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Political favoritism in post-conflict settings: evidence from Afghanistan after the Taliban takeover

Krystal Ha*

Abstract

I examine political favoritism based on prior support during conflicts. In particular, I identify whether or not the new Taliban regime in Afghanistan, which took over in August 2021, is systematically favoring its past allies using a difference-in-differences method. I proxy economic activity using nighttime light intensity and conflict alignment using a database of 75,915 militarily significant conflict events occurring in Afghanistan from 2004-2009. I find evidence that the Taliban are discriminating against their former enemies. I also find evidence that the Taliban are actively favouring their past allies in periods of low economic activity. This paper augments the literature on political favoritism by creating a new measure for political alignment and also suggests that the Taliban could be contributing to regional instability through favoritism.

JEL codes: D72, F51
Keywords: Afghanistan, favoritism, spatial analysis, georeferenced data, conflict

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1 Introduction

From 2001-2021, Afghanistan was mired in a conflict between the US-backed Afghan government, whose soldiers were part of the Afghan National Security Force (ANSF) and the Taliban, a violent, fundamentalist political organisation (henceforth also referred to as insurgents). 176,000 people, including Afghan civilians, ANSF, Taliban and coalition forces (predominantly US forces as well as some forces from other Western democratic countries), died directly as a result of the war [Crawford and Lutz, 2021]. In August 2021, the Taliban overran ANSF to govern Afghanistan under an authoritarian regime [Center for Preventative Action, 2022]. The regime has made dramatic changes to Afghanistan's institutions and perpetuated various human rights abuses, including conducting revenge killings of their former enemies [UNAMA, 2023]. Policymakers and NGOs are therefore interested in understanding whether the Taliban have favored or discriminated against groups on a national scale because it has been difficult to get nationwide data on such an opaque regime.

This paper examines whether or not the Taliban is systemically economically favoring its allies and discriminating against its former opponents in Afghanistan. It contributes to the literature on distributive politics by identifying a new form of political favoritism – favoritism based on prior support during conflict – by using SIGACTS, a dataset of 75,915 conflict events in Afghanistan to proxy political alignment at the ADM2 district level. I combine this with nightlight intensity data across 2020 (pre-Taliban takeover) and 2022 (post-Taliban takeover) to proxy economic activity, allowing us to create a dataset covering 398 districts over 2 years, which gives 796 observations. I also collect data on ethnic groups and population density at the district level to control for ethnic favoritism and district population.

Our results shed light on how Afghanistan's governance will affect regional stability. Because Afghanistan is a least developed country, poor governance, including through political favoritism, could contribute to a downward economic spiral, which in turn could exacerbate regional instability in the Middle East. This is particularly important in the context of two earthquakes in Afghanistan – a magnitude 6.2 earthquake in late June 2022 and a magnitude 6.3 earthquake in October 2023 – that have further hobbled the Afghan economy, as well as the destabilising Israel-Hamas war that broke out in October 2023. It is also important to understand political favoritism in Afghanistan for policy reasons. Many countries, particularly Western democratic countries, have conditioned aid to Afghanistan and any form of diplomatic recognition of the Taliban on its human rights record and ability to govern [European Union, 2021]. Understanding levels of political favoritism helps inform the Taliban's performance on these measures.

I use a difference-in-differences method, where I compare economic activity proxied by nightlight data before and after the Taliban takeover between districts aligned and unaligned with the Taliban. I proxy three potential mechanisms for favoritism: first, the Taliban rewards districts that contributed more to the war effort; second, they compensate districts that suffered more attacks from coalition forces; and third, they reward districts that achieved more successful war outcomes. I also test whether or not the Taliban is discriminating against districts that supported or benefited from relations with the US-backed coalition. To test the robustness of our results, I add in controls for conflict intensity and district population, which control for post-conflict reconstruction and rural development favoritism respectively. I also control for ethnic favoritism. As an additional robustness check, I also remove particularly significant dips in nightlight and outlier districts in our alignment variables.

I find evidence that the Taliban have been discriminating against their former opponents, such that coalition-aligned districts have 4.85% to 8.19% less nightlight than expected post-takeover relative to other districts. I also find evidence that the Taliban have been favoring their allies on the basis of their effort during the insurgency – high-effort districts have 4.66% to 12.55% more nightlight than expected post-takeover relative to other districts – and on the basis of sacrifice for the insurgency – districts that suffered more attacks from the US-backed coalition have 3.85% to 10.86% more nightlight than expected post-takeover relative to other districts. Our results do not consider population displacement or how alignment may have changed from 2009 to 2020, which adds noise to our alignment proxies and makes our estimates more likely to be conservative.

Some early literature has examined the Afghan economy following the Taliban takeover. Following the withdrawal of development aid, the World Bank [2023] estimates that GDP in Afghanistan contracted by 26%. Similarly, Sänger et al. [2023] combine nightlight data with synthetic controls to arrive at a decrease in GDP of 28%. However, these papers do not identify potential mechanisms for regional differences in economic growth. Literature examining earlier periods of Taliban governance in Afghanistan provide some indications for how public policy can influence potential regional differences. Cramer and Goodhand [2002], for example, shows that the Taliban ruled from the country districts of Afghanistan over the cities, indicating that they may economically favour rural areas. Noury and Speciale [2016] and Chung and Partridge [2023] illustrate that the Taliban instead discriminate on the basis of gender, as women had much fewer education opportunities under Taliban rule with long-term effects. Terpstra [2020] suggests that the insurgents have learned from their last period in power to be more inclusive of other ethnic groups to improve governance. This suggests that the Taliban could undertake various forms of favoritism or discrimination. Our paper provides clarity on how political favoritism can create regional differences in a post-takeover Afghan context.

Favoritism occurs in a variety of contexts. Our work is similar to De Luca et al. [2018], which identifies ethnic favoritism using nightlight data and finds it to be a global phenomenon. There is particularly strong evidence for authoritarian regimes engaging in favoritism. Do et al. [2017], for example, shows how under Vietnam's one-party system, public officials have sought to allocate more infrastructure improvements to their hometowns, whilst Markevich et al. [2021] finds that ethnic discrimination biases in authoritarian Soviet policy cascaded down to cause famine in Ukraine. This indicates the Taliban may also choose to engage in favoritism.

I contribute to the literature by looking at a different form of political favoritism – favoritism based on prior support during conflict. This is enabled by the novel application of SIGACTS, which lists conflict events of military importance from 2004-2009. This method is particularly applicable in post-conflict and authoritarian settings, where there is little or unreliable electoral data. Our findings indicate that both political favoritism and discrimination in these settings can be systemic and affect economic activity.

2 Institutional Background

Afghanistan is a least developed country. Economic activity is mostly driven by the security sector, the service sector, mining exports, agriculture, and foreign aid. Historically, a large proportion of agricultural activity has come from poppy farming for opium [Lind et al., 2014], but this may have decreased following Taliban efforts to ban drug production. Most non-agricultural economic activity is centred in the cities, particularly Kabul, Kandahar, and Mazar-i-Sharif. Nightlight is most likely to come from electricity consumption and non-agricultural forms of economic activity, such as mining.

The Taliban is a fundamentalist group that began in 1994, arising from the groups of mujahdeen fighters that fought against the Soviet occupation from 1979-1992 [Crews and Tarzi, 2008]. Timeline 1 shows that the group controlled Afghanistan from 1996-2001, then lost control in December 2001 when, following the 9/11 attacks, the US fought in Afghanistan to overthrow the regime. The 20 years from 2001-2021 represent the insurgency period for the Taliban, during which the Taliban slowly regrouped to oppose US and ANSF forces, eventually succeeding in gaining strongholds in some districts and contesting many others [Roggio, 2017]. During this period, US and international forces provided essential support fighting for and training ANSF forces to combat the insurgency.

Table 1: Timeline of conflict in Afghanistan

Sep 1996	First Taliban rule begins.
Dec 2001	**First Taliban rule ends, pre-takeover period begins**. Coalition forces back a new Afghan government.
Jun 2011	US announces it will begin to drawdown its troops in Afghanistan. The Taliban begin gaining ground in the insurgency.
Feb 2020	US-Taliban peace deal is signed.
Jul 2021	The Taliban take over most districts in Afghanistan.
Aug 2021	**Kabul falls to the Taliban. Pre-takeover period ends, post-takeover period begins.** Taliban begin governing all of Afghanistan.

In 2019, the US and the US-backed Afghan government began negotiating peace talks with the Taliban, during which the Taliban gained progressively more influence in contested districts [Duster, 2019]. In February 2020, the US and the Afghan government struck a peace deal with the Taliban where the US agreed to withdraw their troops, and in return the Taliban promised to harbouring terrorists [U.S. State Department, 2020]. Following the US withdrawal in August 2021, the Taliban quickly seized Kabul and by September had taken over all districts in Afghanistan [Roggio, 2017].

