				(0.653)		(0.862)
Aid × Finances				-1.688**		-2.644**
				(0.819)		(1.255)
Aid × Health				-0.376		0.430
				(0.485)		(1.009)
Aid × Price Change				0.183		0.085
				(0.185)		(0.208)
Aid × Displaced Persons				-0.319*		-1.039**
				(0.181)		(0.472)
Aid × Disaster				1.053		0.509
				(3.142)		(3.383)
Aid × Military Base					-0.191	0.821
					(0.501)	(0.981)
Aid × Friendly Fire					-0.015	0.035
					(0.170)	(0.239)
Aid × Security					0.139	-0.285
					(0.468)	(0.774)
R^2	0.086	0.090	0.193	0.141	0.094	0.252
Observations	1,083	1,083	1,083	1,009	1,013	1,009
Districts	330	330	330	300	302	300

Notes: Dependent variable is the *Corruption* index. Each column represents a separate regression based on Equation 2. District fixed effects and year-quarter fixed effects are included in all specifications. Variable definitions, sources, and summary statistics for these variables are reported in Tables A3 and A4. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level.

Table A6: Baseline government control

	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Security		Conflicts		Opium		Pashtun		Military Base		Urban		Karzai Vote	
	$\leq p50$	$> p50$	$\leq p50$	$> p50$	$\leq p50$	$> p50$	$\leq p50$	$> p50$	=0	=1	=0	=1	$< 50\%$	$\geq 50\%$
Aid	-1.286**	-1.238***	-0.998**	-0.891***	-0.947**	-0.895**	-0.450	-1.260***	-0.812**	-1.817*	-0.778***	-2.146	-0.606*	-1.067***
	(0.561)	(0.313)	(0.399)	(0.342)	(0.388)	(0.374)	(0.383)	(0.366)	(0.325)	(0.923)	(0.264)	(1.918)	(0.364)	(0.358)
	[0.527]	[0.272]	[0.434]	[0.318]	[0.347]	[0.260]	[0.271]	[0.396]	[0.244]	[0.405]	[0.191]	[1.315]	[0.277]	[0.406]
Aid × Fragmentation	0.247	1.308***	1.166***	0.795**	0.696*	1.156***	0.923	1.004***	0.757**	2.581*	0.654**	1.794	0.865	0.982***
	(0.422)	(0.359)	(0.437)	(0.369)	(0.405)	(0.423)	(0.568)	(0.339)	(0.332)	(1.365)	(0.325)	(1.776)	(0.589)	(0.320)
	[0.324]	[0.251]	[0.206]	[0.297]	[0.235]	[0.352]	[0.422]	[0.280]	[0.240]	[0.704]	[0.203]	[1.608]	[0.438]	[0.355]
Fragmentation	-0.540*	-0.748*	-0.491	-0.816*	-0.471	-0.959***	-0.497	-0.812**	-0.596*	-1.510	-0.378	-0.378	-0.598	-0.784**
	(0.324)	(0.431)	(0.307)	(0.448)	(0.429)	(0.338)	(0.379)	(0.383)	(0.314)	(1.129)	(0.350)	(1.082)	(0.444)	(0.353)
	[0.312]	[0.324]	[0.297]	[0.372]	[0.244]	[0.344]	[0.336]	[0.513]	[0.332]	[0.763]	[0.314]	[1.071]	[0.317]	[0.274]
Wald tests [χ^2 (p-value)]														
Fragmentation	0.165 (0.685)		0.410 (0.522)		0.787 (0.375)		0.340 (0.560)		0.048 (0.826)		0.000 (1.000)		0.115 (0.735)	
Aid × Fragmentation	3.406 (0.065)		0.378 (0.539)		0.646 (0.421)		0.012 (0.912)		0.132 (0.717)		0.035 (0.852)		0.035 (0.852)	
R^2	0.153	0.092	0.104	0.089	0.071	0.112	0.091	0.106	0.081	0.233	0.075	0.228	0.059	0.110
Observations	511	502	543	540	627	456	554	529	999	84	964	119	471	602
Districts	153	149	166	164	187	143	169	161	310	20	299	31	140	187

Notes: Dependent variable is the *Corruption* index. Column headers refer to measures of baseline government control at the district level. The definitions of "Security", "Military Bases", "Pashtun", "Urban", "Karzai vote", and "Opium" are described in Table A3. "Conflicts" refer to the number of significant conflict events (SIGACTS), including close combat, indirect fire engagements, and improvised explosive devices in 2007. Conflict microdata are provided by US Central Command. Equation 1 is estimated simultaneously within sub-samples using seemingly unrelated regressions and estimates are compared using a Wald test. The resulting test statistics are reported below the coefficient estimates. District and year fixed effects are included in all specifications. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Table A7: Demand for aid

