The (illegal) resource curse? Opium and conflict in Afghanistan

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Abstract:
To shed more light on the resource-conflict-nexus, we examine how the cultivation of opium, an illegal renewable resource, affects the geography of conflict in Afghanistan. Our identification strategy exploits temporal variation in international drug prices with spatial variation in land suitability for cultivating opium to identify the causal effect of drug cultivation on conflict. Theoretically, opium cultivation can increase the opportunity costs of fighting, but it may also finance rebel groups who offer protection against eradication and expropriation. Using data from the UCDP Georeferenced Event Dataset to measure the intensity of conflict at the district-level, our results show that opium cultivation has a de-escalating effect on conflict over the 2002-2014 period both in a reduced-form and instrumental variable setting. Two explanations of this finding are that opium is relatively labor intensive and that violent competition among producers seems comparably low. The latter explanation is supported by evidence that the conflict-reducing effect is stronger in districts that account for a higher share of value-added along the production chain.

Keywords: Resources, resource curse, conflict, drugs, illicit economy, illegality, geography of conflict, Afghanistan, Taliban
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1 Introduction

An important strand of the resource curse literature argues that the detrimental effects of resources are linked to a higher risk of conflict. Yet, we only begin to understand the micro-foundations behind the relationship between resources and conflict. After focusing on the aggregate country-level for many years, recent contributions linking resources and conflict have discovered large heterogeneity across different commodities. Dube & Vargas (2013) provide micro-level evidence that booms in labor-intensive resources are related to less conflict, whereas booms in more capital-intensive resources lead to more conflict in the Colombian context. This highlights the need to better understand how the type and features of resources influence their effects on the stability of a country. We aim to shed more light on the resource-conflict-nexus by analyzing opium, an illegal renewable resource, that is often linked to conflict and instability.

The cultivation of illegal resources is an important source of revenue, in particular for some developing countries, and clearly correlates with instability and conflict. Nevertheless, the question of causality and the underlying mechanisms and channels remains wide open. Most of the studies on illicit economies and conflict rely on conditional correlations, even though it is essential to identify the actual causes and effects to develop useful policy implications. This paper uses a novel dataset and estimation strategy that allows us to derive causal estimates and to analyze the underlying mechanisms. We focus on Afghanistan, which is not only one of the most severely conflict-ridden countries in the world, but also the major producer of opium in the world.

Our identification strategy combines demand shocks in the international drug market with spatial variation in the suitability to grow opium to estimate the local causal effect of opium profitability on conflict. We show that a decline in opium prices and production leads to more conflict, and explore the mechanisms and channels in detail. This augments the existing literature in several important ways. First, by contributing to the literature on the resource-conflict-nexus and the broader literature on income and conflict. Second, by adding to the scarce causal evidence on the effect of illegal commodities. Third, by shedding more light on the reasons for heterogeneous effects of different resources on conflict. Besides differentiating between resources with low and high labor intensities, we investigate how district specific characteristics related to government influence and the share of value-added along the supply chain of opium production enhance or mitigate the effects. Our results support the importance of considering the labor intensity of different resources as emphasized by Dube & Vargas (2013). Moreover, they also show that market structures and the nature of supplier competition are decisive to whether positive or negative effects prevail, as opposed to the legal status of a crop per se (Mejıa & Restrepo, 2015). Finally, we contribute to a better understanding of conflict dynamics in Afghanistan, which is a region of crucial political importance.

Our first contribution directly relates to the literature on the causes of conflict. The abundance of resources has been discussed as one driver for conflict (see for instance Ross 2004; Fearon 2005; Humphreys 2005; Berman *et al.* 2017), either through its effects on institutions or income.[1] In most studies on the causes of conflict income is found to be one of the strongest correlates of violence (e.g., Fearon & Laitin, 2003; Collier & Hoeffler, 2004; Blattman & Miguel, 2010), but the direction of causality remains highly debated. Most recent studies exploit income shocks – induced by international commodity price changes or rainfall fluctuations– which affect local production and income levels, and can in turn also affect the level of conflict. However, both studies at the cross-country macro-level (e.g., Miguel *et al.* 2004; Brückner & Ciccone 2010; Bazzi & Blattman 2014) and single-country micro-level (e.g., Berman & Couttenier 2015; Dube & Vargas 2013) are far from reaching a consensus yet. This can be due to the fact that the majority of these papers does not properly take the different features of resources and income sources or the role of market structures into account.[2]

Despite the importance of the illicit economy, in particular in conflict-ridden societies, the literature provides very limited convincing empirical evidence on the effects of illegal commodity shocks on conflict. One notable exception is Dell (2015), who uses a regression discontinuity design to identify a causal relationship between drug trafficking, the political approaches to cope with it, and drug-related violence at the municipal level in Mexico. Our paper is similar to the extent that we also foster the understanding of the causal effect of drug cultivation and the related activities along the supply chain on the behavior of people in affected regions. Most closely related to our paper is Angrist & Kugler (2008) and Mejıa & Restrepo (2015), who exploit supply and demand shocks for cocaine in Colombia. Mejıa & Restrepo (2015) show that when cocaine production was estimated to be more profitable the number of homicides increases. This effect is stronger in municipalities with a high suitability to grow cocaine, while a higher profitability of alternative crops as cocoa, sugar cane and palm oil tends to reduce violence. Our study helps to evaluate whether this negative effect and their main explanation for it, the illegality of cocaine production, is supported in a different country context.

Finally, we add to the emerging literature on conflict and violence in Afghanistan, which reflects the recently increased interest in the country. For instance, Sexton (2016) uses plausibly random variation in the allocation of US counterinsurgency aid to show that more aid leads to more conflict in contested districts. In an experimental set up, Lyall *et al.* (2013) study the determinants of International Security Assistance Force (ISAF) support and show that harm caused by Western forces increases support for the Taliban. ,The evidence on the

[1] Theoretically, resource booms create the potential for pareto-improvements. Nevertheless, resources are often not equally distributed and asymmetric information and the lack of credible commitment devices often makes efficient sharing-mechanisms unfeasible. In developing countries this is often linked to secessionist conflict (Morelli & Rohner, 2015), and in developed countries it was shown to foster the success of secessionist parties (Gehring & Schneider, 2016).

[2] Ross (2004) and Lujala (2009) differentiate between various types of resources, but do not address endogeneity. Ross (2004) analyses 13 cases and provides evidence on a relationship between oil, non-fuel minerals, and drugs with conflict. He finds no evidence for legal agricultural commodities to affect conflict. Contrary to that, Lujala (2009) finds a negative correlation with drug cultivation, but suggests a conflict-increasing effect of gemstone mining and oil and gas. Some studies address the relation between diamonds and conflict, as for instance La Ferrara & Guidolin (2007). Contrary to us, the authors analyze the effect of conflict on diamond production.

relationship between opium and conflict, in contrast, is scarce and inconclusive. The opium market accounts for the largest share of profits in Afghanistan (Felbab-Brown 2013) and, according to UNODC (2009), one out of seven Afghans is somehow involved in cultivation, processing or trafficking. Opium represents an important source of income for at least 15% of Afghans, with the share being much larger in rural areas.

Two studies address opium production and conflict in Afghanistan empirically. Bove & Elia (2013) show a negative correlation between conflict and opium prices for a sample of 15 out of 34 provinces and monthly data over the 2004 to 2009 period. Lind *et al.* (2014) find a negative impact of Western casualties on opium production over the 2002 to 2007 period, and no effect in the opposite direction. Both studies are very interesting and add to the literature in important ways, but cannot fully establish causality. Bove & Elia (2013) cannot exploit any exogenous source of variation, and Lind *et al.* (2014) focus on Western casualties. They argue that Western forces were not involved in drug eradication, which reduces endogeneity concerns with respect to opium production. There is, however, evidence suggesting that this holds true only for a limited period of time.[3]

We propose a new identification strategy to shed more light on the complex relationship between opium production and conflict. Afghanistan itself accounts for about 70% of global opium production (UNODC 2016), so international opium prices cannot serve directly as a plausible exogenous source of variation. Within our period of observation, other sources estimate even higher shares of up to 93% (e.g., Bove & Elia 2013). Instead we use shocks related to changes in international prices of other drugs that are not produced in Afghanistan, but correlate positively with opium demand and prices and hence the returns to growing it. We then combine this temporal variation with cross-sectional variation in district-level land suitability for cultivating opium. This Difference-in-Difference (DiD) like setup exploits the fact that changes in the demand and price for opium have differential effects depending on the suitability of a district to grow opium. The interaction term of the two variables induces plausibly exogenous variation in opium cultivation, which is comparable to the strategies employed in Nunn & Qian (2014) andDreher & Langlotz (2017). The farmers' or landowners' decision to grow opium is likely to be directly affected by changes in the profitability of opium production. Indeed, the main reasons to grow opium according to a survey conducted by the United Nations Office on Drugs and Crime (UNODC) are the "high price" followed by "poverty alleviation" (Mansfield & Fishstein 2016).[4]

We use this variation to measure the intention-to-treat (ITT) effect directly, but also employ it as an instru-

[3] Due to the ISAF mandate that says that ISAF "is not directly involved in the poppy eradication or destruction of processing facilities, or in taking military action against narcotic producers" (http://www.nato.int/isaf/topics/mandate/index.html), the authors argue that Western casualties are more exogenous compared to total battle-related-death numbers. Nevertheless, several sources indicate that Western forces have been involved in eradication during the observation period 2002-2007, as for instance declared in the 2004 United Nations Security Council Resolution 1563. In the resolution it says that „Stressing also the importance of extending central government authority to all parts of Afghanistan, [...], and of combating narcotics trade and production", see `http://unscr.com/en/resolutions/doc/1563`.

[4] From 2006 to 2014 the "high price" has always been the most frequent response apart from the years 2007 and 2008 (Mansfield & Fishstein 2016, page 13). Note however, that Mansfield & Fishstein (2016) criticize that the UNODC reports only a single response from farmers and ignores other responses.

mental variable (IV) for the actual opium cultivation. Opium cultivation data relies on estimates that contain measurement error, which is why we focus on the reduced form (ITT) effect as our baseline specification. To measure the geography and intensity of conflict we use georeferenced conflict data from the UCDP Georeferenced Event Dataset (GED). For the measure of the external price shock we rely on international drug price data from the European Monitoring Center for Drugs and Drug Addiction (EMCDDA) and a new measure of the suitability to grow opium (Kienberger *et al.* 2016). This approach and the precise spatial information allows us to identify whether there is a causal link between opium cultivation and conflict.

From a theoretical perspective, it is *ex ante* unclear in which direction income in general, and opium-related income in particular, influences conflict. The existing literature mainly distinguishes between two different channels, the opportunity cost model (e.g., Grossman 1991; Collier & Hoeffler 2004) and the contest model (e.g., Hirshleifer 1988, 1989, 1995). The first theory hypothesizes that with a rise in income the opportunity costs of fighting increase, leading to less violence on average. For an individual, joining or supporting anti-government troops like the Taliban can be a reaction to a negative opium-related income shock to secure income. In our case, supporting the Taliban and fighting should become less likely when alternative and less risky options become more attractive. The contest model or rapacity effect, in contrast, would hypothesize that a higher opium profitability makes suitable territory more attractive as it increases the potential gains from fighting. This would predict more fighting in these districts when opium prices are high.

Usually, in Afghanistan, the main alternative to growing poppy is considered to be growing wheat (Bove & Elia, 2013; UNODC, 2013a; Lind *et al.*, 2014). Many studies suggest that growing poppy is generally far more profitable and the gross wheat-to-opium income-ratio ranges between 1:4 to 1:27 (UNODC 2005, 2013a). Nevertheless, Mansfield & Fishstein (2016), among others, criticize this over-simplified approach. Their main argument is that prior analysis have focused on gross instead of net returns, and ignored differences in the production process, in particular the large differences in labor-intensity. We consider this a valid critic, in particular in light of the evidence provided by Dube & Vargas (2013) that labor-intensity is crucial to understand the effect of resource shocks on conflict. The differences are large: Mansfield & Fishstein (2016, p. 18) report "opium requiring an estimated 360 person-days per hectare, compared to an average of only 64 days for irrigated wheat". In addition, opium production is costlier in terms of other inputs like requiring more fertilizer. This leads to two important conclusions.

First, whether opium is profitable (and more profitable than an alternative) depends on the price in the respective year and the input costs in a particular district. Mansfield & Fishstein (2016) report that there were years were opium was profitable across nearly all locations they examined, and other years where this depends on the specific location. This means that price changes will have heterogeneous effects, which we are going to exploit by using the interaction between the suitability to grow and prices. Second, other crops are plausible alternatives when considering the net returns. We take this into account by controlling for shocks on wheat profitability in a similar manner than for opium.[5] Due to the differences in labor intensity and legal status, we expect different effects of both shocks. The effect of a positive wheat shock on opportunity costs is ambiguous: While the income of some producers and farmers increases, most farmers grow wheat as a staple crop only and most households are net buyers of wheat (Mansfield & Fishstein, 2016). The net effect on opportunity costs is hence a combination of a positive and a negative shock.

Studying the production process and the interrelation between different crops also reveals another channel why lower opium prices could lead to more conflict. If opium becomes relatively less profitable compared to wheat, some marginal (small or large) landowners will decide to switch to the less labor-intensive wheat production.[6] This will decrease the demand for labor. For those Afghans owning some land themselves, it means that they loose a potentially more lucrative alternative or complementary source of income in addition to cultivating crops for subsistence. Tenant farmers and cash-croppers do not even have this alternative or back-up option; for them joining anti-government troops who pay a minimal salary or provide some social services might be the only viable alternative.