Following the Taliban takeover, most countries withdrew development aid, crippling the Afghan economy. The UN has nonetheless continued to distribute humanitarian aid to Afghan citizens, particularly during natural disasters, which the Taliban has increasingly tried to gain control over [Semple, 2023]. The Taliban themselves have made sweeping economic and social reforms, including repressing women's freedoms and overhauling tax collection practices. Notably, they have sought to reduce corruption by centralising revenues [Mansfield, 2022]. However, there is zero transparency around how the Taliban allocated budget expenditures [USIP, 2023].

There is anecdotal evidence of political favoritism and discrimination under the Taliban regime. Most notably, despite the Taliban leadership claiming to offer all ANSF soldiers amnesty, UNAMA [2023] has reported at least 800 human rights violations against former ANSF and government officials, including extrajudicial killings, torture, confiscation of possessions and threats and harassment. Whilst such violations are unlikely to appear in changes in nightlight intensity, they indicate Taliban officials' willingness to discriminate against their former enemies. In terms of favoritism that is more likely to affect economic activity, Mansfield [2022] has suggested that mineral industry contracts, aid delivery, and the drug industry could provide mechanisms for more systemic favoritism or discrimination.

Besides political favoritism, ethnic favoritism is also likely to occur in Afghanistan. Afghanistan has at least 23 ethnic groups, with the Pashtuns as the largest ethnic group and comprising approximately 40% of the population. Other ethnic groups include the Tajiks, the Uzbeks, the Turkmen, the Hazara, and the Baloch.

The Taliban's origins are closely linked to Pashtun nationalism [Crews and Tarzi, 2008]. However, during the insurgency period, the movement increasingly sought to appeal to ethnic minorities in Afghanistan, including the Tajiks and the Uzbeks [Terpstra, 2020]. It is difficult to assess ultimately whether or not the Taliban would be more likely to favour these groups, as they also often comprised significant parts of the US-supported Afghan government – Tajiks, for example, formed a significant proportion of ANSF forces [Johnson, 2006]. The exception to this are the Hazaras, who had political power within the previous Afghan government but are discriminated against by the Taliban because many of them are Shia Muslims, whilst the Taliban is comprised predominantly of fundamentalist Sunni Muslims. Consequently, our empirical strategy controls for favoritism of Pashtuns and discrimination against Hazaras, but I ignore other ethnic groups as it is uncertain whether they would be favoured or discriminated against.

3 Data

I build a panel dataset at the subnational administrative boundary (ADM2) and year level. Our outcome variable is logged nightlight, which proxies economic activity, and I use four different explanatory variables: complex insurgency attacks; insurgents wounded or killed; ANSF soldiers wounded or killed; and non-violent coalition activities. I control for ethnic favoritism, conflict intensity and population.

I use ADM2 data from the geoBoundaries database created by the Geospatial Evaluation and Observation Lab at William & Mary. There are 398 ADM2 districts in Afghanistan and I use data from 2020 and 2022, which gives us 796 observations in our base model. The following sections discuss the sources and construction of our variables in more detail.

3.1 Nightlight data

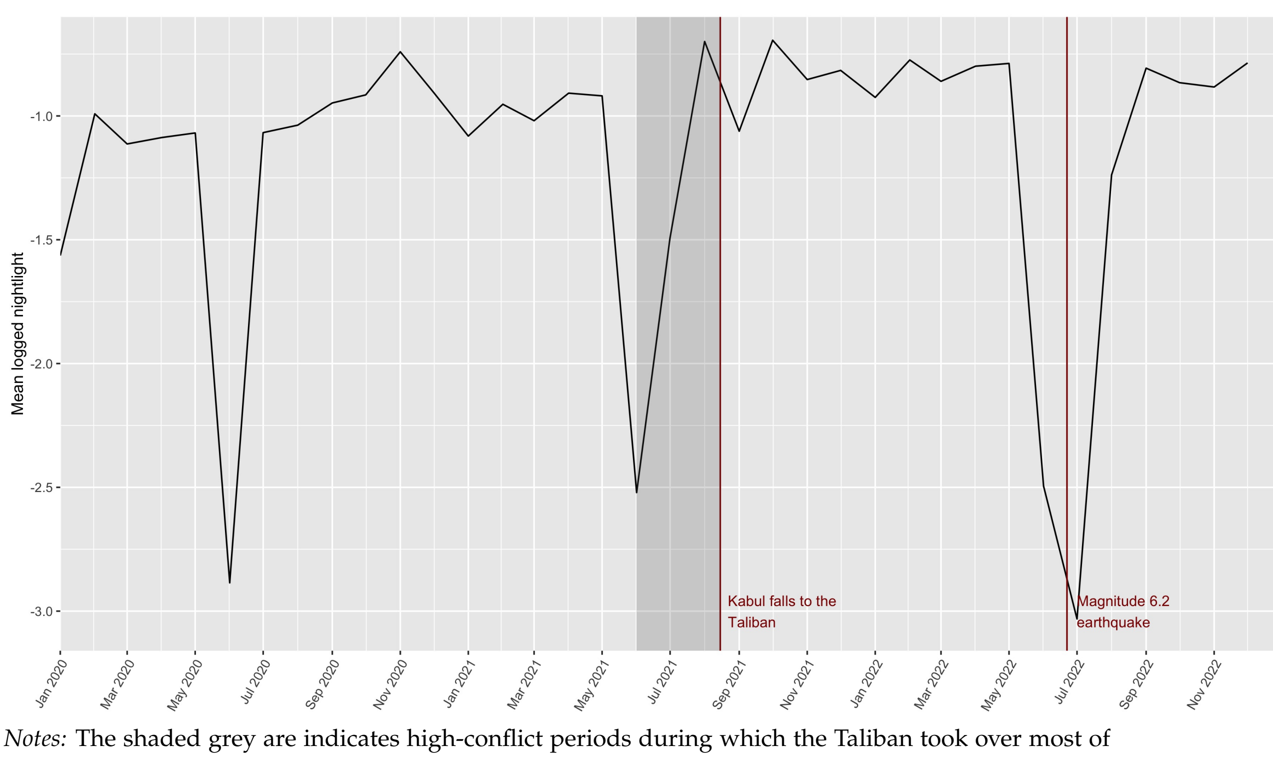
To proxy economic activity, I use the VIIRS monthly cloud-free DNB composites, corrected for stray light, provided by the Earth Observation Group at the Payne Institute for Public Policy. To form our outcome variable, I take all months from 2020 and 2022, aggregate the nightlight data at the ADM2 district level, and then take yearly averages to get an average yearly nightlight value for each district.

For our final outcome variable, I add 0.015 to the yearly district average and then take logs of these values. I add 0.015 to correct for negative values, which appear because of the stray light correction procedures.

As with most nightlight data, the data is very granular – the image resolution is 15 arc seconds, or approximately 400 metres, which is sufficient for attaining nightlight values at the ADM2 district level. The nightlight has been corrected for stray light, but is unmasked because data that has been consistently masked across 2020 and 2022 is not currently available. This makes it more likely that the data picks up on non-economic light sources, such as aurora effects, and some light that may be disproportionately bright, such as gas flares [Elvidge et al., 2017]. It has similar predictability for economic activity as DMSP nightlight sources [Gibson and Boe-Gibson, 2021].

Some months have much lower levels of nightlight and much higher variance across districts, as illustrated in Figure 1 below. These months are different from the others because of seasonality (June 2020 and June 2022) or because of sharp, sudden economic shocks (such as a magnitude 6.2 earthquake that occurred in late June 2022 and affected nightlight in July 2022). In our robustness checks, I remove these months from our yearly averages, so that our 2020 data is an average of 11 months and our 2022 data is an average of 10 months.

Figure 1: Monthly mean logged nightlight, 2020-2022



Notes: The shaded grey are indicates high-conflict periods during which the Taliban took over most of Afghanistan. 0.015 is added to nightlight intensity values before they are logged, as some nightlight values are negative due to stray light correction.

The sharp decrease in nightlight during the earthquake indicates that nightlight captures changes in economic activity. There is also a dip in nightlight from August 2021 to September 2021, when the takeover is complete. However, the decrease is not as sharp as may be expected. This may be because this graph averages nightlight across all districts. Many districts have little light, and the takeover is likely to have caused disproportionate decreases in nightlight in areas with military bases or high urban activity. This is seen in Bagram, a district containing a military air base, and Kandahar, the second largest city in Afghanistan. This is shown in the Appendix as Figures B.1 and B.2. Our estimates of nightlight are also likely noisier since I am not working with masked data.