	(1)		(2)		(3)		(4)		(5)	
	Hunger		Job Opportunities		Employment Provision		Employment Income		Income Improved	
	$\leq p50$	$> p50$	$\leq p50$	$> p50$	$\leq p50$	$> p50$	$\leq p50$	$> p50$	$\leq p50$	$> p50$
Aid	-0.982***	-0.711	-0.840**	-1.322***	-0.426	-1.156***	-0.750	-1.085***	-0.890***	-0.949**
	(0.346)	(0.457)	(0.353)	(0.420)	(0.437)	(0.349)	(0.472)	(0.294)	(0.291)	(0.415)
	[0.277]	[0.483]	[0.285]	[0.374]	[0.422]	[0.325]	[0.237]	[0.335]	[0.164]	[0.397]
Aid × Fragmentation	0.982**	0.628*	0.950**	0.840*	0.860**	1.035**	0.554	1.248***	0.998**	0.528
	(0.440)	(0.364)	(0.387)	(0.507)	(0.400)	(0.411)	(0.488)	(0.317)	(0.429)	(0.359)
	[0.405]	[0.149]	[0.240]	[0.371]	[0.303]	[0.413]	[0.408]	[0.129]	[0.340]	[0.357]
Fragmentation	-0.543	-0.532	-0.806**	-0.539	-0.698**	-0.727	-0.413	-0.967***	-0.455	-0.886**
	(0.418)	(0.364)	(0.325)	(0.528)	(0.339)	(0.443)	(0.465)	(0.340)	(0.411)	(0.347)
	[0.296]	[0.453]	[0.271]	[0.341]	[0.291]	[0.488]	[0.305]	[0.453]	[0.302]	[0.381]
Wald tests [χ^2 (p-value)]										
Fragmentation	0.000 (0.985)		0.249 (0.618)		0.003 (0.958)		1.033 (0.309)		0.672 (0.412)	
Aid × Fragmentation	0.357 (0.550)		0.034 (0.853)		0.093 (0.760)		1.679 (0.195)		0.740 (0.390)	
R^2	0.132	0.099	0.111	0.086	0.093	0.089	0.053	0.140	0.099	0.111
Observations	557	522	567	446	549	534	544	539	530	553
Districts	166	162	159	143	166	164	166	164	166	164

Notes: Dependent variable is the *Corruption* index. Column headers refer to measures of demand for aid at the district level. The definitions and data sources of "Hunger" and "Job opportunities" are described in Table A3. *Employment Provision*, *Employment Income*, and *Income Improved* are district averages of ANQAR survey responses to the following questions. *Employment Provision*: How satisfied are you with the provision of jobs/employment in your area? [1: very dissatisfied, ..., 5: very satisfied]. *Employment Income*: Does your family currently have income through employment or other means? [0: no, 1: yes]. *Income Improved*: Has your family's economic situation gotten better, stayed the same or gotten worse compared to 12 months ago? [1: worse, ..., 3: better]. Equation 1 is estimated simultaneously within sub-samples using seemingly unrelated regressions and estimates are compared using a Wald test. The resulting test statistics are reported below the coefficient estimates. District and year fixed effects are included in all specifications. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Appendix B Robustness

B.1 Related outcomes

Here we examine the impact of aid and fragmentation on two related outcomes of interest: public opinion of the development and reconstruction (D&R) effort, and perceptions of misuse of power.[34] Both outcomes are related to perceptions of corruption, but we remain agnostic regarding their respective positions in the causal pathway liking aid, fragmentation, and institutional quality. As with corruption, we glean these opinion data from ANQAR survey questions posed with reference to various levels of authority.[35] Accordingly, we calculate district-average opinions of national, provincial, and district government D&R performance. Likewise, we calculate district-average perceptions of misuse of power among provincial and district Governors and police chiefs. Composite indices across all levels of authority are also calculated for each domain. Heatmaps of spatial variation in the indices of these two outcomes are provided in Figures B1a and B1b.