In Afghanistan, a further channel linking illegal crop production and conflict activities is that producers turn to rebel groups who offer protection against eradication or expropriation in exchange for some sort of a taxation. In a survey conducted in southern Afghanistan more than 65% of the farmers and traffickers surveyed stated that protection of the opium cultivation and of the trafficking are the main activities of the Taliban (Peters, 2009). UNODC (2013, p.66) states that "[i]n some provinces, notably those with a strong insurgent presence, some or all farmers reported paying an opium tax." If as anecdotal evidence suggests the Taliban uses these revenues to finance their activities (Bove & Elia 2013, UNODC 2013a), this could amplify conflict.[7] The effect might also point in the other direction, in contrast, based on a recent contribution about rebel groups as stationary or roving bandits (De La Sierra *et al.* 2015). The Taliban might be more likely to act as stationary bandits and establish monopolies of violence to sustain taxation contracts and to avoid conflict when the profitability of the taxable resources is higher. Taken together, a positive price shock on opium production could lead to less violence through an opportunity cost channel or to more conflict via increased means for financing rebel

[5] Our analysis does not explicitly consider other crops apart from wheat. The main reason is that each individual crop is negligible in importance compared to opium, and cultivation is mostly restricted to certain regions. We do not neglect the importance of these crops, which are in some areas profitable especially when they are intercropped (i.e. when farmers can combine their cultivation on the same land) and when they allow cultivation over two or three seasons per year. However, the cultivation of these alternatives is restricted to certain areas, so that we assume that shocks to the profitability of these crops are not systematically biasing the effect of the exogenous opium shock. Our strategy only requires that there is a marginal producer for whom a change in the price and profitability of opium leads to a change in his selection of crops. This is tested and supported empirically later.

[6] According to UNODC (2004) a large share of farmers decide on their own what they plant, which will usually be the most profitable crop.

[7] This is also described in several newspaper articles, see for instance `http://www.huffingtonpost.com/joseph-v-micallef/how-the-Taliban-gets-its_b_8551536.html`.

activity and higher expected gains from fighting (contest-theory, rapacity-effect).

We start our empirical analysis by showing that the international price of drugs – that with regard to demand constitute complements to opium – interacted with the suitability to grow opium, robustly affect actual opium cultivation. Based on this finding, the ITT effect then documents that a higher profitability of growing opium leads to lower incidence and intensity of conflict, robust to using different conflict thresholds. We also find support for an attenuating effect on the probability of a conflict onset and a higher likelihood of a conflict ending. IV results using actual cultivation and production estimates as the treatment variables allows us to quantify the size of the effect: A 10% increase in cultivation leads to a decrease in the number of battle-related deaths of about 4.4%.

We proceed by examining to which degree districts are differentially affected by changes in opium profitability. Districts in which opium is not only grown in its raw form, but also processed and traded can capture a larger share of the value-added along the supply chain. Ex ante, it is unclear whether this would mitigate or enhance the conflict-reducing effect. If there was significant competition among large drug producers, we would expect that the conflict-reducing effect is smaller in those districts where the gains from fighting are higher. If, in contrast, production resembles more of a local monopoly, relatively higher revenues provide more incentives to maintain peace and an undisturbed production process. To approximate these differences, we georeference further data from UNODC on the location and existence of drug markets, processing plants and drug labs, as well as on potential trafficking routes. We find that the conflict-reducing effect is indeed higher in districts that are estimated to be more profitable.

The local Taliban elites might face a trade-off between accumulating higher profits and pursuing their ideological goal of fighting the government and Western forces. To investigate this hypothesis in more detail, we use several sources including satellite data and newspaper articles to construct proxies for Western and government presence. We find that the conflict-reducing effect of higher opium profitability tends to be smaller in districts that also feature major Western military presence and those with plausibly stronger Afghan government presence. A share of the additional revenue might be used to finance anti-government and anti-Western operations and attacks. Aside from that, the government and to some extent Western forces might also react to increased production by increasing anti-drug measures. However, despite huge amounts of money being spent, efforts to wipe out drug production seem to be limited in scope and mostly unsuccessful for various reasons. Drastic eradication efforts, for instance, have often failed to produce the results they intended to bring (Felbab-Brown 2013; Mejía *et al.* 2015; Rubin & Sherman 2008).

Our results are in line with Dube & Vargas (2013), who highlight that the effect of a resource boom depends on the labor intensity of the production of the respective resource. Opium is by far the most labor-intensive of the major production choices in Afghanistan, so that a shift away from opium sets free a lot of labor without many alternative employment opportunities. At first sight, our results seem, however, at odds with the results in Angrist & Kugler (2008) or Mejıa & Restrepo (2015). Both use comparable identification strategies and find that in Colombia an increase in the estimated profitability of cocaine leads to more homicides. Mejıa & Restrepo (2015) argue that the conflict-enhancing effect of cocaine is caused by the fact that cocaine is an illegal crop, because they find no such relationship for alternative crops. We argue that their and our study might still capture a causal treatment effect, but that the diverging results indicate that it is not illegality per se which causes a resource boom to lead to more or less violence.

Rather, in addition to differences in labor intensity, we show that the structure of production and in particular the degree of competition along the supply chain seem to be crucial. In Afghanistan, there are no indications that within provinces or districts violent competition among producers and traffickers exists that would be to any degree comparable to the Colombian or Mexican context. Although there is competition at the small-scale level among farmers and sharecroppers, the organization of production and trafficking seems to be better characterized as local monopolies. This stresses the need to consider different types of resources and local circumstances as well as market structures before drawing general conclusions about the effect of resources on conflict.

We proceed as follows. Section 2 introduces the data and Section 3 the empirical strategy. The main results are presented in Section 4, where we also discuss heterogeneity of the results and the underlying channels. We discuss sensitivity tests in Section 5. Section 6 summarizes and provides policy implications.

2 Data description

Conflict data. We use the UCDP Georeferenced Event Dataset (GED) as our primary source for different conflict indicators. This dataset includes geocoded information on the "best (most likely) estimate of total fatalities resulting from an event" (Sundberg & Melander, 2013; Croicu & Sundberg, 2015).[8] These battle-related deaths (BRD) include dead civilians and deaths of persons of unknown status. The data also includes specific information about the types of fighting (one-sided, state-based, non-state) and the parties involved as illustrated in Table 8. In our sample period, 94% of the events covered by UCDP are fights between the Afghan government and the Taliban and consequently most fights are classified as state-based. Less than 4% of all cases are classified as one-sided with the Taliban as the perpetrator and the civilians as the victims. In our baseline analysis we take all violent events, but we will also differentiate between these different types in the robustness section (Section 5). As there is no clear standard in micro-level studies of conflict in how to define the thresholds of the casualties number, we report results on a variety of thresholds.[9]

The unit of analysis differs between and within studies, as some report results at the grid cell-level, ADM1- or ADM2-level or a combination of these. Our analysis is at the district and thus ADM2-level. As the 398 Afghan districts are of different area size we regard it as even more important to present results for various conflict thresholds. What is more, inaccuracies in the casualty numbers and the event size bias are two further reasons for having multiple conflict thresholds. In particular in our analysis we use thresholds of 1, 25, 50, and 100 BRD. To capture the lowest level of conflict, we classify a district-year observation with at least one BRD 'small conflict'.[10] We then increase the threshold to 10 for the next level of conflict intensity ('low conflict'). In analogy to the threshold used in macro-level analyses, we call a district-year observation 'conflict' if there are more than 25 BRD. At the top, we take a threshold of 100 BRD for the most severe level of violence what we call 'war'. All classifications are to some degree arbitrary, which is why we use these different thresholds to ensure transparency and to capture conflict at this local level in a comprehensive way. To achieve this, we take the log of the number of BRD per district-year as a continuous conflict measure, in addition to binary conflict indicators. In a robustness test, we exchange the UCDP GED conflict data with data provided by the Armed Conflict Location & Event Data Project (ACLED) on the number of violent events. ACLED conflict data for Afghanistan is, however, only available for a shorter time period (2004-2010) and we are less convinced about the reliability of this data set for Afghanistan. To verify the reliability of the GED data, we also compare

8 An event is defined as "[a]n incident where armed force was by an organised actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date" (Sundberg & Melander, 2013; Croicu & Sundberg, 2015). For more details see Appendix A.

9 Although it is standard at the macro-level to only use the two thresholds of 25 and 1000, the latter threshold is apparently not appropriate to apply at the district-level.

10 This is in line with how Berman & Couttenier (2015) define a conflict cell. Though their cells are of a much smaller size than ADM2-level.

the distribution of this objective conflict measures with a subjective conflict indicator at the household-level derived from the Afghan National Risk and Vulnerability Assessment (NRVA) household surveys.[11] Figure 9 in Appendix D shows that the objective (BRD) and subjective (violence and insecurity shock from NRVA) conflict measures are quite highly correlated, increasing our confidence in the reliability of our main conflict measure.

Opium suitability index. We exploit a novel data set measuring the suitability to grow opium based on exogenous underlying information about land cover, water availability, climatic suitability, and soil suitability. Conceptually, the index is comparable to indices on the suitability to grow other crops, which are provided by the Food and Agricultural Organization (FAO). It was developed in the context of a study in collaboration with UNODC, and is described in detail in a publication in a geographical science journal (Kienberger *et al.* 2016). Figure 1 plots the distribution of the opium suitability index across Afghan districts. While an index of one would indicate perfect suitability in terms of land cover, water availability, climatic suitability, and suitability of soils, an index of zero means that the district is least suitable for growing opium. The environmental as well as climatic suitability to cultivate opium poppy (Papaver somniferum) is characterized by different factors such as the prevailing physio-geographical and climatic characteristics (using climatic suitability based on the EcoCrop model from Hijmans *et al.* (2001)).

The data and the index itself was modeled on a 1km² resolution and then aggregated to the district units by an area weighted mean approach. The original indicator values were normalized using a linear min–max function between a possible value range of 0 and 100 to allow for comparison and aggregation. Only the land cover indicator was normalized integrating expert judgments through an Analytical Hierarchy Process (AHP) approach. The four indicators were then subsequently aggregated applying weighted means (weights were verified through expert consultations building on the AHP method). None of the input factors constituting the index is itself to a major degree affected by conflict, which is the outcome variable. Consequently, the index values by district can be considered as exogenously given. Given that it is generally possible to grow opium in many parts of Afghanistan and that it is "renewable", the suitability can also be understood as the actual "resource" that varies across districts.

Drug prices. For the measure of the external price shock we rely on international drug price data from the European Monitoring Center for Drugs and Drug Addiction (EMCDDA). EMCDDA provides price data for a large number of drugs in European countries (e.g., also including Turkey that is being crossed by many drug

[11] The three NRVA survey waves 2005, 2007/09 and 2011/12 include between 21,000 and 31,000 households and cover 341 to 388 districts of the 398 official districts in Afghanistan. The sampling design of the NRVA surveys, which is based on a two-stage cluster design, is done in a way that results are representative at national and provincial-level.

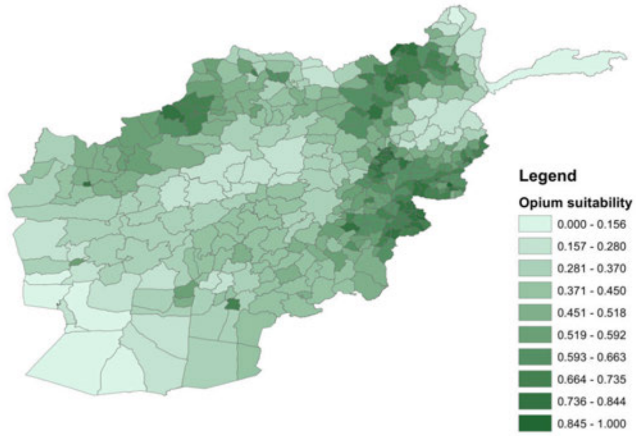


Figure 1: Distribution of opium suitability across districts (based on Kienberger *et al.*, 2016)

trafficking routes). We take the mean prices for each country-year and calculate the average across all countries for which data is available to eliminate the effects of country specific shocks. The average variation should be a clearer estimate of global demand shock.[12] For the analysis we convert all drug prices into constant 2010 EU per gram. Local price data on opium is derived from the annual Afghanistan Opium Price Monitoring reports by UNODC. These reports include (monthly) province-level dry opium prices by farmer and by traders as well as country-wide yearly data on fresh opium farm-gate prices, that are weighted by regional production. The province-level opium prices of farmers and traders are highly correlated, with a correlation coefficient close to 1 (0.998). The correlation between the country-level farm-gate price and the province-level farm-gate price is 0.66, significant at the 1%-level. While the province-level prices are only available from 2006 to 2013 and for a subset of provinces, they are still very helpful in identifying whether international prices are correlated with local prices. We will discuss these correlations in more detail in Section 3.

Actual drug cultivation. Information on actual opium cultivation and opium yield is retrieved from the annual UNODC opium survey reports. District-level cultivation are estimates derived from province-level cultivation data from UNODC survey questionnaires and remote sensing methods. From opium cultivation and the respective yields we were able to calculate actual opium production at the district-year-level.

Other data. In terms of covariates we draw on a variety of different data sources. As GDP data at the district-level is not available, we use the average luminosity computed using nighttime satellite data instead. This has become the standard in the literature when other reliable data are not available, e.g. by Michalopoulos &

[12] In the robustness section (Section 5), we try alternative definitions by first normalizing the drug prices of different drugs before we take averages across them and second by taking price deviations from the long-term mean. Our results are not affected by these choices.