3.2 Determining district alignment with the Taliban

To determine each district's alignment with the Taliban, I use the 2004-2009 Afghan Significant Activities (SIGACTS) dataset. SIGACTS contains 75,915 events of military importance recorded by the US Army under Operation Enduring Freedom, the US-led combat mission in Afghanistan from October 2001 to December 2014. The operation aimed to destroy Taliban and Al-Qaeda training camps and infrastructure within Afghanistan, and as part of their activities, the US Army recorded each of their own attacks, attacks by insurgency forces, and a variety of other events, such as political meetings, aid distribution, and civilian casualties and their causes. SIGACTS covers events from 2004 to 2009 recorded by most of the units from the US Army active in Afghanistan in that period. The dataset aggregates each event by event type and each event has a location attached to it, so that I can identify the number of events by event type that occurred in each district.

SIGACTS has several advantages over other conflict datasets, including datasets commonly used to study the Afghan war. The war logs are granular in recording the details of each event, allowing us to aggregate more specific classifications of events. Notably, it allows us to identify which party launched a given attack, which then allows us to proxy how much 'effort' insurgents invested in a given district. This differs from the Armed Conflict Location & Event Data (ACLED) and Uppsala Conflict Data Program (UCDP) datasets, which do not have this information. SIGACTS is also free from the biases and inaccuracies in media-based reporting data sources.

Other researchers have been able to access SIGACTS datasets that extend from 2002 to 2015 (Condra et al., 2018). Due to time constraints, I was unable to access and use this data, but our SIGACTS dataset is sufficient for capturing alignment with the Taliban during the earlier, riskier stages of its insurgency.

I use SIGACTS to capture alignment with the Taliban in four different ways: the number of complex attacks in a district, as districts that contributed more to the insurgency war effort could be more aligned; the number of enemies wounded or killed in a district, as districts that sacrificed more for the insurgency could be more aligned; the number of ANSF soldiers wounded or killed in a district, as districts that were more successful in the insurgency war effort could be more aligned; and finally, the number of non-violent activities conducted by coalition forces in a district, as an indicator of which districts were more anti-Taliban. These measures of alignment capture different potential reward functions the Taliban could be using to motivate its political favoritism.

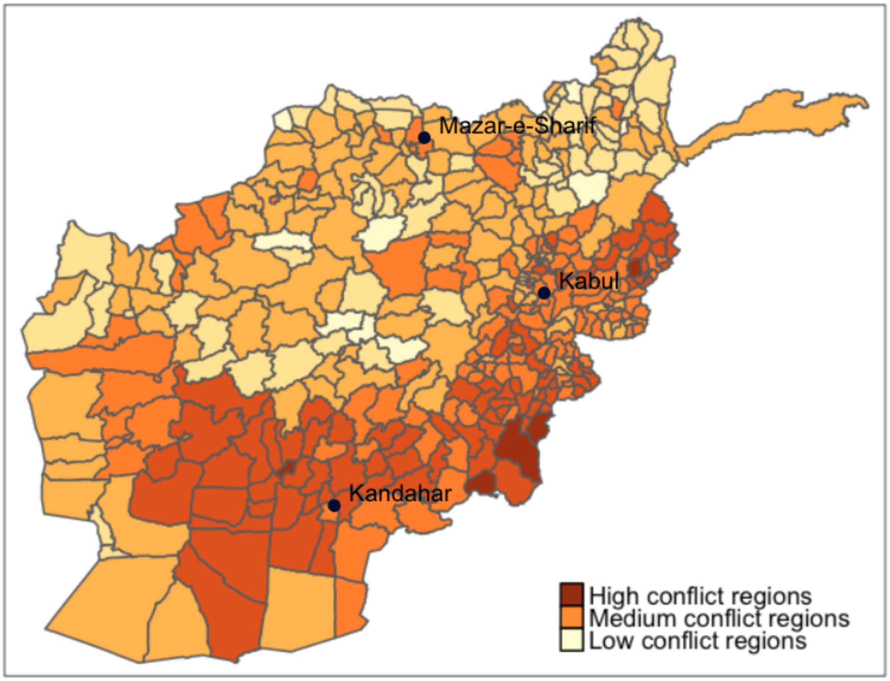
Due to the large range of events captured in SIGACTS, I am able to use another proxy for the first three measures of alignment to check the robustness of our results. (SIGACTS does not contain any other proxy variables for our fourth measure of alignment, which measures which districts were more likely to be anti-Taliban.) I re-test contribution to the insurgency war effort using the number of improvised explosive devices (IEDs) detected or exploded in a district; sacrifice for the insurgency using the number of coalition attacks launched in a district; and success in the insurgency war effort by the number of coalition soldiers wounded or killed by an insurgency attack.

From 2004 to 2009, the Taliban re-emerged as a quasi-coordinated set of groups, some of which had different goals and methods for achieving their ends (Crews & Tarzi, 2008). This, combined with the fact that the dataset represents events from 12-17 years prior to the takeover, means that the alignment captured then may not match districts' alignment with the Taliban today. However, this means that our results are more likely to be more conservative, and to identify political favoritism towards more long-term allies of the Taliban, who were part of the movement even during the riskier stages of the insurgency. Our measures of alignment are also designed to identify which districts have more allies of the Taliban, and do not imply that everyone in a district was an ally.

Figure 2 below shows the distribution of conflict events in Afghanistan. During the 2004-2009 period of the insurgency, conflict events were centred in the southern parts of Afghanistan. The regions roughly overlap with districts with a majority of Pashtuns, likely because the Taliban sought to represent and to some extent further Pashtun interests.

All the conflict events have heavily right-skewed distributions, where most districts have no or very few events of a given event type. Because of this, I create dummies at the 75th percentile for each of the eight conflict variables I use (which equal 1 when a district is in the top 25% of districts with that event and 0 otherwise) and use these dummies for all empirical analysis. Taking the 75th percentile is also useful because we do not know how the Taliban would choose to reward its supporters or

Figure 2: Distribution of conflict events in Afghanistan



Notes: Conflict events are from 2004-2009 and logged in this graph.

discriminate against its opponents. Using the number of events of a given alignment variable, for example, would assume a linear relationship between the number of events and favoritism, which is difficult to verify. The dummy variables help us identify the strongest insurgency supports so that it is more likely for us to identify a favoritism effect if it exists.

3.3 Determining ethnic favoritism

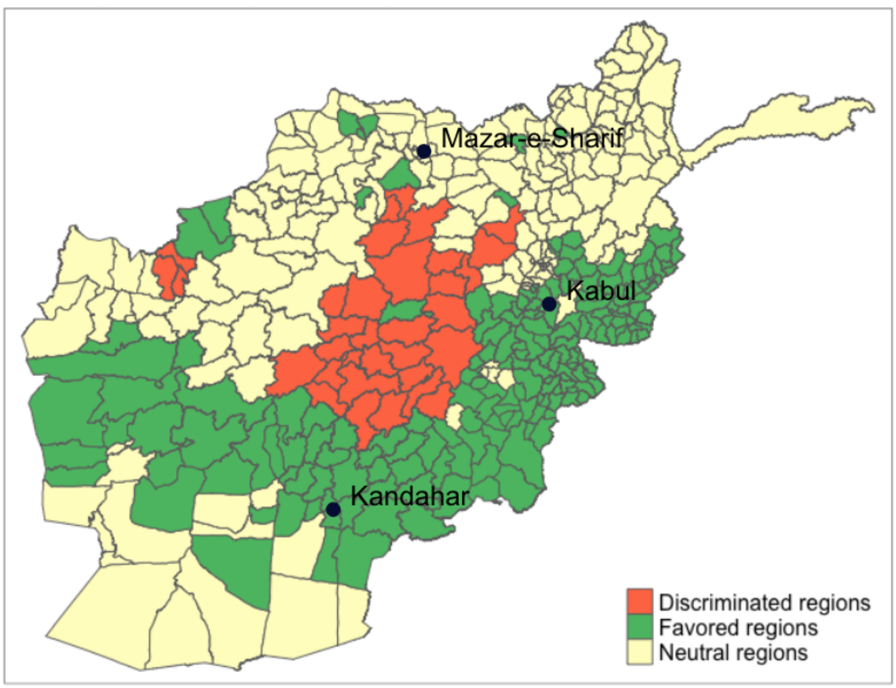
I use ethnic favoritism as a control variable. To determine ethnic favoritism, I first had to identify the make-up of ethnic groups within each district. I used the Geo-referencing Ethnic Groups (GREG) dataset, which represents group territories as polygons, and lists up to three ethnic groups within each polygon [Weidmann et al., 2010]. This dataset has the advantage of including more minority groups than other ethnic groups datasets. It identifies the location of 22 ethnic groups in Afghanistan, whereas other maps of ethnic groups are either not easily accessible in a data format or focus on only the largest ethnic groups. Whilst the GREG data is based on the classical Soviet Atlas Narodov Mira, which was created in the 1960s, it broadly aligns with more recent maps, such as Vogt et al. [2015].