Panel A of Table B1 presents estimates from Equation 1 using D&R performance as the dependent variable. Aid appears to positively affect community appraisals of national, provincial, and district-level D&R efforts. In particular, a standard-deviation increase to nonfragmented aid leads to an approximately one-standard-deviation improvement to public opinion of D&R efforts. These effects are consistent with our documented benefits of nonfragmented aid on perceptions of corruption. In district-quarters characterized by high donor fragmentation, however, the effectiveness

[34] Various government actors may be exclusively or primarily involved in specific types of projects while others play a relatively minor role. Although our data describes the donors involved and project type, we lack the information required to separate aid flows by: (i) the actors responsible for reconstruction effectiveness; or (ii) the actors most likely to misuse their administrative powers. It is also not certain whether civilians' attributions of credit (or blame) would map well to these bureaucratic divisions of labor. Instead, this analysis presents a set of reduced form results, drawing our measures of aid and fragmentation from the broad flow of assistance to each district over time.

[35] The exact wording of the questions are as follows. *D&R Approval*: How well does the [Government of Afghanistan / Provincial Governor / District Governor] do its job at development and reconstruction? Responses are on a 5-point scale, with larger responses indicating greater dissatisfaction. *Misuse of Power*: Do you believe the following persons misuse their power: [Provincial Governor / Provincial Police Chief / District Governor / District Police Chief]? Responses are on a 3-point scale, with larger responses indicating more frequent misuse of power.

of aid in boosting public support is nullified. It therefore appears public sentiment responds to aid in a way consistent with aid's effectiveness at reducing corruption (notwithstanding the direct effects of fragmentation itself). These results on nonfragmented aid in Afghanistan are consistent with Beath, Christia and Enikolopov (2018). But since corruption persists relatively unabated in the presence of *fragmented* aid, this type of aid does not yield public opinion dividends (a finding consistent, by contrast, with Böhnke and Zürcher (2013)).

Next we conduct analogous tests examining the misuse of power among governors and police chiefs. Panel B of Table B1 provides evidence that aid is effective at reducing the perceived misuse of power. A standard-deviation increase in aid generally yields an approximate one-half-standard-deviation decline in the perception of power abuses. Results also suggests donor fragmentation has a direct beneficial impact on the misuse of power. As with our results on perceptions of corruption, however, donor fragmentation substantially mitigates aid's capacity to improve institutional outcomes in this regard. Roughly, our point estimates suggest an increase in fragmentation equal to the interquartile range would neutralize almost all of aid's beneficial effects in this domain.

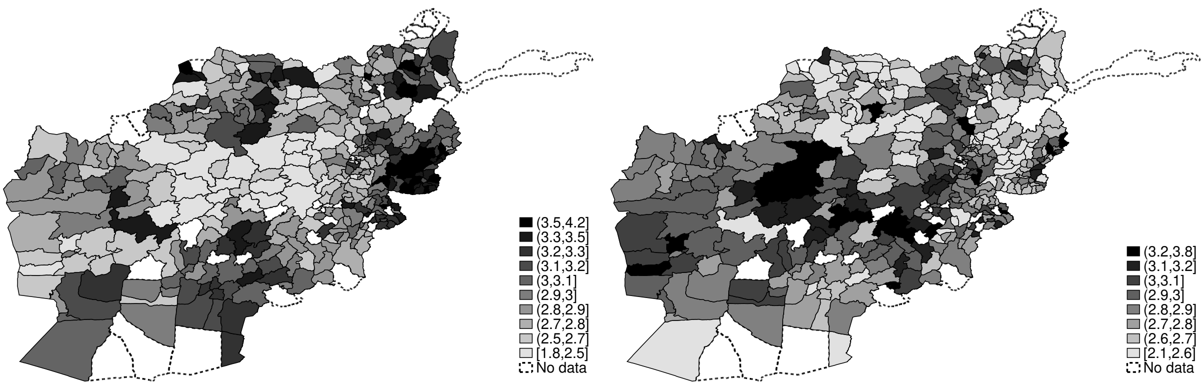
B.2 Sensitivity to sample periods

Our district-quarter panel spans 5 quarters from July 2008 to September 2009. The panel is relatively short and overlaps with the Afghan presidential election of August 2009 (yet excludes the November 2009 runoff). Accordingly, one may wonder if our results are driven by special circumstances characterizing a given period. To help alleviate such concerns, we drop one quarter at a time and re-estimate Equation 1 with the remaining four quarters. Resulting coefficients for aid, fragmentation, and their interaction are presented in Figure B2. We find consistent estimates for all three coefficients when dropping any one quarter from the analysis, suggesting that any given quarter does not drive the overall effect estimated in the pooled sample.