Papaioannou (2014, 2013), and correlates strongly with changes in GDP (Henderson *et al.*, 2012). Development is potentially affected by our outcome variable conflict and thus endogenous, so that we will only use it as a robustness test and always take the (pre-determined) lagged value. Population data is available at five-year intervals. We also mainly use it in robustness tests in a lagged version as reverse causality with regard to conflict could make it a bad control. Using district-fixed effects and only within district variation ensures that our main estimations are not affected by differences in population size. Population data is derived using GIS software from the Gridded Population of the World, Version 4 (GPWv4), data set. Climate conditions on the other hand are exogenous factors that are likely to affect opium cultivation and yield. To capture inter-annual variations in drought conditions we used the vegetation health index (VHI) provided by FAO (van Hoolst et al 2016). VHI is an index based on earth observation data and is available on a monthly basis with a resolution of 1km². As the opium cultivation and harvest times differ within Afghanistan, we used the yearly average of the monthly means from March to September. We are thus able to cover the different vegetation seasons relevant for opium poppy which starts in March in the south-western regions and ends in September in the north-western part (UNODC 2008). Low values of the VHI indicate drought conditions. This remote sensing based index is operationally used to monitor drought conditions in the Global Early Warning System (GEWS). The index is thus superior to simply using precipitation data, which does not enable to directly measure drought conditions. Using precipitation data, in particular in Afghanistan, has severe limitations in terms of quality and resolution, and does not directly translate into actual drought conditions.[13] We will use climate as an exogenous control variable in some specifications, and as for creating additional exogenous variation in the treatment in a robustness test. Moreover, we use additional time-invariant data on geographic conditions and further potentially relevant factors for robustness tests. To analyze heterogeneous effects, we also georeference district-level information about opium production and trafficking, as well as on military and government presence that are explained in the respective section (Section 4 and 5). All variables are described with their sources in Appendix A and descriptive statistics are reported in Appendix B.

3 Identification strategy

Our preferred specification focuses on the reduced-form intention-to-treat (ITT) effect to understand causality in the best possible way. In addition, we use actual opium cultivation data to assess the size of our effect in an instrumental variable setting. We prefer the first specification for two main reasons. First, cultivation data at the district-level is an estimate derived by UNODC based on province-level data, and might thus exhibit

[13] Using the VHI rather than simply precipitation is also in line with Harari & La Ferrara (2013).

considerable measurement error which would bias our estimates towards zero.[14] Second, using district-level cultivation directly in an OLS regression would obviously be highly endogenous. Using actual cultivation or production levels would thus only allow us to identify conditional correlations, but not establish causality. To circumvent these concerns we exploit exogenous variation in international prices that affect opium cultivation combined with district-level data on the suitability to grow opium. Our specification and operationalization of conflict is comparable to Berman & Couttenier (2015), and we estimate the following baseline equation at the district-year-level over the 2002 to 2014 period:

$$conflict_{d,t} = \beta opium\,shock_{d,t-1} + \zeta wheat\,shock_{d,t-1} + X_{d,t-2}\gamma + \tau_t + \delta_d + \tau_t\delta_p + \varepsilon_{d,t}, \tag{1}$$

with $opiumshock_{d,t-1}$ and $wheat\,shock_{d,t-1}$being defined as follows:

$$opium\,shock_{d,t-1} = drug\,price_{t-1} \times opium\,suitability_d, \tag{2}$$

$$wheat\,shock_{d,t-1} = wheat\,price_{t-1} \times wheat\,suitability_d. \tag{3}$$

The outcome variable $conflict_{d,t}$ is the incidence or intensity of conflict in district d in year t based on the different thresholds and definitions described above. The treatment variable is $opium\,shock_{d,t-1}$, which measures the relative extent of the exogenous income shock induced by world market price changes in district d. It is defined as the interaction of international prices $drug\,price_{t-1}$ with the exogenous district-specific $opium\,suitability_d$. Regarding the timing, world market sales price changes could plausibly influence opium cultivation in the same or the following year. There are two main vegetation seasons for opium in Afghanistan, one starting in the fall and the other in March, depending on the region (Mansfield & Fishstein, 2016). In our preferred specification, the $opium\,shock$ is lagged by one year. This accounts for the fact that local producers need time to update their information set, incorporate news about price changes in the end-customer market and adjust production. Opium production is also particularly labor-intensive in the harvesting phase towards the end of a season. Moreover, the world market prices we use are yearly averages and could thus be influenced by growing decisions earlier in the same year. Using one lag as a time structure is supported by Caulkins *et al.* (2010, p.9), who writes in his book that "the largest driver of changes in hectares under poppy cultivation is not eradication or enforcement risk, but rather last year's opium prices." We will also test for a contemporaneous effect in an alternative specification shown in Appendix C.

Our main specification does not rely on control variables because the exogeneity of our opium stock should

[14] As stated in UNODC (2015, 63) "District estimates are derived by a combination of different approaches. They are indicative only, and suggest a possible distribution of the estimated provincial poppy area among the districts of a province."

not be conditional on control variables, but we will show that our results hold with and without using X_d, a vector of district-level time-varying covariates including climate conditions, luminosity and population. Climate conditions can also be used as contemporaneous values as they are clearly exogenous, while the other two covariates can to some degree be endogenous to conflict.[15] This is partly circumvented by using the lagged value, assuming that we then only use the pre-determined value. Results conditioning on luminosity, population and climate conditions are reported in Appendix D. For robustness tests, we also employ further time-invariant covariates X_d interacted with time-fixed effects or a time trend.

We include wheat-related income shocks ($wheat\ shock_{d,t-1}$), since wheat is the main alternative crop which farmers grow throughout Afghanistan (Afghanistan Statistical Yearbook 2015/16). The inclusion of this variable allows us to identity differential effects for the two types of income shocks, where one shock affects the main legal and the other shock the main illegal crop. The variable $wheat\ shock_{d,t-1}$ is defined in analogy to $opium\ shock_{d,t-1}$, where we use variation in the international wheat price interacted with the suitability to produce wheat ($wheat\ suitability_d$). Since Afghanistan is not contributing by more than 1% to the global wheat supply, we can follow the literature in taking the international price for wheat as exogenous (e.g., Berman & Couttenier 2015). We lag the effect of $wheat\ shock$ for the same reason we lag $opium\ shock$. Note, that our results are not depending on the inclusion of this alternative shock.

Finally, we employ different sets of fixed effects. τ_t and δ_d are year- and district-fixed effects. District-fixed effects account for time-invariant unobservable characteristics at the district-level, and country-wide time-varying changes are captured through time-fixed effects.The year-fixed effects for instance capture country-wide crop diseases and changes in anti-drug policies, which affect Afghanistan as a whole. Large shares of the drugs trade is organized at the ethnic or provincial-level, and institutions provided by ethnic groups or warlords (Giustozzi, 2009) are in many provinces more important than the central government. Accordingly, we also employ a specification that includes province-times-year-fixed effects $\tau_t \delta_p$. This is arguably a rather conservative specification, but important as it captures, for instance, changes in conflict that are related to changes in leadership and institutions at the provincial-level, which in turn can plausibly affect conflict and drug cultivation. Identification in this setting relies only on within-province variation in a particular year due to differences in opium suitability. Standard errors are clustered at the district-level, but our results are robust to different choices including the use of province-level clusters and a wild-cluster bootstrap approach that performs well for a small number of clusters (see Table 26).

Whereas Berman & Couttenier (2015) and the majority of the literature use international prices of the respective crop under analysis, this clearly creates an endogeneity problem in our case because Afghanistan

[15] Opium eradication data provided by UNODC is only available from 2006 on and of unclear quality. We therefore do not include it in the vector of covariates. When we include eradication in year t (or in year t-1) in the regression with time- and district-fixed effects results remain qualitatively unchanged and significant.

cultivates a large share of the global opium production (UNODC 2013b). Conflict in Afghanistan is thus likely to affect international opium (heroin) prices through changes in the supply of raw opium used for heroin production. Heroin is an opiate made from morphine, which is produced from opium poppy. Usually we would expect that more conflict leads to a decrease in supply as production becomes more difficult, which would upward-bias estimations. It is however also possible that conflict-prone districts are less affected by anti-drug policies (even though the extent and success of those seems limited), so that more conflict could relate to more opium cultivation and thus results in a potential downward bias.

Our alternative identification strategy needs to fulfill two main criteria. First, we want a proxy variable for which big supply side shocks are uncorrelated with supply side shocks for opium in Afghanistan. Second, the proxy variable should correlate positively with the demand for opium to capture opium-related demand shocks. In economic terms, it should be another drug for which the cross-price elasticity with opium is positive. This means we need to identify complementary drugs for which supply side shocks are ideally exogenous to shocks in Afghanistan. Drugs are usually classified as upper or downer drugs. Upper drugs are stimulants, and downer drugs depressants. Heroin falls in the latter category.

There is a consensus among experts about a high share of polydrug users, i.e., users that combine two or more different drugs. According to EMCDDA (2016) polydrug use is a common phenomenon,and a significant number of drug users consume an upper and a downer drug. Leri *et al.* (2003) conclude from eight studies in their review on heroin and cocaine co-use that the “prevalence of cocaine use among heroin addicts not in treatment ranges from 30% to 80%” (p. 8). This can take place in form of “speed-balling” (mixing both types of drugs, i.e., heroin and cocaine) or with some time lag (e.g. weekend versus workday drug consumption). At least for the group of polydrug users these two types of drugs clearly constitute complements in terms of demand. Accordingly, we expect a positive cross price-elasticity and a positive correlation in prices. We thus take increases in the prices of three common complementary drugs cocaine, amphetamine (EMCDDA, 2016), and ecstasy as indicating positive demand shocks for opium. Our choice of the best proxy is then a trade-off based on the criteria outlined above.

Cocaine has the advantage that its supply is most clearly exogenous to supply shocks in Afghanistan, as cultivation and production exclusively take place in South America. There is also nearly no overlap with regard to trafficking routes as low cocaine seizures in Asia suggest (UNODC 2013b), so that shocks affecting drug trafficking would not simultaneously affect the supply of both drugs. In addition, there is clear evidence of joined consumption in the form of "speed-balling". Nevertheless, relying on one only drug price means that due to supply side shocks for cocaine our data might contain a lot of noise, which might make it difficult to identify a significant relationship or increase the likelihood to identify a spurious correlation.

The alternative is to form an index of the prices of all three upper drugs. The disadvantage here is that taking

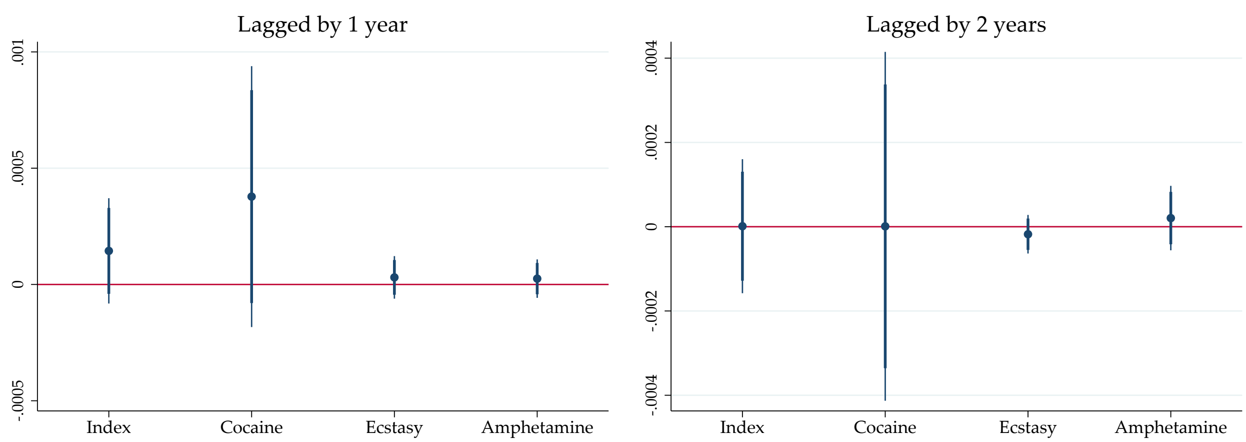


Figure 2: Correlation of opium cultivation with European drug prices

an average eliminates potentially useful variation, which might bias our results towards zero. A clear advantage, however, is that averaging across drugs also eliminates a potential bias due to drug-specific supply side shocks to a large extent. Given that our goal is to identify demand shocks for opium, this is an important feature of an index. Overall, we weight the advantages of the index higher and use it for our main estimations. However, Appendix D shows that our main results also hold when using cocaine prices only.

In Figure 2 we check to what degree opium supply shocks in Afghanistan correlate with European end-customer sales prices one and two years later, respectively.We plot the relationship with both the index and the three separate prices and find no significant correlations. Note that because our main specification uses the value of world market prices in t-1 and conflict in t, supply changes in the year t would have to be anticipated by supply changes in complementary drugs to affect the validity of our strategy.

In the following, we will show that (i) international prices of the complements relate to changes in international heroin prices, (ii) result in economically relevant changes in the price in Afghanistan, and in the next section (Section 4) that they (iii) affect opium cultivation in line with the time structure we suggested. Figure 2 displays the variation in the international prices of heroin, cocaine and the index in constant 2010 Euro per gram. Instead of proposing a specific set of equations for supply and demand, which has to hinge on questionable assumptions (about e.g., demand elasticity, cross-elasticities and the nature of competition and structure of production chains), we only assume that the index value correlates positively with the demand for opium. If this correlation would be too low, as it may happen since computing the index eliminates a lot of variation, this would bias our results towards zero.