The polygons of group territories do not align with ADM2 district boundaries, so I join the two datasets using population density data from the Socioeconomic Data and Applications Center (SEDAC) [Center for International Earth Science Information Network, 2017]. I assume that the ethnic groups are equally and uniformly distributed within a polygon, then overlay the population density data to approximate the number of people in a given ethnic group for every ADM2 district. The population density data helps ensure that ethnic groups that cover large spatial areas are not over-counted, as Afghanistan is a moutainous country, and ethnic groups that cover large spatial areas may not necessarily have high populations.

To measure ethnic favoritism, I create two dummy variables at the district level. The first identifies ethnic favoritism, and equals 1 if the majority of a population of a district is from a Pashtun ethnic group (which encompasses the Pashtun, Parachi, Pashai, Ormuri and Tirahi peoples) and 0 otherwise. The second identifies ethnic discrimination, and equals 1 if the majority of a population of a district is from a Hazara ethnic group (which encompasses the Hazara-Deh-i-Zainat and Hazara-Berberi peoples) and 0 otherwise. Both dummies are included in all ethnic favoritism controls.

The results of this joined dataset are illustrated in Figure 3. The favored regions cover the southern parts of the country, whereas the discriminated regions are concentrated in the centre of Afghanistan.

Figure 3: Favored and discriminated regions in Afghanistan



Notes: Discriminated regions are districts with a majority of Hazara people, whilst favored regions are districts with a majority of Pashtun people. All other districts are coded as neutral regions.

3.4 Summary statistics

Tables 2, 3, and 4 show our summary statistics. Table 2, which looks at all districts, shows that Afghanistan has relatively low levels of nightlight, which is expected given Afghanistan is a least-developed country. 8.3% of the districts have a majority of discriminated ethnic groups, whereas 47.7% of the districts have a majority of favored ethnic groups.

Table 3 compares the outcome and control variables across different alignment variables. Across the three favoritism variables, aligned districts tend to have slightly higher levels of nightlight, fewer ethnically discriminated districts, substantially more ethnically favored districts, and much higher conflict intensities. Unaligned districts also tend to have higher levels of nightlight, fewer ethnically discriminated districts, more ethnically favored districts and higher conflict intensities, though to a lesser extent. This makes our ethnic favoritism and conflict intensity controls particularly important for our analysis.

Table 4 shows summary statistics for all alignment variables, including alignment variables used in our robustness checks. Across all conflict events, the maximum tends to be much higher than the mean, indicating the conflict events are heavily right skewed.

Table 2: Summary statistics, outcome and control variables, all districts

	Mean	Standard deviation	Minimum	Maximum
Radiance (nW/cm^2/sr) (logged)	-1.191	0.365	-1.653	1.722
Discriminated ethnic groups	0.083	0.276	0.000	1.000
Favored ethnic groups	0.477	0.500	0.000	1.000
Total events count	190.741	433.124	0.000	3223.0
District population (logged)	11.192	0.812	8.074	15.521

Table 3: Summary statistics, mean of outcome and control variables by alignment

	Bottom 75% complex attacks (control)	Top 25% complex attacks (favored)	Bottom 75% insurgents wounded or killed (control)	Top 25% insurgents wounded or killed (favored)	Bottom 75% ANSF soldiers wounded or killed (control)	Top 25% ANSF soldiers wounded or killed (favored)	Bottom 75% non-violent coalition activities (control)	Top 25% non-violent coalition activities (discriminated)
Radiance (nW/cm^2/sr) (logged)	-1.219	-1.113	-1.225	-1.091	-1.236	-1.060	-1.231	-1.076
Discriminated ethnic groups	0.103	0.028	0.101	0.029	0.101	0.029	0.095	0.049
Favored ethnic groups	0.325	0.896	0.358	0.824	0.345	0.863	0.386	0.738
Total events count	56.449	560.679	67.385	548.716	59.845	570.598	123.624	382.971
District population (logged)	11.184	11.217	11.178	11.235	11.112	11.427	11.165	11.272

Table 4: Summary statistics, alignment variables

	Mean	Standard deviation	Minimum	Maximum
Complex attacks	4.563	13.122	0.000	126.000
Complex attacks (75th percentile dummy)	0.266	0.442	0.000	1.000
Enemies wounded or killed	10.420	35.473	0.000	318.000
Enemies wounded or killed (75th percentile dummy)	0.256	0.437	0.000	1.000
Afghan soldiers wounded or killed	30.520	61.033	0.000	543.000
Afghan soldiers wounded or killed (75th percentile dummy)	0.256	0.437	0.000	1.000
Non-violent friendly actions	15.834	54.651	0.000	665.000
Non-violent friendly actions (75th percentile dummy)	0.259	0.438	0.000	1.000
IEDs	39.467	93.872	0.000	857.000
IEDs (75th percentile dummy)	0.251	0.434	0.000	1.000
Coalition attacks	1.470	7.954	0.000	117.000
Coalition attacks (75th percentile dummy)	0.101	0.301	0.000	1.000
Coalition soldiers wounded or killed	21.053	52.649	0.000	483.000
Coalition soldiers wounded or killed (75th percentile dummy)	0.254	0.435	0.000	1.000

4 Empirical Analysis

To analyse the effects of Taliban alignment on nightlight, I estimate the following difference-in-differences model:

$$nightlight_{it} = \alpha_i + \beta takeover_t + \gamma(takeover_t \times align_i) + \epsilon_{it} \tag{1}$$

the i subscript indicates district; t subscript indicates year; *nightlight* is radiance logged; α is district fixed effects; *takeover* is a dummy that equals 0 pre-takeover (in 2020) and equals 1 post-takeover (2022); γ is our coefficient of interest; *align* is the given alignment variable; ϵ is our error term. In our base model, I use four different measures of alignment – 75th percentile dummies of the number of complex attacks, insurgents wounded or killed, ANSF soldiers wounded or killed, and non-violent coalition activities in each district.

For the three favoritism alignment variables, the coefficient of interest indicates how much political favoritism has influenced economic activity relative to non-aligned districts. I expect this coefficient to be positive, as aligned districts should have higher changes in economic activity due to favoritism relative to non-aligned districts. For our indicator of discrimination, I expect our coefficient to be negative, indicating that the Taliban's former opponents have lower changes in economic activity post-takeover.

The district fixed effects control for unchanging geographic features, such as how mountainous an area is, and the strategic value of a district. Standard errors are adjusted for heteroskedasticity. Since conflict intensified before the takeover and may have continued for short periods after, I choose to exclude all 2021 months from our analysis.

In our robustness checks I add controls, which are represented by X_i below:

$$nl_{it} = \alpha_i + takeover_t + \gamma takeover_t align_i + \boldsymbol{\phi X_i} + \boldsymbol{\theta X_i} takeover_t + \epsilon_{it} \tag{2}$$

I first include ethnic favoritism controls, which are comprised of two dummy variables, one representing ethnic discrimination and another representing ethnic favoritism. I also include controls for conflict intensity, which I proxy using the total number of conflict events in a given district. This is designed to control for potential reconstruction efforts – districts that experienced more intense conflict may increase in nightlight relative to other districts because they had more to rebuild. Finally, I include controls for district population, which is logged. This controls for the possibility that the

Taliban's economic policies favor rural areas, as rural areas have lower populations. Other variables, such as a district's distance from the capital of Afghanistan, Kabul, may have been a better proxy for this, but the results section shows that our results do not change much when I control for population, so due to time constraints, I did not include other proxies.

Before running our model, I test for parallel trends. The four graphs below compare average nightlight between districts with high and low numbers of the four conflict alignment variables.