B.3 Demographic balance

ANQAR is a repeated cross-sectional dataset wherein surveyed households vary from one wave to the next. We therefore want to ensure our estimated effects are not spurious byproducts of changes to sample composition within ANQAR (across space, and over time). To this end, we conduct a balancing test replacing the outcome of Equation 1 with demographic characteristics in our sample. In particular, we test for balance using (1) share of females, (2) average age, (3) share of Pashtuns, (4) literacy rate, and (5) average household size. Table B2 presents the correlations between our continuous treatment variables and each of the abovementioned sample characteristics. We find no evidence these demographic variables are correlated with aid, fragmentation, or their interaction. These results suggest our estimates are not attributable to variability in sample composition.

Figure B1: Spatial distribution of related outcomes

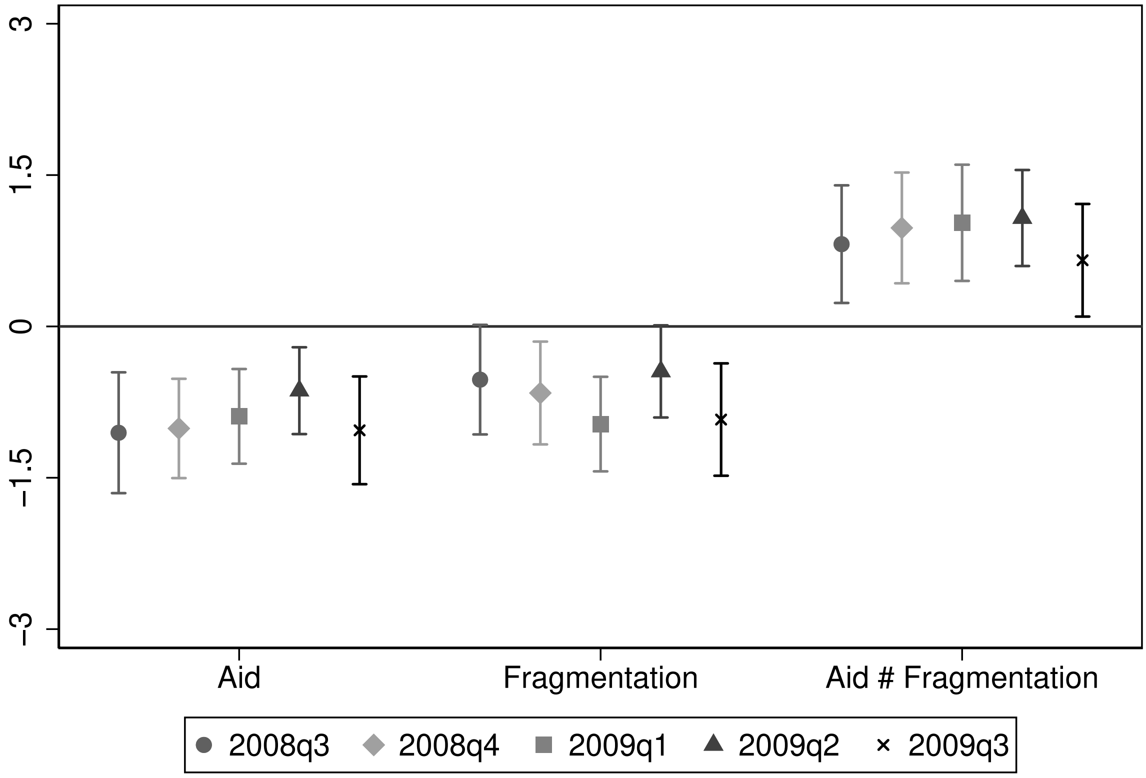


(a) D&R Approval

(b) Misuse of Power

Notes: Subfigures map spatial distributions of sample-wide district averages of related outcomes. Subfigure (a) depicts the public opinion (index) of the development and reconstruction (D&R) effort. Subfigure (b) depicts the perceptions (index) of misuse of power by government officials. Both outcomes are described in Section B.1. Related outcomes (a) and (b) are constructed using survey data from the Afghanistan Nationwide Quarterly Assessment Research (ANQAR) surveys sponsored by ISAF HQ and Resolute Support HQ. Darker shades indicates higher deciles.

Figure B2: Robustness check: dropping one quarter at a time



Notes: This figure overlays the coefficients of Aid, Fragmentation, and Aid × Fragmentation from five separate regressions. In each regression, we drop all observations from one particular quarter between 2008q3 and 2009q3 (spanning our sample period of July 2008 – September 2009). We then estimate Equation 1 using all observations from the remaining four quarters. The dependent variable is the *Corruption* index. District fixed effects and year-quarter fixed effects are included in all specifications. Ninety-percent confidence intervals are based on standard errors clustered at the district level. For comparison, the corresponding coefficients estimated from our full sample are shown in column 1 of Table 2.