To further verify that our assumptions hold, we continue and examine three price series graphically. The local opium farm-gate prices at harvest time in Afghanistan is the one most likely to be driven by opium supply side effects in Afghanistan. The international heroin price is a result of both demand and supply in the world

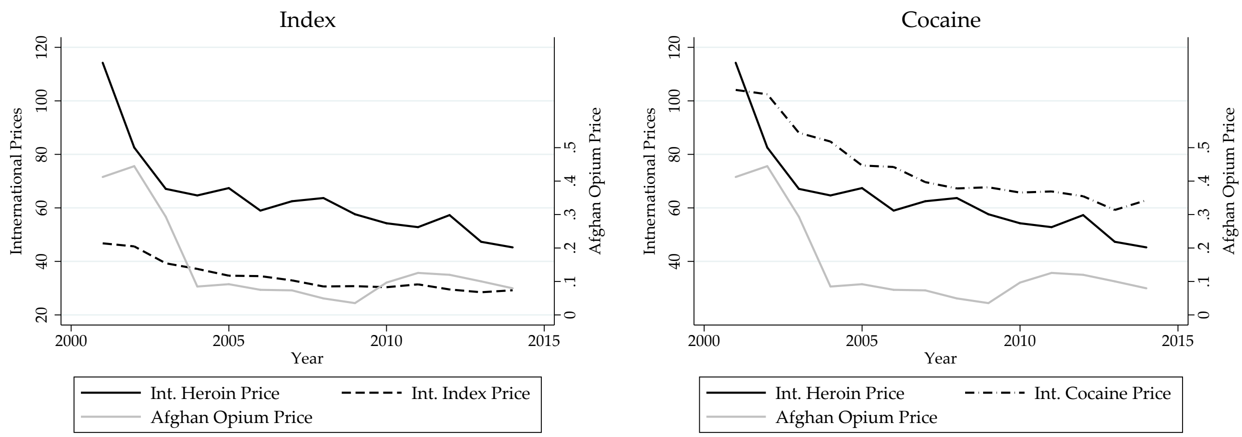
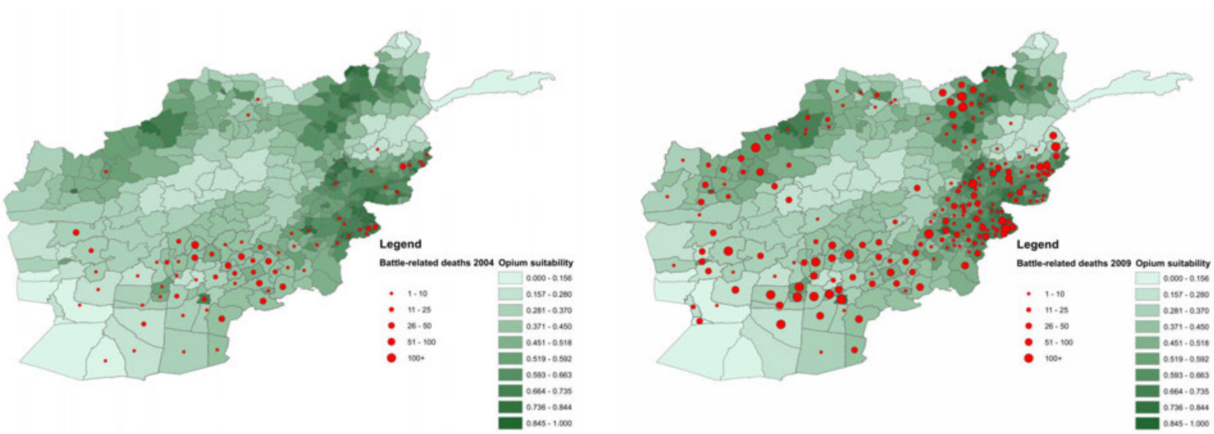


Figure 3: Variation of international and local prices over time

market and in Afghanistan. Finally, the index captures shifts in demand for the three complementary drugs and largely eliminates individual supply shocks by taking the average. All of our assumptions are supported by the patterns we identify in the graphs. The international prices for heroin exhibit a strong positive correlation with the complement index (and also with cocaine individually), which is significant at the 1%-level.[16] What is more, the correlation of the index with the national Afghan opium price is positive as well, and also significant at the 1%-level. Figure 3 also reveals a general negative price trend over time for all drugs, a development that all experts we talked to fail to understand completely. In order to rule out that our findings are driven by a negative time trend, we partial out the time trend in a robustness test and rely only on deviations from the trend.

The measure of the external price shock that we then employ is the interaction of the time-varying complementary drug price index with the district-level suitability to grow opium. The main effects of the two levels of the interaction term ($drug\ price_t$, $opium\ suitability_d$) are captured by the district- and time-fixed effects in our model. In such a setting the interaction of two variables can be interpreted in an exogenous way under relatively mild conditions even if one of the two is endogenous. In our case, however, both variables are plausibly exogenous. We will, however, rely on this assumption to study heterogeneous effects through interacting our treatment variable $opium\ shock$ with other potentially endogenous characteristics of individual districts. As

[16] EMCDDA provides data on white and brown heroin. The bigger bulk of heroin consumed in Europe is brown heroin, which is also much cheaper than white heroin. Figure 3 therefore shows the price variation of brown heroin. The correlation is also significantly positive if we exchange the brown heroin price with the white heroin price. Besides being less common, white heroin is only reported by a small number of European countries and likely to be consumed in less countries as well. Though, both types are products of opium poppies and the correlation between white and brown heroin prices is 0.49, significant at the 1%-level. Correlation tables are presented in Appendix B. Despite having no information that ecstasy and amphetamine are being cultivated or produced in Afghanistan according to UNODC, there is vague evidence on amphetamine-type stimulants (ATS) being seized in the Middle East (UNODC 2013b). Although Afghanistan is never mentioned in this regard and not included in the list of countries of provenance (UNODC 2013b, individual drug seizure database), we want to rule out any endogeneity concern. An effect of conflict on the price through affecting trafficking of these drugs, if at all trafficking routes are passing Afghanistan, could violate our exclusion restriction. This is an additional reason why we show all our results with shocks induced by international cocaine prices only.



Year 2004: High opium prices

Year 2009: Low opium prices

Figure 4: Intensity of conflict in districts with high and low suitability to grow opium

our identification relies on the interaction term, the setting resembles a DiD approach. We expect the effect of international price shocks on opium profitability and cultivation to be larger in districts that are more suitable to grow opium compared to districts with a low suitability. Figure 4 shows a map with the district-level opium suitability overlaid with the distribution of conflict across Afghanistan for two selected years to illustrate this. 2004 represents a year of high prices and thus higher opium profitability (left graph) and 2009 a year of lower prices (right graph). It becomes immediately clear that lower prices are associated with more widespread and more intense conflict, and higher prices with less conflict, indicating support for the opportunity cost hypothesis at the country-level. Our identification however, relies on within-district variation over time conditional on suitability. This DiD intuition becomes clear when comparing the relative change in conflict for a different levels of opium suitability. Districts with a higher suitability experience a much higher increase in conflict when prices and opium profitability decline. This is evident not only in the notorious provinces Hilmand and Kandahar in the Southeast, but also in the North, Northeast, and East.

4 Results

4.1 *International prices and opium cultivation*

After showing that the international price index is indeed positively correlated with the international heroin and the local opium price, we proceed and test whether the index really captures demand shocks for opium that translate into changes in actual opium cultivation at the district-level in Afghanistan. We therefore run the empirical model as defined in equation (1) but with the actual opium cultivation and revenues from opium cultivation (both in logarithms) as the dependent variables. Table 1 presents the results for opium cultivation in Panel A and opium revenues in Panel B. Opium revenues are defined as the production in kg multiplied with the Afghan opium farm-gate price at harvest in constant 2010 EU/kg. We see that external price shocks, measured by the interaction of international prices of upper drugs with the suitability to grow opium, lead to an increase in actual opium cultivation and opium revenues. This holds both when using the value in t-1, as well as when using the potentially more difficult contemporaneous value. These results are significant at the 1%-level. It is also reassuring that the wheat shock, which can also be interpreted as a kind of placebo test here, has no effect on opium cultivation and revenues.

Quantitatively, a 1% increase in the price leads to about a 4 to 5% increase in cultivation for those districts where opium suitability reaches one (perfect suitability). For districts characterized by the mean suitability (0.51) the effect would roughly decrease by half (0.51*3.850 to 0.51*4.891) but the elasticity is still bigger than one. The same increase in prices would lead to a 14.5 to 17.5% increase in opium revenues in districts with the highest possible suitability to grow opium. This estimation does not include province-times-year-fixed effects as the actual cultivation data is gathered at the province-level and we only estimated it for the district-level. Note that the results are robust to changing 1) the definition of the dependent variable and 2) the definition of the price shock including the exchange of the index with the cocaine price. Based on this evidence we are convinced of the validity of our strategy and proceed with estimating the effect on conflict.

4.2 *Main results*

We now turn to our main results, where we start with the effect of income shocks on the incidence of conflict. Table 2 is structured as follows. In Panel A we report the baseline results with year- and district-fixed effects only and Panel B adds province-times-year-fixed effects. We report results for different dependent variables, where column (1) uses the continuous measure (log of BRD), columns (2) to (5) define conflict as a binary indicator with increasing thresholds of BRD. Panel A allows to control for time-invariant characteristics at the district-

Table 1: Effect of income shocks on opium cultivation, 2001-2014 period

	Shock in t (1)	**Shock in t-1** (2)
	Panel A: Opium cultivation	
Opium shock	4.891***	3.850***
	(1.304)	(1.250)
Wheat shock	0.801	0.583
	(0.624)	(0.617)
Number of observations	5572	5572
Adjusted Within R-Squared	0.005	0.004
	Panel B: Opium revenues	
Opium shock	17.498***	14.427***
	(3.651)	(3.469)
Wheat shock	1.973	1.544
	(1.753)	(1.659)
Number of observations	5502	5502
Adjusted Within R-Squared	0.011	0.010

Notes: The dependent variables opium cultivation and revenues are in logarithms. Standard errors clustered at the district-level are displayed in parentheses. Significance levels: * 0.10 ** 0.05 *** 0.01.

level. These characteristics include for instance the respective ethnic group(s) living in that district, geographical conditions such as ruggedness, and the distance to the borders, to main trafficking routes and to major opium markets. Year-fixed effects capture country-wide variation in a particular year, like a change in Western military strategy. Panel B, which is the more stringent specification, allows us to control for all further potential omitted variables at the province-year-level. We thus capture time-varying effects of provincial (and to the degree that they overlap ethnic) institutions and other important features as well as changes in the distribution of power between ethnic groups within a province through the province-times-year-fixed effects.

Turning to our results, Panel A supports the intuition derived from looking at Figure 4. A positive opium shock has a consistently negative effect on conflict incidence. The coefficients are statistically significant in columns 1 to 3. Panel B adds the province-times-year-fixed effects, which should eliminate a large share of the remaining omitted variable bias (remember that we run specifications without relying on control variables here). All point estimates become more negative across the different proxies for conflict incidents. Moreover, the first four coefficients are significant at the 1%-level, and even the coefficient for large-scale conflicts with more than 100 deaths turns significant at the 10%-level. Comparing the coefficients in Panel A and Panel B gives a clear indication that naive estimations of the relationship between opium profitability and conflict are upward biased. When turning to the legal alternative crop, wheat, there is generally no significant effect, with the exception of column (2) in Panel B. Contrary to opium price-related shocks, the point estimates of wheat price-related shocks are generally positive. Nevertheless, there does not seem to be a clear relationship, and in two specifications (column 4 and 5) the effect even switches signs and turns negative. Wheat and opium differ in a number of ways which could explain the differential results on conflict. While opium is illegal, more labor intensive and a clear export product, wheat is a legal crop, relatively less labor intensive and on average an import and subsistence crop. As most households are net buyers of wheat (Mansfield & Fishstein, 2016), price increases of wheat would result in less income, leading to more conflict if the opportunity costs channel is relevant.[17]

Table 2: Effect of income shocks on conflict incidence, 2002-2014 period

	(log) BRD	**1 if >0**	**1 if >10**	**1 if >25**	**1 if >100**
	(1)	(2)	(3)	(4)	(5)
			Panel A: Year- and district-fixed effects		
Opium shock (t-1)	-2.237**	-1.032***	-0.520*	-0.146	0.069
	(0.958)	(0.290)	(0.273)	(0.221)	(0.108)
Wheat shock (t-1)	0.411	0.150	0.113	0.067	0.053
	(0.452)	(0.122)	(0.126)	(0.116)	(0.069)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.006	0.009	0.003	0.000	-0.000
			Panel B: Province×year- and district-fixed effects		
Opium shock (t-1)	-4.976***	-1.035***	-1.215***	-0.973***	-0.346*
	(1.287)	(0.388)	(0.376)	(0.339)	(0.189)
Wheat shock (t-1)	0.292	0.296*	0.095	-0.011	-0.020
	(0.555)	(0.154)	(0.161)	(0.153)	(0.091)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.012	0.007	0.006	0.005	0.001

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

4.3 *Instrumental Variable*

In a next step, we use an IV regression, where we instrument the endogenous variables opium cultivation and opium revenues with the income shock. This step allows us to quantify the size of the effect in an economically meaningful way. While the reduced form approach in Table 2 presents the ITT effect, we identify the Local Average Treatment Effect (LATE) for compliers in Table 3 and Table 4. Note that we prefer the reduced form results presented in Table 2, as the data on opium cultivation are estimates only and there might be non-random measurement error in the data.

In both tables (3 and 4), Panel A reports OLS results and Panel B reports second-stage IV results where we

[17] Chabot & Dorosh (2007) use the NRVA household survey and state that in the 2003 wave calorie intake through wheat consumption amounts to 60 % of total calorie consumption.

instrument opium cultivation (opium revenues) with the external price shock. Despite the potential measurement error problems, OLS and IV results point in a similar direction as the results presented in Table 2. We find a negative coefficient for opium cultivation in columns (1)-(2) in Panel A and Panel B. Though, while the coefficients tend towards zero in the OLS regressions, they are much higher in the IV regressions. The fact that OLS coefficients are consistently more positive indicates a positive omitted variable bias. What is more, the IV results reveal that the opium shock works well as an instrument. In both panels, the Kleibergen-Paap F-statistics clearly exceed the critical threshold of ten proposed by Staiger & Stock (1997). As in Table 1, we do not include province-times-year-fixed effects as district-level opium cultivation data are estimates from province-level data. Column (1) in Panel B shows that an increase of opium cultivation by 10% leads to a decrease in the number of battle-related deaths of about 4.4%. This result is comparable in size to the result in Mejıa & Restrepo (2015), but the effect points in the opposite direction. Our IV results are robust and a bit stronger when using exogenous changes in the vegetation health index (VHI) as an (additional) alternative instrumental variable (see Section 5).