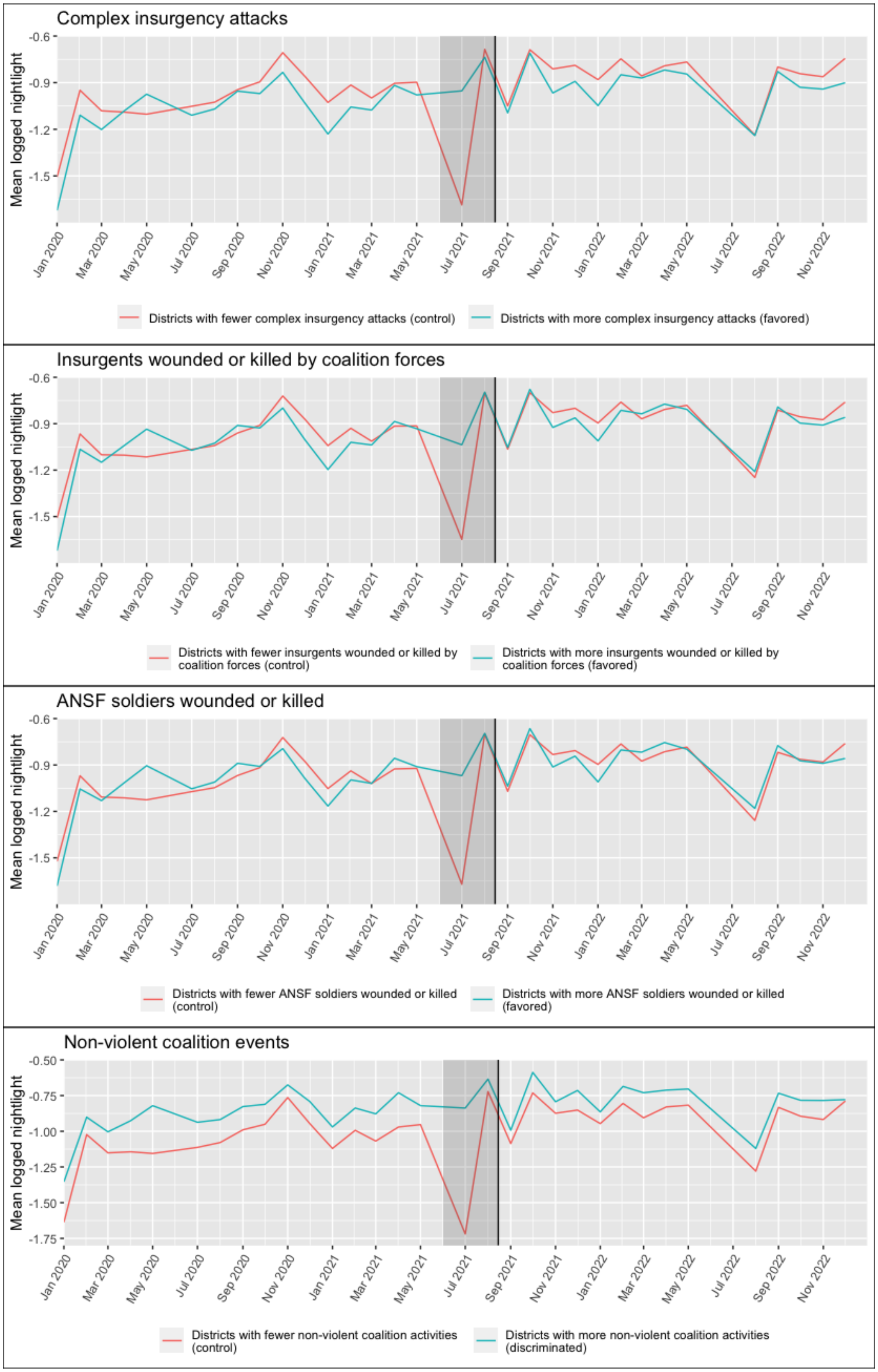
The graphs show that before the Taliban takeover in August 2021, districts trended similarly in nightlight, which gives some evidence for parallel trends. Across the three measures of favoritism, aligned and unaligned districts seem to match nightlight more closely post-takeover. There is little visual evidence of favoritism, except during months with more significant dips in nightlight. On the other hand, the gap between districts that would be discriminated against and other districts seems to narrow post-takeover. Districts with fewer non-violent coalition activities seem to increase in nightlight on average from approximately -1 pre-takeover to -0.85 post-takeover, whereas districts with more non-violent coalition activities hover around -0.8 both pre and post-takeover.

As discussed earlier, I remove high-variance months as an additional robustness check. Finally, though using a dummy already partially controls for this, I also remove districts that have particularly high numbers of the alignment conflict variable (more than three standard deviations above the mean) to check that it is not these districts alone that are driving the results.

5 Results

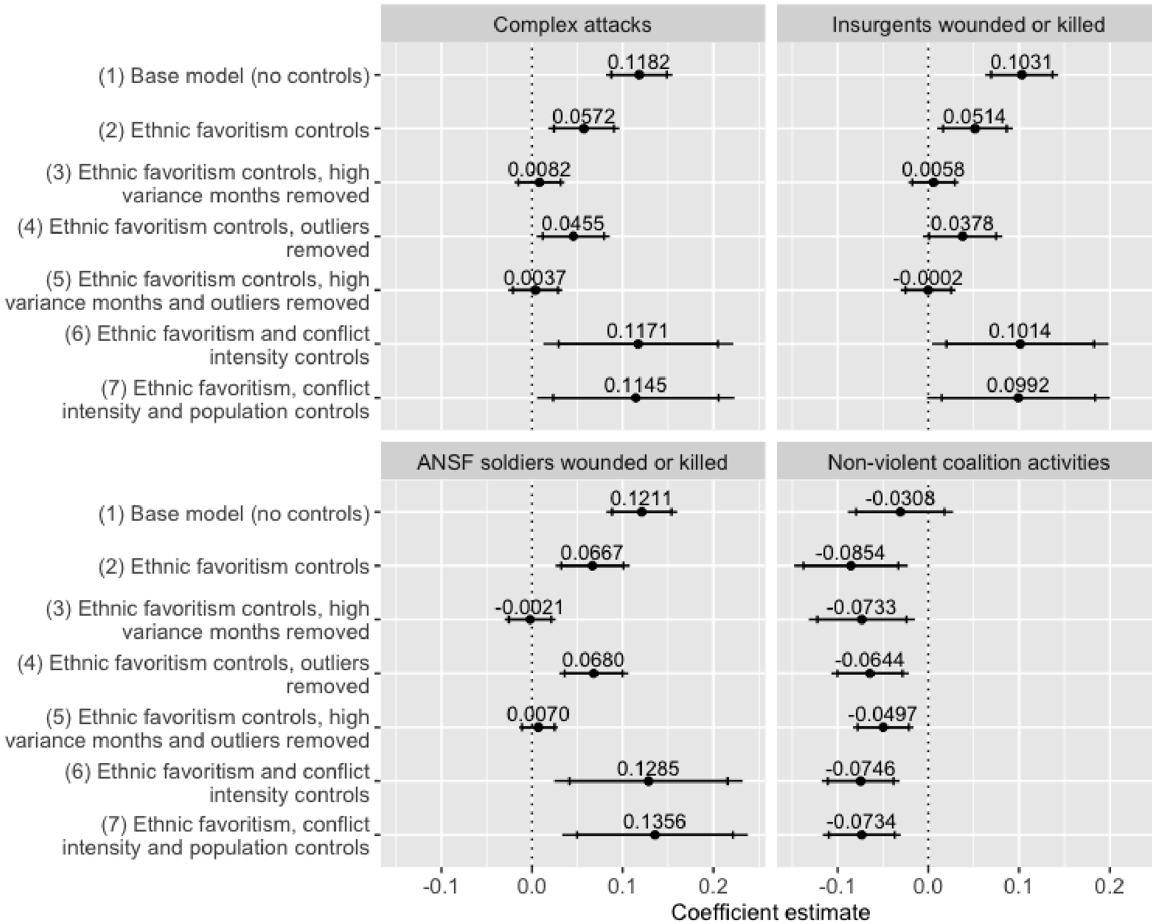
Figure 5 shows the coefficient of interest across the three forms of favoritism and single form of discrimination. Model 1, our base model, shows statistically and economically significant favoritism across all three mechanisms, and economically significant but not statistically significant discrimination against former opponents. Since our outcome variable, nightlight intensity, is logged, I interpret the coefficients by using them as exponents. The coefficient on complex attacks of 0.1182, for example, implies that since $e^{0.1182}$ equals 1.1255, an increase in 1 of our 75th percentile dummy on complex attacks – which means being a district with the top 25% number of complex attacks – leads to 12.55% higher nightlight intensity post-takeover relative to the bottom 75% of districts. Correspondingly, this means that districts with the top 25% number of insurgents wounded or killed had 10.86% higher nightlight intensity post-takeover; districts with the top 25% number of ANSF soldiers wounded or killed had 12.8% higher nightlight intensity; and districts with the top 25% of non-violent coalition activities had 3.03% lower nightlight intensity. The three measures of favoritism are statistically

Figure 4: Parallel trends in mean logged nightlight



Notes: The shaded grey are indicates high-conflict periods during which the Taliban took over most of Afghanistan. High variance months (June 2020, June 2021, June 2022 and July 2022) are removed from the graphs so that it is easier to compare nightlight levels. All alignment variables are separated at the 75th percentile, such that districts with fewer complex attacks, for example, are in the bottom 75% of districts in terms of number of complex attacks. 0.015 is added to nightlight intensity values before they are logged, as some nightlight values are negative due to stray light correction.