Table B1: Related outcomes

	(1)	(2)	(3)	(4)	(5)
Panel A:					
	D&R Approval	Nat Gov	Prov Gov	Dist Gov	
Aid	0.501**	0.635***	0.542**	0.501*	
	(0.253)	(0.233)	(0.246)	(0.275)	
	[0.164]	[0.145]	[0.197]	[0.148]	
Aid × Fragmentation	-0.476**	-0.557**	-0.552**	-0.686***	
	(0.208)	(0.220)	(0.234)	(0.253)	
	[0.134]	[0.148]	[0.129]	[0.167]	
Fragmentation	0.179	-0.023	0.251	0.557**	
	(0.204)	(0.243)	(0.188)	(0.257)	
	[0.183]	[0.165]	[0.110]	[0.212]	
R^2	0.074	0.047	0.068	0.066	
Observations	1,083	1,083	1,083	1,083	
Districts	330	330	330	330	
Panel B:					
	Misuse of Power	Prov Gov	Prov PC	Dist Gov	Dist PC
Aid	-0.559***	-0.287	-0.512***	-0.477**	-0.717***
	(0.194)	(0.229)	(0.185)	(0.216)	(0.198)
	[0.182]	[0.185]	[0.225]	[0.157]	[0.202]
Aid × Fragmentation	0.826***	0.592**	0.826***	0.789***	0.733***
	(0.200)	(0.259)	(0.246)	(0.214)	(0.207)
	[0.330]	[0.241]	[0.395]	[0.369]	[0.266]
Fragmentation	-0.535**	-0.694***	-0.314	-0.442*	-0.422*
	(0.225)	(0.249)	(0.240)	(0.239)	(0.243)
	[0.072]	[0.116]	[0.097]	[0.124]	[0.140]
R^2	0.082	0.060	0.066	0.076	0.060
Observations	1,082	1,082	1,082	1,082	1,082
Districts	330	330	330	330	330

Notes: Dependent variables are public opinion of the development and reconstruction effort, and perceptions of misuse of power (both described in Section B.1). Each column of Panels A and B represents a separate regression based on Equation 1. District fixed effects and year-quarter fixed effects are included in all specifications. Panel A shows the effect of aid fragmentation on public opinion of the development and reconstruction effort. *Nat Gov*, *Prov Gov*, and *Dist Gov* refer to government authorities at the national, provincial, and district level, respectively. Panel B shows the effect of aid fragmentation on public perceptions of misuse of power. *Prov PC* and *Dist PC* refer to police chiefs at the provincial and district level, respectively. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.

Table B2: Demographic balance

	(1) Female	(2) Age	(3) Pashtun	(4) Formal Schooling	(5) Household Size
Aid	0.016	1.124	0.028	-0.001	0.393
	(0.037)	(1.114)	(0.039)	(0.041)	(0.417)
	[0.039]	[0.989]	[0.030]	[0.034]	[0.506]
Aid × Fragmentation	0.037	1.850	0.046	-0.051	-0.440
	(0.029)	(1.229)	(0.052)	(0.046)	(0.375)
	[0.022]	[0.755]	[0.033]	[0.039]	[0.250]
Fragmentation	-0.011	-0.960	-0.062	0.065	0.769
	(0.018)	(1.326)	(0.059)	(0.047)	(0.563)
	[0.009]	[0.981]	[0.056]	[0.036]	[0.427]
R^2	0.041	0.075	0.011	0.022	0.015
Observations	1,083	1,083	1,083	1,083	1,083
Districts	330	330	330	330	330

Notes: Dependant variables are indicated in column headers. Each column represents a separate regression adapted from Equation 1. The sample spans 5 quarters from July 2008 to September 2009. District fixed effects and year-quarter fixed effects are included in all specifications. *Female* is the share of female respondents for a given wave in a district. *Age* is the mean age of the respondents for a given wave in a district. *Pashtun* is the share of Pashtun respondents. *Formal schooling* is the share of respondents that ever attended formal school. *Household size* is the average household size. *, **, *** denote statistical significance at the 10, 5, and 1% level. Robust standard errors in parentheses are clustered at the district level. Conley (1999, 2010) standard errors in brackets account for spatial correlation among districts less than 1000 km apart.