Table 3: OLS and IV - Effect of opium cultivtaion on conflict incidence, 2002-2014 period

	(log) BRD (1)	**1 if >0** (2)	**1 if >10** (3)	**1 if >25** (4)	**1 if >100** (5)
			Panel A: OLS		
(log) Cultivation (t-1)	-0.020*	-0.014***	-0.002	0.002	0.000
	(0.012)	(0.004)	(0.004)	(0.003)	(0.002)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.004	0.009	0.002	0.000	-0.000
			Panel B: IV		
(log) Cultivation (t-1)	-0.440*	-0.203***	-0.102	-0.029	0.014
	(0.228)	(0.077)	(0.063)	(0.045)	(0.021)
Number of observations	5174	5174	5174	5174	5174
Cragg-Donald F stat.	31.135	31.135	31.135	31.135	31.135
Kleibergen-Paap F stat.	14.684	14.684	14.684	14.684	14.684
Kleibergen-Paap LM stat.	13.798	13.798	13.798	13.798	13.798
K-P LM stat. p-val.	0.000	0.000	0.000	0.000	0.000
			Panel C: First Stage		
Opium shock (t-1)	5.083***	5.083***	5.083***	5.083***	5.083***
	(1.327)	(1.327)	(1.327)	(1.327)	(1.327)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.006	0.006	0.006	0.006	0.006

Notes: Linear probability models with province-times-year and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 4: OLS and IV - Effect of opium revenues on conflict incidence, 2002-2014 period

	(log) BRD (1)	1 if >0 (2)	1 if >10 (3)	1 if >25 (4)	1 if >100 (5)
			Panel A: OLS		
(log) Revenue (t-1)	-0.011**	-0.008***	-0.001	0.001	0.001
	(0.005)	(0.002)	(0.001)	(0.001)	(0.000)
Number of observations	5104	5104	5104	5104	5104
Adjusted R-Squared	0.005	0.012	0.002	0.000	-0.000
			Panel B: IV		
(log) Revenue (t-1)	-0.122**	-0.056***	-0.027*	-0.009	0.004
	(0.059)	(0.019)	(0.016)	(0.013)	(0.006)
Number of observations	5104	5104	5104	5104	5104
Cragg-Donald F stat.	60.597	60.597	60.597	60.597	60.597
Kleibergen-Paap F stat.	24.797	24.797	24.797	24.797	24.797
Kleibergen-Paap LM stat.	21.962	21.962	21.962	21.962	21.962
K-P LM stat. p-val.	0.000	0.000	0.000	0.000	0.000
			Panel C: First Stage		
Opium shock (t-1)	18.342***	18.342***	18.342***	18.342***	18.342***
	(3.683)	(3.683)	(3.683)	(3.683)	(3.683)
Number of observations	5104	5104	5104	5104	5104
Adjusted R-Squared	0.012	0.012	0.012	0.012	0.012

Notes: Linear probability models with province-times-year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Taken together, we find that positive income shocks are important determinants of conflict incidence in the ITT and IV estimation. The effects are stronger and more robust for income shocks relating to opium cultivation, and we find no such relationship for shocks relating to wheat as one main legal alternative. The results are robust to a) using different conflict measures, b) altering the definition of the income shock including the exchange of the price index with the price of cocaine, c) different lag structures including contemporaneous effects, d) including covariates and trends, e) adjusting how we cluster the standard error, and f) different empirical models.[18] Our findings are in line with the results for positive income shocks in Berman *et al.* (2010) and they support the conclusions in Dube & Vargas (2013) that the labor intensity of a resource compared to counterfactual alternatives is a decisive factor. However, our results are at odds with conclusion in Mejıa & Restrepo (2015) that an income shock for an illegal resource is related to more conflict. While coca has a similar labor intensity as the alternative crops cacao, palm oil, and sugar cane in Colombia (Mejıa & Restrepo, 2015), opium cultivation is much more labor-intensive then all alternative crops. The next section will elaborate more on why this context differs, and why illegality per se is not the decisive factor moderating the effect on conflict.

4.4 Mechanisms and transmission channels

This section examines to which degree the effect of opium production on conflict depends on particular features of a district. We are interested in examining how the relationship between opium and conflict is moderated by factors relating to the share of value-added along the production chain of a district, and by variables indicating the presence of government institutions and Western forces. This should help us to better understand the role of local market conditions, identify important actors and their incentives, and potential trade-offs between lucrative drug production and ideologically driven conflict activities. For this endeavor, we georeference data on whether a district contains a heroin or morphine lab, an opium market (major or sub-market), whether it is crossed by potential drug trafficking routes, and if it features an unofficial border-crossing point used for smuggling drugs out of the country. Profit margins are higher further up the production chain, markets create more jobs and additional revenue, and trafficking routes and border-crossings allow the local leaders to raise income through some form of taxation or road charges.

To approximate the strength of government institutions and the presence of Western military, we compute distances to the seat of government and assemble information about military camps and Western casualties. Lind *et al.* (2014) also uses the distance to Kabul as an indicator for low governmental law enforcement and weak institutions. We also include information on whether the ethnic group of Pashtuns is present in a district, and whether the district has been controlled by the Taliban in 1996 (Dorronsoro, 2005). There is no available reliable time-varying data about Taliban-dominated territory. Moreover, current control would of course be

[18] Results on robustness tests are presented in Appendix D.

highly endogenous. Accordingly, we prefer to rely on variation determined before our observation period. In both types of districts we expect government institutions to be potentially less strong. Anecdotal evidence and personal conversations with experts suggest that ethnic institutions are more relevant in Pashtun areas. For areas formerly under Taliban control we would expect that due to the common past the Taliban could face less resistance (of course not everywhere). We use a variety of different sources to code these variables, ranging from maps provided by experts at the United Nations, to American military data, satellite images and newspaper reports to confirm the presence of a military camp in a particular district. Appendix F documents the steps involved in the construction of all variables and its sources in detail.

Figure 5 shows the data used for the first part of this analysis. The information contained in the map is based on UNODC reports regarding drug markets, labs, trafficking routes and border-crossings. Some things are important to keep in mind when using and interpreting our these results. Note that there is no reliable information about yearly changes in trafficking routes and opium markets or labs. Accordingly, it is more precise to think of these variables as proxies for trafficking routes, border-crossings, and probable market and lab locations. Some of the markets, for instance, might have moved or been closed. Nevertheless, we find it plausible that due to the lack of a really comprehensive anti-drug campaign and limited state capacity, most of the locations and trafficking routes would remain relevant throughout the sample period. As we use markets, labs, and trafficking routes as proxies for a higher share of value-added of a district, we prefer to speak of a potential for relatively higher revenues. The information on military installations that we use later is time-varying, but it is also important to acknowledge that there will be some measurement error in these data.

Table 5 begins with considering interactions with variables that signal if a district is able to extract more or less of the value-added along the production chain. This can help us to verify assumptions about the market structure, which could explain differences to the Colombian (and potentially Mexican) context. Based on the existing qualitative academic literature as well as reports and newspaper articles, it seems apparent that there is not much (violent) competition on the supplier side in Afghanistan. Provinces, and the respective drug production and trafficking process, are either controlled by the Taliban (in cooperation with local elites), by warlords or even by people linked to the official government.[19] Warlords are more relevant in the Northern provinces (Giustozzi, 2009). A report on opium production networks states that "in Badakhshan, one is aware of the strict control of the commanders of the Northern Alliance whose militia-type army controls all weaponry" (Kreutzmann, 2007, p. 617).

In the Taliban controlled areas, the interconnection between the Taliban and the drug production process is strong. A report about a particular local Taliban leader, Mullah Rashid, describes him as "just one of dozens of

[19] Note that this does not mean there is no competition at the small-scale level between individual farmers and sharecroppers. What is important is that there is a local (district or province-level) elite that has established control over the district.

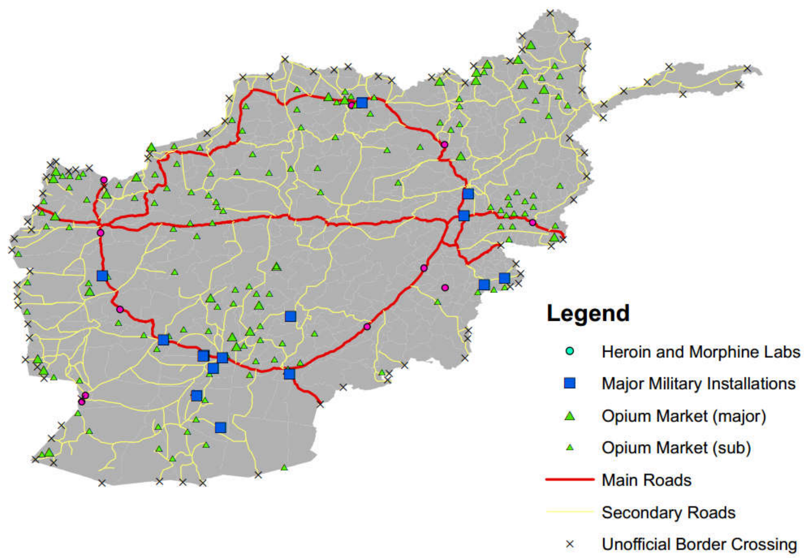


Figure 5: International drug prices and mean levels of conflict in districts with high and low suitability to grow opium

senior Taliban leaders who are so enmeshed in the drug trade that it has become difficult to distinguish the group from a dedicated drug cartel."[20] This is in line with another statement that "in Afghanistan, the drug cartel is the Taliban".[21] Overall, despite huge amounts of money being invested by Western countries, drug producers also apparently have little to fear from the government. Researchers describing their fieldwork in Badakhshan "observed neither restrictions to poppy farmers nor any repercussions or a need to hide the fields from outsiders" (Kreutzmann, 2007, p.616). And in those areas supposedly controlled by the government, "officials at all levels are benefiting from the proceeds from drug trafficking." Despite the official government communicating that "poppy cultivation only takes place in areas controlled by the Taliban", a U.S. counter-narcotics official in Afghanistan claims that "(president) Karzai had Taliban enemies who profited from drugs, but he had even more supporters who did."[22] Accordingly, the evidence suggests that most provinces and districts are controlled by different groups, often the Taliban, which enjoy a local monopoly, and that in particular those districts further away from the seat of government (or military camps) are relatively unaffected by anti-drug measures. This is a stark contrast to Colombia, where many competing groups are involved in the production of drugs.

We can now use the additional georeferenced data to test whether quantitative evidence supports this. If there was competition among producers (between cartels or rival groups), we would expect that in a district which

[20] See https://www.nytimes.com/2016/02/17/world/asia/afghanistan-opium-Taliban-drug-cartel.html.

[21] See https://qz.com/859268/americas-failed-war-on-drugs-in-afghanistan-is-threatening-to-doom-its-war-on-terror-as-w

[22] See http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204. The same source also reports reports a case where a drug trafficker possessed a letter of safe passage from a counter-narcotics police leader, and a new director of an anti-corruption agency was revealed to be a formerly convicted drug trafficker.

features not only raw production, but also intermediate steps along the value-chain like processing, trading or trafficking, rents associated with opium and accordingly the gains from fighting are higher. The contest theory would then predict that the conflict-decreasing effect of positive income shocks is relatively smaller in these districts. In contrast, if there was no or little producer competition, higher profits would increases the incentives to avoid fighting even more in those districts that can extract a larger share of the value-added, amplifying the conflict-reducing effect of higher prices. Uncontested province or district elites have higher incentives to maintain peace within their area of power to avoid distorting the production process, the more profitable production is. For instance, a local farmer describes that in an opium growing area "the Taliban have a court there to resolve people's problems. The security situation is good for the people living there."[23]

The results in Table 5, Panel A indicate that the link between profitability of opium production and conflict is more pronounced in districts that account for a potentially larger share of the value chain. This is visible in the negative interaction effects for all four indicators: heroin and morphine labs, opium market, main roads, and unofficial border crossings. Apart from column (4) all coefficients of the interaction term are significant at least at the 5%-level. In all columns the interaction term points in the same direction, irrespective of which set of fixed effects we include. The interaction effects for the existence of heroin and morphine labs become statistically insignificant when we add province-times-year-fixed effects, but the point estimates still point in the same direction. Although the measures employed might contain measurement error, this consistent results across four indicators strongly suggests that there is no relevant producer competition. The absence of (violent) competition can help to explain why we find the opposite result than in the Colombian setting. Rather than the *de jure* legal status per se, the local market structure seems decisive in moderating the relationship between resource profitability and instability.

Districts that can profit more from opium production show a stronger conflict-reducing effect of higher prices. There are at least two possible explanations. First, if the producers are at the same time the local leaders of a rebel group (the Taliban) they are facing a trade-off between the gains from opium production and the gains from fighting the government or Western forces. Fighting or attacks in the same district can be potentially harmful for production by drawing attention to the illegal activities and increasing the likelihood of eradication. All else equal, a higher profitability of opium production relatively increases the incentives to maintain peace (or at least some form of truce). Second, the fact that these districts cover additional steps in the production chain also means that more workers benefit from the increases in profitability, either through more jobs or higher wages, leading to a larger increase in opportunity costs of fighting (respectively decrease when the price drops).

[23] See http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204.