Figure 5: Coefficient estimates of the impact of alignment on nightlight



Notes: Middle point shows the coefficient estimate. Notches indicate 90% confidence intervals and the full line indicates 95% confidence intervals. High variance months were visually identified as sharp drops in nightlight. District outliers had more than three standard deviations above the mean of each given alignment variable. Standard errors were corrected for heteroskedasticity. All alignment variables are dummies at the 75th percentile and equal 1 when a district is in the top 25%. This table is available as regression tables in the Appendix.

significant at the 1% level, whereas the measure of discrimination, non-violent coalition activities, is not.

These results are economically significant. Consistent with anecdotal evidence, they imply that the Taliban has been economically favoring its insurgency allies on the basis of effort (number of complex attacks), sacrifice (number of insurgents wounded or killed), and results (number of ANSF soldiers wounded or killed.)

The results also show strong evidence of discrimination towards districts that benefited from coalition relations. This is illustrated in our robustness checks. Whilst the results are not statistically significant in our base model, once ethnic favoritism controls are added in Models 2-7, the coefficient approximately doubles in magnitude (implying decreases in nightlight intensity from 4.85% to 8.19%) and is consistently statistically significant at the 1% or 5% level across all other checks and controls. This is likely because the ethnic group that is likely to be favored, the Pashtuns, are a group that could be both favored and discriminated against for political reasons. Indeed, the pre-takeover, US-allied Afghan government was run by a Pashtun president and had Pashtuns in many key positions of power, creating a positive correlation between favored Pashtun ethnic groups and disfavored prior enemies that would understate the true level of purely political favoritism. The ethnic favoritism controls therefore help us capture discrimination for purely political reasons, and indicate that whilst the Taliban on the whole discriminated against its past opponents in conflict, they reduced levels of discrimination against prior opponents that were Pashtuns.

For the three measures of favoritism, the results vary more across the checks. Model 2 shows that when ethnic favoritism controls are added, the estimated favoritism effect lessens, but is still statistically significant at at least the 5% level. This is expected as the majority of the Taliban is from the Pashtun ethnic group, creating a positive correlation between ethnic and political favoritism. It is hard to exactly unravel the two different forms of favoritism, but it likely means that the base model, without ethnic favoritism controls, could be overstating the level of political favoritism, whilst adding the ethnic favoritism controls could be understating political favoritism. I include ethnic favoritism controls in all our robustness checks as a conservative coefficient estimate.

Models 3 and 5 show the effect of removing high variance months, which are the months with particularly significant dips in nightlight. The discrimination coefficient is smaller, but is still statistically significant at the 5% and 1% levels respectively. However, across all three favoritism measures, the coefficients lose significance. This suggests that a significant proportion of the favoritism occurred during the 6.2 magnitude earthquake in late June. The Taliban may have had access to more aid resources to distribute during this period, which may have given more opportunities for favoritism.

Removing outlier districts, as shown in Model 4 and 5, has little effect on its own. This is expected as the alignment variables are dummy variables, meaning even if a district has a disproportionately high number of a conflict event used to calculate alignment (such as complex attacks), it will not disproportionately skew the results.

Models 6 and 7 show the impact of controlling for conflict intensity, which is proxied by the total number of conflict events in a district. This has little impact on our discrimination measure. For the three favoritism measures, the coefficients mirror the results of our base model, and the results are all still significant at the 5% level except for our measure for favoritism based on sacrifice - the number of insurgents wounded or killed - when population controls are included (it is significant at the 10% level and not substantially different from Model 6 estimates.) This indicates that our coefficient estimates are not capturing reconstruction efforts in high-conflict areas instead of favoritism. However, the confidence intervals for the favoritism measures become much wider. This is likely because of the correlation between each alignment variable and the total event count, since the conflict events are likely to be positively correlated with each other. Adding in the conflict intensity controls thus also adds more noise to our estimates and makes it more difficult to capture the treatment variable. On the other hand, non-violent coalition activities are less likely to be correlated with other (violent) conflict events, which could be why the confidence intervals do not widen.

Model 7 controls for district population. This has little effect on any of the estimates, which gives some evidence that our estimates do not reflect favoritism of rural areas that would have lower populations.

As the dataset allows it, I then apply our model and robustness checks to different alignment proxies for each of the three favoritism mechanisms. I use a 75th percentile dummy for all models. Tables 3-5 report the results.

Our second alignment proxy for war effort, IEDs, give statistically significant results in the base model and with conflict intensity and population controls (Models 6 and 7), with similar effect sizes to the complex attacks proxy. They are positive but lose significance when ethnic favoritism controls are added, and become negative when high-variance months are removed. This strengthens the argument that favoritism is particularly strong during periods of low nightlight, which correspond with when the Taliban has received more international aid.

Because IEDs are by definition improvised, they are more likely to be perpetrated by individuals. This means that they are less likely to be strongly coordinated by the Taliban and are more likely to occur in locations far from Taliban heartlands. This helps address potential endogeneity concerns, particularly with complex attacks, that higher nighttime light intensity post-takeover reflects more economic activity in Taliban heartlands purely because the Taliban are more active now that they are governing, not explicit political favoritism. However, it also means that the favoritism effect is likely to be noisier, as it is more difficult for the Taliban to identify support from individuals that are more decentralised from Taliban heartlands and Taliban leadership. The estimates provide evidence that even outside of Taliban heartlands, there was political favoritism on the basis of war effort during lower nighttime intensity periods.

The second alignment proxy for sacrifice in war, which is the number of coalition attacks on a district, is consistently statistically significant at the 1% and 5% level in the base model, when ethnic favoritism controls are applied, and when high variance months and outliers are removed, and are statistically significant at the 10% level when conflict intensity controls are added. The economic significance decreases when ethnic favoritism controls and high variance months are removed, and increases when conflict intensity controls are added. This is consistent with the other estimates of favoritism and provides further evidence that the Taliban compensate districts on the basis of their sacrifice during the war.

Finally, the additional alignment proxy for results in war, the number of coalition forces wounded or killed in a given district, is statistically significant at the 5% level in the base model, and 10% when conflict intensity and district population controls are added, but otherwise gives insignificant results with some negative coefficients. This weakens the evidence that the Taliban have favored districts on the basis of the results during the war effort. It could be because it is more difficult for the Taliban to identify results during a war - whilst they may have coordinated most insurgency attacks or know where they have suffered more casualties, it is more difficult for them to assess how many casualties their opponents suffered.

Overall, these results give evidence that the Taliban has systemically discriminated against their prior opponents during conflict, such that they have caused nighttime light intensity to be 4.85% to 8.19% lower in coalition-aligned districts post-takeover relative to other districts. When considered in conjunction with our parallel trends graph, it indicates that the Taliban have closed the gap between the more economically active coalition-aligned districts and the rest of the country by choosing to help other districts more. As opposed to undermining economic activity in coalition-aligned districts, it suggests the Taliban have chosen to discriminate against them by actively ignoring them and supporting other districts instead. There is also evidence that the Taliban have favored districts that were more allied to the Taliban during the insurgency. This is particularly on the basis of districts' effort during the conflict, which meant high-effort districts had 4.66% to 12.55% higher nighttime light intensity relative to other districts, and on the basis of sacrifices that districts endured for the Taliban, which meant high-sacrifice districts had 3.85% to 10.86% higher nighttime light intensity relative to other districts. This favoritism occurred most during periods of low nightlight, such as following a June 2022 earthquake. It indicates a mechanism for this favoritism could be that the Taliban have disproportionately distributed natural disaster aid to their allies during the insurgency.

Table 5: Impact of alignment, proxied by IEDs, on nightlight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IEDs × Takeover	0.1097***	0.0520	−0.0475	0.0450	−0.0483	0.1243***	0.1375***
	(0.0283)	(0.0395)	(0.0363)	(0.0422)	(0.0389)	(0.0316)	(0.0292)
Ethnic favoritism controls	No	Yes	Yes	Yes	Yes	Yes	Yes
High variance months removed	No	No	Yes	No	Yes	No	No
Treatment outliers removed	No	No	No	Yes	Yes	No	No
Conflict intensity controls	No	No	No	No	No	Yes	Yes
District population controls	No	No	No	No	No	No	Yes
R^2	0.9311	0.9376	0.9590	0.9403	0.9625	0.9415	0.9424
Adj. R^2	0.8616	0.8740	0.9173	0.8795	0.9243	0.8816	0.8833
Observations	796	796	796	780	780	796	796

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 6: Impact of alignment, proxied by coalition attacks, on nightlight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coalition attacks × Takeover	0.1142***	0.0648***	0.0324***	0.0497**	0.0311**	0.1657*	0.1602*
	(0.0205)	(0.0222)	(0.0122)	(0.0240)	(0.0135)	(0.0876)	(0.0930)
Ethnic favoritism controls	No	Yes	Yes	Yes	Yes	Yes	Yes
High variance months removed	No	No	Yes	No	Yes	No	No
Treatment outliers removed	No	No	No	Yes	Yes	No	No
Conflict intensity controls	No	No	No	No	No	Yes	Yes
District population controls	No	No	No	No	No	No	Yes
R^2	0.9290	0.9375	0.9586	0.9376	0.9586	0.9415	0.9417
Adj. R^2	0.8575	0.8739	0.9165	0.8742	0.9164	0.8817	0.8817
Observations	796	796	796	774	774	796	796

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table 7: Impact of alignment, proxied by coalition forces wounded or killed, on nightlight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coalition forces wounded or killed × Takeover	0.0656**	0.0045	−0.0513	−0.0004	−0.0501	0.0653*	0.0722*
	(0.0290)	(0.0369)	(0.0337)	(0.0385)	(0.0355)	(0.0396)	(0.0381)
Ethnic favoritism controls	No	Yes	Yes	Yes	Yes	Yes	Yes
High variance months removed	No	No	Yes	No	Yes	No	No
Treatment outliers removed	No	No	No	Yes	Yes	No	No
Conflict intensity controls	No	No	No	No	No	Yes	Yes
District population controls	No	No	No	No	No	No	Yes
R^2	0.9283	0.9368	0.9592	0.9398	0.9626	0.9392	0.9398
Adj. R^2	0.8561	0.8726	0.9176	0.8784	0.9245	0.8771	0.8780
Observations	796	796	778	778	796	796	796

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: High variance months were visually identified as sharp drops in nightlight. District outliers had more than three standard deviations above the mean of each given alignment variable. Standard errors were corrected for heteroskedasticity. All alignment variables are dummies at the 75th percentile and equal 1 when a district is in the top 25%, except for the coalition attacks proxy, which is a dummy at the 90th percentile as over 75% of districts had 0 coalition attacks.

A limitation of my findings is that I do not consider the impact of population displacement. The Afghan war caused significant inter-district migration, which could affect the location of both prior conflict allies and opponents. This could be slightly mitigated by the fact that some migration may have occurred due to fear of discrimination, meaning that lower nightlight in the districts people have migrated out of reflects expected discrimination. However, there is no inter-district migration data available for us to detect this displacement. Our proxies of alignment are thus noisier, which makes out estimates more conservative.

Similarly, alignment during the 2004-2009 period may be different from alignment in 2021, when the Taliban took over. This also makes our proxies of alignment noisier. However, there is no possible way to perfectly capture alignment of a given district, and I was unable to access the more updated SIGACTS dataset due to time constraints. Our results are therefore likely to be conservative, and predominantly capture favoritism and discrimination towards stronger, longer-term supporters and opponents of the Taliban respectively.

6 Conclusion

Following the Taliban takeover in Afghanistan in August 2021, the Taliban have made sweeping social reforms and committed various human rights abuses, including revenge killings on their former opponents during the 2001-2021 Afghan conflict. This has created fears that the Taliban may send the fragile Afghan economy into a downward spiral, contributing further to geopolitical instability in the region. Political favoritism could exacerbate this dynamic by undermining economic growth and sowing dissent.

This paper identifies whether or not political favoritism has been occurring under the new Taliban regime. I use conflict data to proxy pre-takeover alignment with the Taliban at the district level, then combine this with data on nightlight intensity in 2020 (pre-takeover) and 2022 (post-takeover) to create a dataset with 796 observations, comprised of 398 districts across 2 years. I also add controls for ethnic favoritism, population and conflict intensity at the district level.

I run a difference-in-differences model, and as it is difficult to guess how the Taliban may have chosen to reward its allies, I test four hypotheses: that the Taliban rewarded districts that put in more effort during the insurgency; that the Taliban rewarded districts that sacrificed more casualties for the insurgency; that the Taliban rewarded districts that achieved results during the insurgency; and that the Taliban punished districts that benefited from close relations with the coalition. I run robustness checks by adding in our controls, as well as removing conflict event outliers and months with particularly low nightlight.

I find that the Taliban have been discriminating against their former enemies, such that coalition-aligned districts have 4.85% to 8.19% lower nightlight intensity due to discrimination relative to other districts. I also find evidence that the Taliban have been favoring their allies. Districts that put more effort into the insurgency had 4.66% to 12.55% higher nightlight intensity due to favoritism and districts that suffered more casualties for the insurgency had 3.85% to 10.86% higher nightlight intensity due to favoritism. The favoritism in particular appeared to occur most following the June 2022 earthquake, when the Taliban had more aid resources it could distribute. Our findings do not account for population displacement or alignment changing over time, which could make our estimates more conservative.

Our results indicate that whilst the Taliban's economic governance may have been less destabilising than expected, it may be undermined by the Taliban's propensity for political favoritism, which could erode its trust with the governments and NGOs giving and distributing aid. They also provide more reason for caution that aid given in post-conflict, authoritarian settings can be used for political favoritism, even in response to exogenous, acute events such as natural disasters.

This paper contributes to the literature on political favoritism by examining a new way to proxy political alignment – alignment forged in conflict settings. It provides a new method for exploring political favoritism in post-conflict, authoritarian settings, where this is little to no reliable electoral data available. Future research should examine whether these results hold using masked nightlight data when it is available, which should reduce noise in the results, whether conflict-based political favoritism continues long-term and other settings outside of Afghanistan where such favoritism may occur to identify whether there is a consistent pattern of political favoritism in post-conflict settings.

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Appendix

A Additional Tables

Table A.1: Impact of alignment, proxied by complex attacks, on nightlight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Complex attacks X Takeover	0.1182***	0.0572***	0.0082	0.0455**	0.0037	0.1171**	0.1145**
	(0.0186)	(0.0200)	(0.0141)	(0.0205)	(0.0151)	(0.0533)	(0.0553)
Ethnic favoritism controls	No	Yes	Yes	Yes	Yes	Yes	Yes
High variance months removed	No	No	Yes	No	Yes	No	No
Treatment outliers removed	No	No	No	Yes	Yes	No	No
Conflict intensity controls	No	No	No	No	No	Yes	Yes
District population controls	No	No	No	No	No	No	Yes
R^2	0.9319	0.9377	0.9585	0.9383	0.9584	0.9413	0.9416
Adj. R^2	0.8633	0.8743	0.9162	0.8755	0.9160	0.8813	0.8816
Observations	796	796	796	780	780	796	796

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A.2: Impact of alignment, proxied by insurgents wounded or killed, on nightlight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Insurgents wounded or killed X Takeover	0.1031***	0.0514**	0.0058	0.0378*	-0.0002	0.1014**	0.0992*
	(0.0205)	(0.0212)	(0.0142)	(0.0224)	(0.0153)	(0.0494)	(0.0512)
Ethnic favoritism controls	No	Yes	Yes	Yes	Yes	Yes	Yes
High variance months removed	No	No	Yes	No	Yes	No	No
Treatment outliers removed	No	No	No	Yes	Yes	No	No
Conflict intensity controls	No	No	No	No	No	Yes	Yes
District population controls	No	No	No	No	No	No	Yes
R^2	0.9306	0.9376	0.9585	0.9381	0.9584	0.9409	0.9412
Adj. R^2	0.8607	0.8741	0.9162	0.8751	0.9160	0.8804	0.8807
Observations	796	796	796	774	774	796	796

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Table A.3: Impact of alignment, proxied by ANSF soldiers wounded or killed, on nightlight