Table 5: Mechanisms: Supply side competition and share of value-added, 2002-2014 period

	Heroin/ morphine labs (1)	**Opium market** (2)	**Main roads** (3)	**Border crossing** (4)
		Panel A: Year- and district-fixed effects		
Opium shock (t-1)	-2.294**	-2.068**	-1.734*	-2.127**
	(0.960)	(0.934)	(0.973)	(0.959)
Opium shock (t-1)*X	-2.546**	-2.089***	-2.088***	-0.961
	(1.142)	(0.737)	(0.650)	(0.889)
Number of observations	5174	5174	5174	5174
Adjusted Within R-squared	0.010	0.011	0.012	0.006
		Panel B: Province×year- and district-fixed effects		
Opium shock (t-1)	-4.855***	-4.501***	-3.674***	-4.937***
	(1.308)	(1.288)	(1.302)	(1.285)
Opium shock (t-1)*X	-0.790	-1.531**	-2.619***	-0.502
	(0.912)	(0.703)	(0.644)	(0.732)
Number of observations	5174	5174	5174	5174
Adjusted Within R-squared	0.012	0.015	0.020	0.012

Notes: Linear probability model with different sets of fixed effects as indicated. The dependent variable is the log of battle-related deaths. Regressions include interactions of the opium shock with a variable X as indicated in in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Table 6: Mechanisms: Presence of government and Western forces, 2002-2014 period

	(log) Western casualties (1)	**Military camp** (2)	**Proximity to Kabul** (3)	**No Pashtuns** (4)	**No Taliban (1996)** (5)
			Panel A: Year- and district-fixed effects		
Opium shock (t-1)	-2.521***	-2.404**	-2.029**	-3.724***	-3.984***
	(0.917)	(0.950)	(0.944)	(0.932)	(0.941)
Opium shock (t-1)*X	-0.002	0.000	0.007***	3.876***	3.178***
	(0.039)	(0.569)	(0.002)	(0.563)	(0.594)
Number of observations	5174	5174	5148	5174	5174
Adjusted Within R-squared	0.039	0.014	0.013	0.026	0.022
			Panel B: Province×year- and district-fixed effects		
Opium shock (t-1)	-4.002***	-4.828***	-3.599**	-6.313***	-6.431***
	(1.222)	(1.283)	(1.663)	(1.305)	(1.548)
Opium shock (t-1)*X	0.145**	-0.301	0.006	2.840***	2.310*
	(0.063)	(0.392)	(0.004)	(0.775)	(1.249)
Number of observations	5174	5174	5148	5174	5174
Adjusted Within R-squared	0.014	0.014	0.013	0.019	0.014

Notes: Linear probability model with different sets of fixed effects as indicated. The dependent variable is the log of battle-related deaths. Regressions include interactions of the opium shock with a variable X as indicated in in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

In a second step, we use data on Western casualties, the existence of Western military camps, the the proximity to Kabul, Taliban control and Pashtun presence as proxy for the influence of the Afghan government to further understand the behavior within districts. Higher prices and a higher profitability of opium production are also likely to lead to more funds available to the Taliban to finance their operations. Some of the revenues will also end up financing consumption goods, but one could expect that more funds are also used to finance operations. The hypothesis we want to test is that the presence of Western people or Western camps proxies for more available possibilities for an attack. Proximity to Kabul could proxy for the existence of government agencies or institutions, also related to more possibilities.

Table 6, Panel A shows the interaction effects with Western casualties, military camps, the proximity to Kabul, and the dummy variables indicating those districts with historically no ethnic Pashtuns and those districts that have not been under control of the Taliban in 1996. Panel B again includes the stricter set of fixed effects. There is only limited evidence that Western presence plays an important role. The interaction term with Western casualties becomes positive and significant as expected in Panel B. One reason for the insignificance of military camps could be the the challenge of reliably identifying all camps. There is much stronger evidence that Afghan government presence is important, following the pattern that we expected. In Panel A, all interaction terms that proxy government presence are positive and significant with a p-value of less than 0.01 (columns 3-5). Even in Panel B, the point estimates of proximity to Kabul remains barely affected, and the interactions with Pashtun and former Taliban presence remain statistically significant. Within-province differences in the proximity to Kabul might be too small and add further noise to this already imprecise proxy for the strength of government institutions. This could explain why the point estimate remain similar, but the effect is no longer statistically significant.

This result support the notion that the conflict-reducing effect of a positive income shock is less pronounced in districts with a stronger influence of the Afghan government. Of course, this is not sufficient to establish causality, but it is in line with an interpretation where local Taliban forces use part of the revenue extracted from opium producers to finance anti-government conflict and attacks. Local revenues could partly be used for violent operations if there are relevant targets within a district. Of course, revenues need not fully remain within the district, and could be pooled to help countrywide operations. As an additional test, we check whether there is a correlation between the overall cultivation (revenues) and country-wide violence and plot the variation in total opium cultivation in ha (and opium revenues) across Afghanistan in tandem with total BRD in Figure 6. The graph provides no indication that more opium cultivation or revenue is associated with more conflict; rather the relationship also seems to go in the opposite direction at the country-level. Overall, we conclude that in addition to labor intensity, the market structure is decisive in explaining the effect of an illegal resource on conflict.

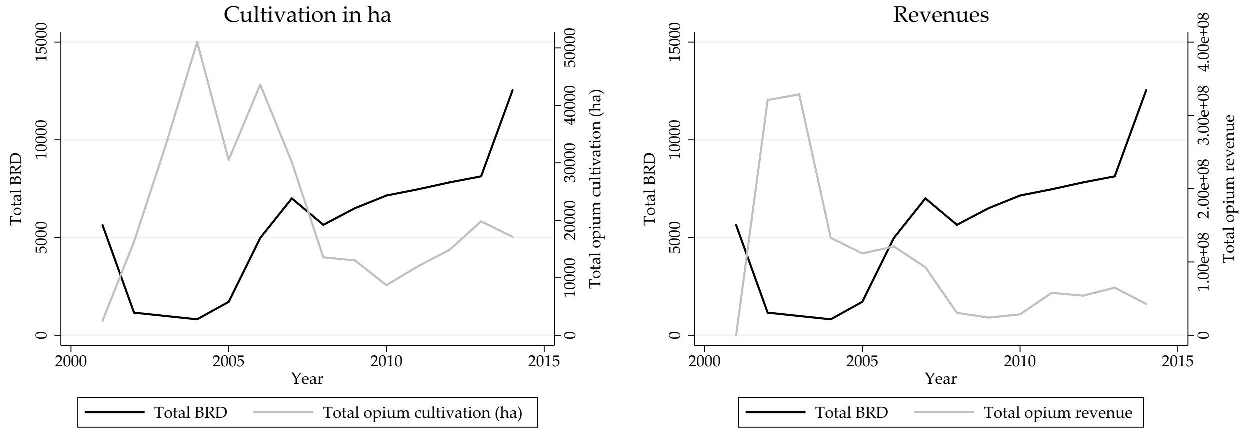


Figure 6: Variation of total opium cultivation (revenue) and total BRD

5 Further results and sensitivity analysis

5.1 Further results

Alternative instrumental variable. In a first step, we exploit an alternative instrumental variable, similar to what has been used in previous studies on income shocks and conflict (Miguel *et al.*, 2004; Nillesen & Verwimp, 2009). All results discussed in this section are reported in Appendix C. We use our measure for climate conditions, i.e., the vegetation health index (VHI), as an instrumental variable. Having a second alternative source of exogenous variation enables us to compare the LATE of the two instrumental variables, our demand shock caused by international price changes and the VHI. Furthermore with two instruments at hand we can perform an overidentification test, which can provide some indirect support for the validity of the instruments. In Table 10, we first use VHI as a single instrumental variable before we include both instruments at the same time in Table 11. From Table 10, we can conclude that the VHI serves as well as a powerful instrument with an F-statistic of 10.75 and second that the LATE does not differ much in terms of sign and significance from the LATE caused by the external demand shocks.

The coefficient of cultivation is negative in all columns and statistically significant in three out of five. The measures employed in column (2), more than one BRD, and column (5), more than 100 BRD, are the least robust measures of conflict throughout the analysis. In a next step, we include both types of exogenous shocks, VHI and the demand shock, at the same time. All point estimates in the second stage remain negative and the F-statistics increase slightly, indicating that both instruments work well jointly. What is more, the Hansen overidentification test-statistics indicate that the instruments are valid, with the sole exception of column (4), where the p-value is below 0.1. It is very reassuring that a second identification strategy relying on different exogenous variation leads to the same result, and that the overidentification tests support the validity of our instruments.

Different timing of shocks. In a second step, we consider different lag structures in our main analysis. We do so by first including shocks in period $t + 1$, t, and $t - 1$ at the same time in Table 12, with $t + 1$ serving as a falsification test. Second, we compare our main findings using shocks in $t - 1$ to including the contemporaneous shock separately in Table 13. Table 12 shows that the shock in $t - 1$, which is our preferred timing, is indeed the shock that predominates the other two, with coefficient sizes even exceeding the ones from the main regression (Table 2). It is reassuring to see that neither of the two other variables becomes significant, supporting the causal order and mechanism that we hypothesize. Future international opium prices interacted with the suitability to grow opium should not and do indeed not have a significant effect on conflict. In Table 13 we can then see that including the contemporaneous and lagged shocks one by one results in very similar coefficients across the two regressions. Since growing seasons differ across Afghanistan, the effects should hit farmers in different regions and thus also people involved in processing and trafficking at different points in time.

Sample splits and outlier analysis. Third, we analyze sample splits to identify heterogeneous effects and to control for potential outliers. In particular, we exclude all border districts from the specification in Table 14. In that table we also report results for border districts only. Border districts could be either very different to other districts or shocks in neighboring countries could affect border districts differently. Furthermore, we expect a large share of trafficking occurring close to the borders. This could drive the results if international price increases would not reach the farmers but only the traders, i.e., the ones that are closer to the final customer along the supply chain. Our results remain very similar across the two groups of districts when we include the strict fixed effects (Panel B).

In a similar vein, in Table 15 we drop districts in the three southern provinces Nimroz, Kandahar and Hilmand and find our results to remain robust to this choice. These provinces are of specific interest for a number of reasons. First, the Taliban had their origins in the southern region and is thus likely to still get most support there. Second, these provinces are known to be the largest producers of opium. Third, simply because of their direct connection to Pakistan, which is related to trafficking but also to the Taliban getting military support from Pakistan. Note that even if we only included districts of these three provinces, the results remain significantly negative and the effect size even increases (see Table 15).

As a final sample split we differentiate between districts that belonged to Taliban territory after they entered Kabul and established the Islamic Emirate of Afghanistan in 1996 and those that did not (Dorronsoro, 2005). Figure **??** in Appendix C shows the division of the political control in the country in fall 1996.[24] Districts which

[24] As discussed before, there is no time-varying data available for Taliban territory over the time and as this is of course a highly endogenous variable, we prefer to rely on information from before our observation period.

previously belonged to the Taliban territory are likely to be still characterized by institutions set up by the Taliban and are also likely to be more prone to a current presence of the Taliban. We hypothesized that one channel from higher opium income to conflict could be via increased financing means of the Taliban. On the other hand we argued that they might not have the interest in fighting where they have control and where there is a higher opium cultivation. As it is ex ante not clear, which channel predominates the other one, it remains an empirical question. Table 16 report the empirical results of the sample splits. Our results are not driven by either group, with coefficients staying negative in all specifications in both sub-samples (apart from Panel A, 16 column 5). However, we do see that the districts that where under Taliban control in 1996 are characterized by stronger effects.

Apart from these rather obvious heterogeneous groups we systematically investigate whether results are driven by one particular province or year. Figure 7 reports the coefficients and the 90% and 95% confidence intervals when we drop each year or each province at the time. All coefficients remain within an very narrow band, showing that the results are not driven by outlying years or provinces.

Alternative outcome measures. To better understand who is fighting and which type of violence is used, we now have a closer look at different types of violence and parties involved. In Table 8 we present descriptive statistics on who is fighting. Interestingly, almost all events reported by UCDP are conflicts between the Taliban and the Afghan government, i.e., two-sided violence involving the state. Only a minor share, not even 4%, concerns one-sided violence by the Taliban, which does not involve the state and is directed at civilians. In our main regressions we did not distinguish between who is fighting, but from the descriptive statistics it becomes apparent that most results will be driven by two-sided violence between Taliban and government forces. In Table 17 we report our baseline results for all battle-related deaths in column (1) and compare these to a more distinct analysis of who is fighting. In column (2) where we define our outcome as all casualties that occurred from violence perpetrated by the Taliban against civilians, we see a much smaller but still significantly negative effect in our preferred specification (Panel B). Note that this classification does not include many cases, as less then 4% of all events fall into this definition. This indicates that the conflict-reducing effect is also leading to less violence started by the rebels. Columns (3) to (5) cover violent events between Taliban and government. In all specifications, irrespective of whether we look at total casualties or only casualties at one side, we see the negative effect persisting. This exercise provides evidence for a very robust conflict-reducing effects of opium income on all types of violence that persist throughout our observation period.

As another alternative outcome, we consider heterogeneous effects on onset and ending of conflict events. So far, we have not addressed dynamics. Though, as conflict is a persistent phenomenon, we also investigate the effects from a more dynamic perspective. While the literature at the micro-level mainly ignores the role of persistence and state-dependence, a new trend in the macro-literature stresses this role, theoretically (Acemoglu & Wolitzky 2014) and empirically (Bluhm *et al.* 2016).[25] In a first step, we follow the micro-level literature in measuring the effects in separate models. Results are presented in Table 18. For comparison to the results with our main outcome variable, conflict incidence, we plot conditional logit results for conflict incidence in Panel A. Panel B then reports the results for onset and Panel C for ending of a conflict. Onset and ending are defined as binary indicators, which take a value of one conditional on the previous state of conflict. More precisely, we define conflict onset as the incidence of a conflict in a district, where there was no conflict in the previous year ($Conflict_{i,t} = 1|Conflict_{i,t-1} = 0$). Years of ongoing conflict are set to missing. In analogy, a conflict ending is defined when conflict persisted in the previous year but not anymore in the current year ($Conflict_{i,t} = 0|Conflict_{i,t-1} = 1$).[26] Panel A supports our main finding using linear probability models, as we see that our main results are robust to using a non-linear model. In Panel B we find that an opium shock reduces the likelihood of a conflict onset for conflicts measures up to a threshold of 25 BRD. For conflict ending, we only find a significantly positive effect in column (1). This result indicates that a positive income shock, which increases opium cultivation, raises the likelihood of a conflict - measured in the strictest sense - to end. In a second step, we account for conflict dynamics by including the lagged dependent variable. This again, does not change our main results. The opium shock remains negative (in Panel A and B) and in all columns statistically significant in the specifications with the stricter fixed effects (Panel B). Results are reported in Table 19.