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ANSF soldiers wounded or killed X Takeover	0.1211***	0.0667***	-0.0021	0.0680***	0.0070	0.1285**	0.1356***
	(0.0199)	(0.0208)	(0.0142)	(0.0193)	(0.0108)	(0.0529)	(0.0520)
Ethnic favoritism controls	No	Yes	Yes	Yes	Yes	Yes	Yes
High variance months removed	No	No	Yes	No	Yes	No	No
Treatment outliers removed	No	No	No	Yes	Yes	No	No
Conflict intensity controls	No	No	No	No	No	Yes	Yes
District population controls	No	No	No	No	No	No	Yes
R^2	0.9320	0.9381	0.9585	0.9299	0.9548	0.9421	0.9429
Adj. R^2	0.8636	0.8751	0.9162	0.8586	0.9087	0.8828	0.8841
Observations	796	796	796	778	778	796	796

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

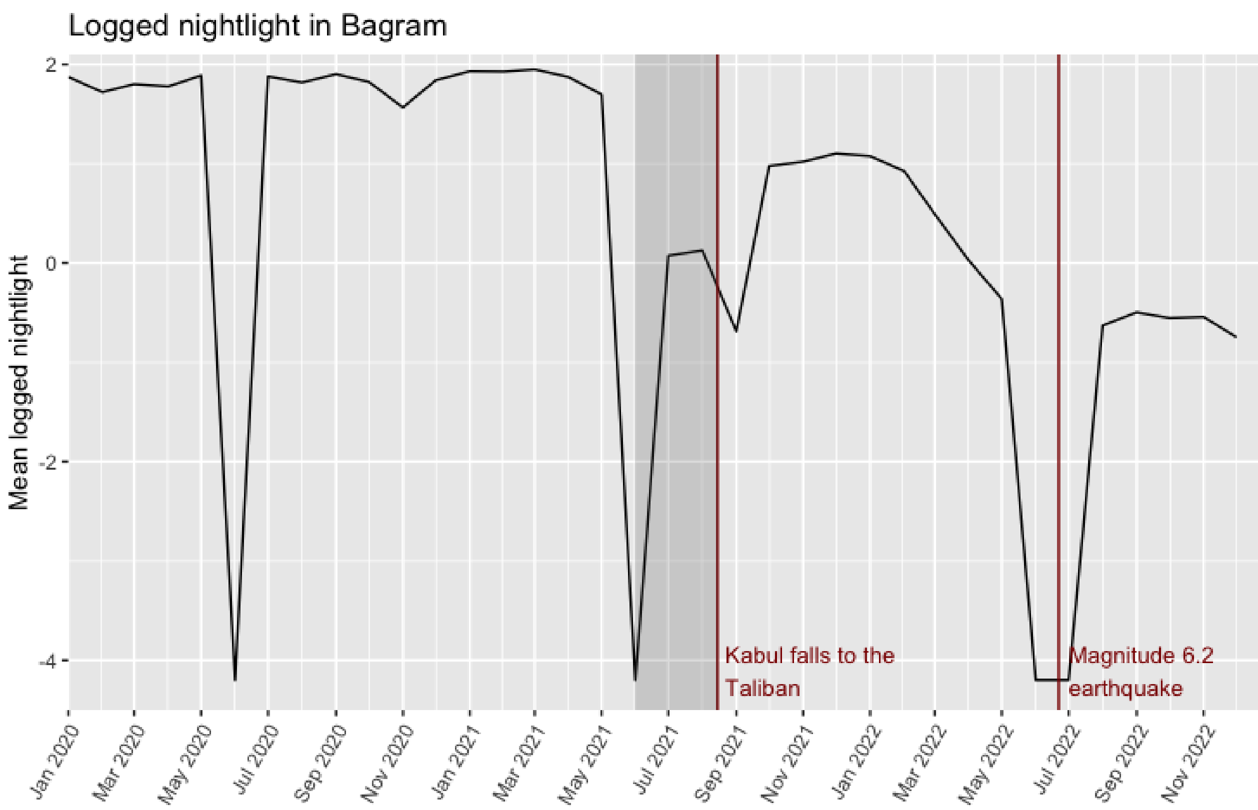
Table A.4: Impact of political discrimination, proxied by non-violent coalition activities, on night-light

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Non-violent friendly coalition activities X Takeover	−0.0308	−0.0854***	−0.0733**	−0.0644***	−0.0497***	−0.0746***	−0.0734***
	(0.0296)	(0.0318)	(0.0298)	(0.0218)	(0.0170)	(0.0219)	(0.0219)
Ethnic favoritism controls	No	Yes	Yes	Yes	Yes	Yes	Yes
High variance months removed	No	No	Yes	No	Yes	No	No
Treatment outliers removed	No	No	No	Yes	Yes	No	No
Conflict intensity controls	No	No	No	No	No	Yes	Yes
District population controls	No	No	No	No	No	No	Yes
R^2	0.9271	0.9392	0.9601	0.9545	0.9757	0.9401	0.9405
Adj. R^2	0.8537	0.8773	0.9194	0.9082	0.9509	0.8789	0.8793
Observations	796	796	796	776	776	796	796

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

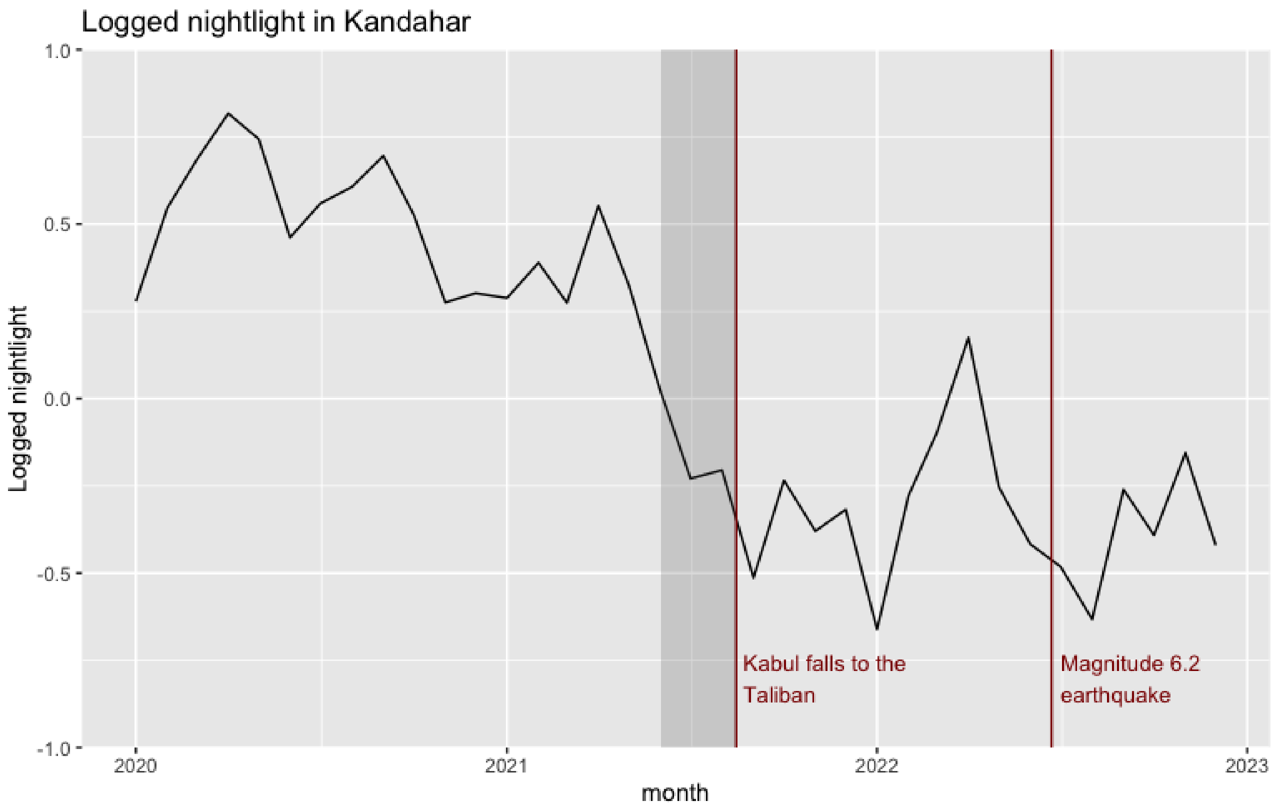
B Additional Figures

Figure B.1: Bagram, monthly logged nightlight, 2020-2022



Notes: The shaded grey are indicates high-conflict periods during which the Taliban took over most of Afghanistan. 0.015 is added to nightlight intensity values before they are logged, as some nightlight values are negative due to stray light correction.

Figure B.2: Kandahar, monthly logged nightlight, 2020-2022



Notes: The shaded grey are indicates high-conflict periods during which the Taliban took over most of Afghanistan. 0.015 is added to nightlight intensity values before they are logged, as some nightlight values are negative due to stray light correction.