Lastly, we alter the dependent variable by using ACLED conflict data. We create three different measures from the ACLED dataset. Precisely, we take the logarithm of the number of all events reported, the subset of violent events, and the subset of violent events against civilians. We report results for the most stringent fixed effects specification in Table 20 in Panel A-C. Panel A and B report results with standard errors clustered at the district-level (Panel A) and at the province-level (Panel B). In Panel C we exchange the opium suitability measure with the weighted suitability measure. Despite having a much shorter period of observation our results still point to the conflict-reducing effect of positive income shocks. Results are, however, less strong in Panel B where standard errors are clustered at the province-level. Though, the general picture remains very similar when we use ACLED rather than UCDP (GED) conflict data.

Taken together, we have seen that our results do not depend on the specific income shock we employ. We find very similar results when exploiting climate conditions to induce exogenous variation in opium cultivation.

[25] Berman & Couttenier (2015) for instance argue that persistence is very low at their level of analysis (a cell equivalent to 55×55 kilometers at the equator) compared to country-level data. Consequently, they do not include the lagged dependent and rather estimate separate models for onset and ending. We report transition probabilities of the different conflict intensities from peace to war in Table 9.

[26] We also set the ending variable missing for observations which have been at peace in the previous year and remained in peace in the current year, following the standards in the literature.

This is a reassuring finding that we do not capture a very specific LATE, which might not be representative. What is more, we find the effect throughout the country. When we exclude regions of particular interest or regions likely to be outlying, results still show a conflict-reducing effect of higher opium income. We also find evidence for the effect to remain irrespective of how the outcome variable is defined, i.e., for different types of fighting, conflict onset and ending, and conflict measured by events (ACLED) rather than by the number of BRD.

5.2 Sensitivity analysis

We now investigate the sensitivity of our results to different specification choices even further. All results discussed in this section are reported in Appendix D. First, we adjust our variable of main interest, the external income shock. Second we run several robustness checks by using different choices on how we cluster the standard errors. Third we include further control variables and trends.

Modifications of the treatment variable. As discussed, we replace the average international price index (cocaine, amphetamines and ecstasy) with the international cocaine price in Table 21 and find our results to be unaffected by this choice. We also replace this index with the deviation of the international prices from their long-term mean in Table 22. This is a first attempt to rule out that our results are driven by the long-term negative trend in all international drug prices as seen in Figure 3. The effect of the opium shock still remains significantly negative for columns (1) to (4).[27] Next, we normalize the prices of the three drugs before we take the average and then proceed as before. This could matter as ecstasy and amphetamines are cheaper than cocaine, so that changes in the more expensive drug could dominate changes in the index. The results using normalized prices in Table 23 show that this does not affect our estimations.

What is more, Table 24 replaces the international exogenous prices with the local Afghan price for opium in constant 2010 EU/kg, measured at the farm-gate-level. We are aware that this introduces endogeneity, but also that the interaction term between an endogenous variable (the Afghan price) and an exogenous variable (the suitability) could still produce causal estimates under some assumptions (see Dreher *et al.*, 2016). Moreover, the Afghan price is the best proxy for the prices supplier in Afghanistan receive, whereas the world market price is many times higher. We make two main observations. First we note that the sign of the effects remains negative and significant in most specifications. Second, the pattern that the more conservative fixed effects specifications lead to more negative estimates is repeated (with the exception of column 2). This is in line with our previous findings that on average omitted variable bias tends to be positive.

Besides adjusting the price variable we also try an alternative opium suitability index. This alternative

[27] Specifically, we use the mean over the entire observation period. Due to data restrictions we cannot calculate longer-term means.

weights the suitabilities of opium and wheat by the (lagged) population distribution within the districts. As can be seen in Table 25, the results for the opium shock remain virtually identical for all specifications. The main difference is that the wheat shock is now negative in most specifications as well, also more in line with an opportunity cost based explanation of resources and conflict in Afghanistan.

Standard errors. In a next step, we use different choices on how to cluster the standard errors. In the baseline models we used the district-level, allowing for serial correlation over time within a district. Table 26 clusters at the province-level in Panel A allowing for spatial correlation within a province over time. In Panel B and C we use two-way clustering , i.e. district and year clusters and province and year clusters, respectively (Cameron *et al.*, 2011). The number of clusters using the province-level might be too small using the regular formula for clustered standard errors, which can lead to the over- or under-rejection of the null hypothesis (Cameron & Miller, 2015). Accordingly, we also use the wild-cluster bootstrap method with the null imposed with 1000 replications and Webb's weights (Webb, 2013), which has been shown to provide valid inference even for few clusters. Figure 8 plot the distribution of the bootstrap estimates. The null hypothesis of no effect if is rejected in all cases (except for war) at least at the 5%-level. This is apparent in the graphs by the fact that the 95%-confidence intervals do not include zero.

Further covariates and trends. Finally, we include further covariates and trends. So far, we have only included the wheat shock and different fixed effects in the regressions and no other covariates. In Table 27 (Panel A) we add the baseline set of pre-determined covariates as luminosity and population as well as an exogenous measure of droughts, the VHI. In further specifications (Panel B), we also allow for time-varying effects of time-invariant control variables. The set of time-invariant covariates includes ruggedness, heroin/morphine lab, major/sub opium markets, main/secondary roads, military camps, proximity to Kabul, unofficial border crossings, presence of Pashtuns, Taliban territory in 1996. One way to model that is by adding interactions between these variables and a time trend. Another more flexible way is to interact the time invariant control variables with year dummies (Panel C). In both panels, our main treatment variable remains significant with p-values below at least 0.1 for all conflict proxies. Furthermore, in analogy to Christian & Barrett (2017) we include linear and nonlinear suitability specific trends. We classify the suitability to grow opium into quartiles and include a linear and a nonlinear quartile specific trend in our main regression analysis. Our results are not affected by this change.

6 Conclusion

This paper identifies the causal effect of opium cultivation on conflict in Afghanistan, with opium being an illegal renewable resource that is often linked to conflict and instability. To induce exogenous variation in opium cultivation we make use of external demand shocks that affect income and conflict through changes in opium cultivation. Our identification strategy exploits variation in international prices of alternative drugs as well as in land suitability for growing opium. The interaction term of the two variables thus combines temporal and spatial variation. We apply this to a reduced form equation and an instrumental variable approach in a panel data setting at the Afghan district-level over the 2002 to 2014 period.

Many papers have analyzed the relationship between resources and conflict, but yet we are far from understanding the micro-foundations. In particular, the role that features of resources and market structures play are highly under-researched. Our findings thus augment the literature on the determinants of conflict and more specifically on the resource-conflict nexus in important ways. First, we suggest a new identification strategy to identify the causal direction of the link between illicit economies and violence. With notable exceptions (Angrist & Kugler 2008; Mejıa & Restrepo 2015) this has not been addressed in the literature. Second, by investigating the reasons for heterogeneous effects across different types of resources and across different characteristics of a country or sub-national area. More precisely, we differentiate between resources according to their labor intensity and legality and we compare the effects across districts which differ according to the extent of government presence and share of value-added along the supply chain of opium. This helps to better understand the mechanisms behind the effect of resources on conflict. Third, we augment the literature by providing new insights on the geography of conflict in Afghanistan, which also provides important political insights.

We find that the external price shock works well as an instrument for actual opium cultivation. Our findings at the district-level show that international price changes in other drugs robustly affect opium cultivation and local opium prices, irrespective of the empirical model and the exact definition of the dependent variable. Higher opium profitability and cultivation leads to a lower incidence of conflict. All models indicate that the coefficient of the income shock is biased upwards in OLS regressions. This is visible by the fact that the point estimates become more negative when adding a stricter set of fixed effects and when replacing the endogenous direct opium income shocks with the plausibly exogenous income shocks. The results are further backed by using a different instrumentation strategy relying on exogenous weather changes.

What is more, we find a number of heterogeneous effects of the external income shock on the risk of conflict. The conflict-reducing effect is stronger in districts in which opium is not only grown in its raw form, but also processed and traded. We argue that this is due to the fact that such districts can capture a larger share of the value-added along the supply chain. In contrast, the effect is smaller in districts where Western casualties occurred or where government institutions are likely to be more present. There are several plausible reasons for this. Money raised by drug production might be used to also finance attacks on government or Western ISAF forces. At the same time these districts are likely to be characterized by a stronger presence of the state and police force, which could lead to increased opium eradication efforts or less possibilities to grow and trade opium.

Our results are in line with Berman & Couttenier (2015) who find evidence for the opportunity cost hypothesis. We further add support to Dube & Vargas (2013)'s seminal study, by showing that the importance of labor intensity in determining the effect of a resource boom is not solely restricted to Colombia. Opium is the most labor-intensive crop compared to alternative crops in Afghanistan, so that shifting away from opium production would come along with less labor and thus reduced opportunity costs of fighting. On the other hand, our results are at first sight at odds with the findings in Angrist & Kugler (2008) and Mejıa & Restrepo (2015), who find that an increase in the estimated profitability of cocaine leads to more homicides in Colombia. As Mejıa & Restrepo (2015) identify the opposite effect for legal crops, they argue that the conflict-increasing effect of cocaine is due to its (il-)legal status. Our findings strongly indicate that it is not about the illegality of a crop per se, but rather that the relative labor intensity of alternative crops or income sources and local market structures are crucial.

Our results on heterogeneous effects highlight that it is important not to treat the resource-conflict relationship as a black box, but to consider the individual actors involved in market transactions and conflict. The available data does not allow to distinguish whether opportunity costs considerations are more important at the level of small-scale farmers or local elites. Most likely, both groups benefit from higher profitability and have less incentives to engage in fighting. Still, our results suggest that there might be a trade-off for the Taliban. If government presence is estimated to be stronger in a district, the revenues also seem to support anti-government activities. Accordingly, our results do by no means suggest that revenues from drug production procuring to a dangerous group like the Taliban are not a problem. What they show is that on average, the effect of more opium revenues leads to less conflict. Generally, opium is too important for large shares of the Afghan society for simple prohibition to work. It thus becomes clear that simplistic attempts to fight opium production with large eradication programs will have unintended consequences, if there are no available alternatives that can employ a comparable amount of labor.

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Appendix

A Definition of the Variables

Battle Related Deaths (BRD): The best (most likely) estimate of total fatalities resulting from an event, with an event being defined as "[an] incident where armed force was by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date." A direct death is defined as "a death relating to either combat between warring parties or violence against civilians." Note that UCDP/GED only includes BRD of events that belong to a dyad ("two conflicting primary parties or party killing unarmed civilians") that reached in total at least 25 BRD within a year. If the dyad generated events with less then 25 BRD in the previous or subsequent years, they are still counted if the dyad had reached the 25 BRD threshold in another year. We construct a continuous measure (log of BRD) and binary outcomes from all BRD of any party or any type of violence (state-based, non-state or one-sided violence). Since UCDP/GED provides information on the parties and the type of violence we also construct specific outcome measures according to those categories. From UCDP/GED (Sundberg & Melander, 2013; Croicu & Sundberg, 2015).

Vegetation Health Index (VHI): We use the Vegetation Health Index (VHI) of FAO (van Hoolst et al. 2016). VHI is a composite index joining the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI, Kogan 1995). Low values of VHI represent drought conditions. This is a combination of low values of the observed VCI (relatively low vegetation) and higher values of the TCI (relatively warm weather). For details see van Hoolst et al. (2016). The VHI is calculated from data of Advanced Very High Resolution Radiometer (AVHRR) sensors on board the National Oceanic and Atmospheric Administration (NOAA) and Meteorological Operational Satellite (METOP) satellites.

Consumer Price Index (CPI): (2010 = 100). From the Organization for Economic Cooperation and Development (OECD, 2016) for the Euro area (19 countries) and from WDI (2016) for remaining countries.

Drug Prices (International): The data are average prices per gram in constant (2010) EU across all available countries in Europe. We use data on different drugs: amphetamines, cocaine, ecstasy, heroin (white and brown). To construct the average price of alternative drugs we use a mean of the three upper drugs amphetamines, cocaine, and ecstasy. From European Drug Report 2016, the European Monitoring Centre for Drugs and Drug Addiction (EMCDDA, 2016).

Ethnic groups: We have used the GIS-coordinates of all ethnic groups in the "georeferencing of ethnic groups" (GREG) dataset Weidmann *et al.* (2010). It relies on maps from the classical "Soviet Atlas Narodov Mira" from 1964, and is very extensively used for the construction of ethnolinguistic fractionalization (ELF) indices. GREG is a georeferenced dataset containing the coordinates of the group boundaries of 1120 ethnic groups. One advantage and disadvantage of the data is that it is capturing group locations in the 1960s. This is an advantage as it ensures that the boundaries are not endogenous to changes during our period of observation. It is partly a disadvantage if groups and countries changed over time. In Afghanistan, the country boundary did not change. Ethnic group populations certainly change to some degree over time, so that all variables more precisely capture the historic homelands of ethnic groups rather than the current settlement areas. Our variable (no) Pashtuns is coded in the following way. The GREG polygons can contain more than one ethnic group. Our binary indicator takes on the value one if Pashtuns are not present to any degree in a district, regardless of whether they were the majority group. The idea behind this is that the Taleban are initially a Pashtun group (although not exclusively anymore), so that Pashtun presence could make it easier to establish a presence of the Taliban in a district.

Events: An event is defined according to those within an UCDP/PRIO armed conflict. ACLED differentiates between violent and nonviolent and between different types of violence.We define an event to be nonviolent if it belongs to one of the types: "Non-violent rebel activity", "Riots/Protests", or “Non-violent activity by a conflict actor". Violent events are those that involve a battle between government and rebels or involve violence against civilians. We construct the variable “All Events”, which includes both types of events and a variable “Violent Events” referring to the latter category only. Finally we also construct a variable that included only “Violence against Civilians”. For all event variables we take the logarithm. From ACLED (Raleigh *et al.*, 2010).

Inflation, GDP deflator: (2010 = 100). GDP deflator for the US with 2010 as the base year. From World Development Indicators - The World Bank (2016).

Insecurity/violence shock: The share of sampled households that have experienced a shock due to insecurity/ violence according to the NRVA survey. From the National Risk and Vulnerability Assessment (2005, 2007/08, 2011/12).

Luminosity: Proxy for GDP and development. The files are cloud-free composites made using all the available archived DMSP-OLS smooth resolution data for calendar years. The products are 30 arc second grids, spanning -180 to 180 degrees longitude and -65 to 75 degrees latitude. A number of constraints are used to select the highest quality data for entry into the composites: Data are from the center half of the 3000 km wide OLS swaths. Lights in the center half have better geolocation, are smaller, and have more consistent radiometry. Sunlit data are excluded based on the solar elevation angle. Glare is excluded based on solar elevation angle. Moonlit data are excluded based on a calculation of lunar illuminance. Observations with clouds are excluded based on clouds identified with the OLS thermal band data and NCEP surface temperature grids. Lighting features from the aurora have been excluded in the northern hemisphere on an orbit-by-orbit manner using visual inspection. From Version 4 DMSP-OLS nighttime lights time series, National Oceanic and Atmospheric Administration-National Geophysical Data Center (NOAA/NGDC), 2013.

Opium Cultivation: Opium cultivation in hectares. Data at the district-level is an estimate from the data at the province-level. We use logged values for opium cultivation. From opium cultivation and the respective yields we were able to calculate actual opium production at the district-year-level. We also constructed opium revenues by multiplying opium production in kg with the fresh opium farm-gate prices at harvest time in const. 2010 EU/kg. From UNDCP Annual Opium Poppy Survey (2000) and UNODC Afghanistan Opium Survey (2015).

Opium Eradication: Opium eradication data in hectares. From UNODC (2006-20014).

Opium Suitability: Proxy for potential of opium production. The assessment was developed from data on land cover, water availability, and climatic suitability based on the EcoCrop model (Hijmans *et al.*, 2001) and the suitability of soils. The factor determined to be most important by experts is land cover (S1, 0.41 – the sum of the weights equals 1.0), followed by water availability (S2, 0.28) and climatic conditions (S3, 0.21) respectively. This is in line with additional studies previously carried out by UNODC (2011) for Myanmar. From Kienberger *et al.* (2016).

Population: A minimally-modeled gridded population data collection that incorporates census population data from the 2010 round of censuses. Population estimates are derived by extrapolating the raw census estimates to a series of target years and are provided for the years 2000, 2005, 2010, 2015, and 2020. We use the ipolated data from 2000 till 2015. We take the logarithm. From Gridded Population of the World, Version 4 (GPWv4) (2016), Center for International Earth Science Information Network (CIESIN), Columbia University.

Proximity to Kabul: We use the shape files provided by the Afghan statistical authority on the 398 Afghan districts. Note that the shape files available at `www.gadm.org` are not reflecting the current status of administrative division in Afghanistan. To compute the distances, we create the centroid of each district polygon, and then use the spatial distance formula in ArcGIS, accessed through a Python script, to compute the distance.

Ruggedness: The data on terrain ruggedness is the same that was used in Nunn & Puga (2012), although we use it on a more disaggregated level. We calculate the average ruggedness index for every municipality. While ruggedness refers to the variance in elevation, we also use raw elevation data from the NASA Shuttle Radat Topography Mission (SRTM) data set. The data set and a detailed documentation are available at `http://diegopuga.org/data/rugged/`.

Soil Suitability: The Harmonized World Soil Database (HWSD) is composed of a geographical layer containing reference to some 30,000 soil map units. This information is stored as a 30 arc-second raster in a GIS. For the globe, the raster has 21,600 rows and 43,200 columns, of which 221 million grid-cells cover the globe's land territory. Over 16,000 different soil mapping units are recognized in the HWSD that combine existing regional and national updates of soil information worldwide with the information contained within the 1:5,000,000 scale FAO-UNESCO Soil Map of the World (FAO/UNESCO 1974). The use of a standardized structure in HWSD creates a harmonized data product across the various original soil databases. A detailed description of HWSD and the latest version are available for download at: www.iiasa.ac.at/Research/LUC/luc07/External-World-soil-database/HTML/index.html. From Global Agro-ecological Zones (GAEZ v3.0), the Food and Agriculture Organization of the United Nations (FAO-GAEZ, 2012).

Taliban (1996): The book by Dorronsoro (2005) provides a map indicating the extension of the Taliban in 1996. We georeferenced the map and aligned it with the district boundaries. In many cases, the division was quite clearly aligned or overlapping with a district boundary, in the other cases we chose the closest district boundary. The binary indicators that we create take on the value one if a district belongs to the territory that was not occupied or under the control of the Taliban in 1996. This area is often also referred to as being controlled by a the Northern alliance. More details can be found in Dorronsoro (2005) and Giustozzi (2009).

Western Casualties: Western casualties from hostile encounters involving Western ISAF forces or U.S. forces in Operation Enduring Freedom. We take the logarithm of the casualties as for the continuous measure of UCDP/GED BRD. From iCasualties.org (2016).

Wheat price (International): Source is the International Monetary Fund (IMF) Primary Commodity Prices database, 2013. The IMF first calculates individual commodity price indices in U.S. dollar and SDR terms, basing the price series in those currencies in 2005. Group indices are weighted averages of individual commodity price indices, with respective commodity weights derived from their relative trade values compared to the total world trade as reported in the UN Comtrade database. Price indices are based in 2005.

Wheat Suitability: The FAO-GAEZ (2012) model provides for each crop/Land Utilization Type (LUT) a comprehensive soil suitability evaluation for all the soil units contained in the Harmonized World Soil Database (HWSD). This is done by the use of individual soil quality ratings (SQ). Seven different SQs are calculated and are combined in a soil unit suitability rating (SR, %). The SR represents the percentage of potential yield expected for a given crop/LUT with respect to the soil characteristics present in a soil map unit of the HWSD and is depending on input/management level. From the From Global Agro-ecological Zones (GAEZ v3.0), the Food and Agriculture Organization of the United Nations (FAO-GAEZ), 2012.

B Descriptive Statistics

Table 7: Descriptive statistics

	Observations	Mean	Stand. Dev.	Min.	Max.
(log) BRD	5174	1.11	1.54	0.00	8.20
Small Conflict: 1 if >0	5174	0.42	0.49	0.00	1.00
Low Conflict: 1 if >10	5174	0.23	0.42	0.00	1.00
Conflict: 1 if >25	5174	0.14	0.34	0.00	1.00
War: 1 if >100	5174	0.03	0.18	0.00	1.00
(log) Violent Events	2786	0.43	1.13	0.00	9.14
(log) Events	2786	0.44	1.14	0.00	9.14
(log) Events: Violence against Civilians	2786	0.11	0.38	0.00	3.64
(log) Taleban-Civilians BRD: side a+b	5174	0.08	0.37	0.00	4.14
(log) Taleban-Government BRD: side a+b	5174	1.05	1.52	0.00	8.20
(log) Taleban-Government BRD: side a	5174	0.53	0.94	0.00	8.03
(log) Taleban-Government BRD: side a	5174	0.77	1.33	0.00	6.39
(log) Wheat Shock	5174	2.76	1.20	0.00	5.68
(log) Opium Shock: Index	5174	1.80	0.64	0.00	3.82
Opium Suitability	5174	0.51	0.18	0.00	1.00
Wheat Suitability	5174	0.52	0.23	0.00	1.00
Ruggedness in 1000	5148	299.18	216.54	4.48	877.01
(log) Cultivation	5174	1.38	2.15	0.00	6.91
(log) Production	5149	0.47	0.92	0.00	4.00
(log) Opium Revenue	5149	4.26	5.83	0.00	16.98
Luminosity	4776	0.49	3.03	0.00	58.01
Vegetation Health Index (VHI)	4378	123.11	24.50	51.28	191.99
(log) Population	5174	3.96	1.24	0.44	9.58
Heroine and Morphine Laboratory	5174	0.14	0.35	0.00	1.00
Opium Market	5174	0.27	0.44	0.00	1.00
Main Roads	5174	0.28	0.45	0.00	1.00
Unofficial Border Crossing	5174	0.12	0.33	0.00	1.00
(log) Western casualties	5174	1.17	1.30	0.00	5.71
Military Camp	5174	0.04	0.21	0.00	1.00
Proximity to Kabul in km	5148	-277.05	181.54	-817.64	-0.00
No Pashtuns	5174	0.26	0.44	0.00	1.00
No Taleban Territory (1996)	5174	0.42	0.49	0.00	1.00

Notes: Sample based on Table 1, column 1.

Table 8: Type of violence and fighting parties

	Frequency (1)	Percent (2)
	Conflict Dyads	
Government of Afghanistan - Taliban	14,853	93.93
Taliban - Civilians	614	3.88
Government of United States of America - al-Qaida	125	0.97
	Type of violence	
State-based violence	15,084	95.39
Non-state violence	631	3.99
One-sided violence	98	0.62

Notes: Summary on types of violence in Afghanistan provided by UCDP/GED between 2002-2014, column 1.

Table 9: Markov transition matrix

	1 if 0	1 if >0	1 if >10	1 if >25	1 if >100
1 if 0	87.49	7.55	2.46	1.85	0.64
1 if >0	36.86	35.41	15.81	9.76	2.17
1 if >10	23.46	30.19	19.81	23.27	3.27
1 if >25	19.90	13.21	16.64	36.54	13.70
1 if >100	19.25	7.55	4.15	28.68	40.38

Notes: Sample based on Table 1, column 1.

C Further Results

Alternative instrumental variable

Table 10: Alternative IV - VHI, 2002-2013 period

	(log) BRD (1)	**1 if >0** (2)	**1 if >10** (3)	**1 if >25** (4)	**1 if >100** (5)
(log) Cultivation (t-1)	-0.547*	-0.067	-0.135*	-0.149**	-0.038
	(0.279)	(0.072)	(0.077)	(0.070)	(0.033)
Number of observations	4776	4776	4776	4776	4776
Cragg-Donald F stat.	10.486	10.486	10.486	10.486	10.486
Kleibergen-Paap F stat.	10.754	10.754	10.754	10.754	10.754
Kleibergen-Paap LM stat.	10.334	10.334	10.334	10.334	10.334
K-P LM stat. p-val.	0.001	0.001	0.001	0.001	0.001

Notes: Linear probability models with year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. Wheat shock in (t-1) included in all regressions. The instrumental variable for opium cultivation is the VHI. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Table 11: Alternative IV - VHI and opium price shock, 2002-2013 period

	(log) BRD (1)	**1 if >0** (2)	**1 if >10** (3)	**1 if >25** (4)	**1 if >100** (5)
(log) Cultivation (t-1)	-0.405**	-0.158***	-0.089*	-0.050	-0.002
	(0.179)	(0.058)	(0.049)	(0.037)	(0.017)
Number of observations	4776	4776	4776	4776	4776
Cragg-Donald F stat.	20.995	20.995	20.995	20.995	20.995
Kleibergen-Paap F stat.	13.051	13.051	13.051	13.051	13.051
Kleibergen-Paap LM stat.	23.550	23.550	23.550	23.550	23.550
K-P LM stat. p-val.	0.000	0.000	0.000	0.000	0.000
Hansen J p-val.	0.549	0.234	0.482	0.050	0.158

Notes: Linear probability models with year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. Wheat shock in (t-1) included in all regressions. The instrumental variables for opium cultivation are the VHI and the opium shock. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Different timing of the shocks

Table 12: Leads and lags, 2002-2014 period

	(log) BRD	**1 if >0**	**1 if >10**	**1 if >25**	**1 if >100**
	(1)	(2)	(3)	(4)	(5)
Opium shock (t+1)	0.037	-0.725	0.923	0.857	0.375
	(4.075)	(1.553)	(1.482)	(1.250)	(0.540)
Opium shock (t)	2.462	-0.219	1.536	-0.192	0.191
	(2.556)	(1.085)	(0.940)	(0.743)	(0.440)
Opium shock (t-1)	-7.007***	-0.448	-2.938***	-1.340*	-0.841*
	(2.572)	(1.042)	(0.919)	(0.693)	(0.489)
Number of observations	4776	4776	4776	4776	4776
Adjusted R-squared	0.648	0.546	0.482	0.456	0.304

Notes: Linear probability models with province-times-year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. Wheat shock in (t-1) included in all regressions. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Table 13: Timing of shocks, 2002-2014 period

	(log) BRD	**1 if >0**	**1 if >10**	**1 if >25**	**1 if >100**
	(1)	(2)	(3)	(4)	(5)
			Panel A: Shocks in t		
Opium shock (t)	-5.351***	-1.384***	-1.248***	-1.033***	-0.288
	(1.403)	(0.426)	(0.410)	(0.369)	(0.195)
Wheat shock (t)	0.439	0.213	0.108	0.035	0.055
	(0.564)	(0.161)	(0.161)	(0.156)	(0.096)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.010	0.006	0.005	0.004	0.001
			Panel B: Shocks in t-1		
Opium shock (t-1)	-4.976***	-1.035***	-1.215***	-0.973***	-0.346*
	(1.287)	(0.388)	(0.376)	(0.339)	(0.189)
Wheat shock (t-1)	0.292	0.296*	0.095	-0.011	-0.020
	(0.555)	(0.154)	(0.161)	(0.153)	(0.091)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.012	0.007	0.006	0.005	0.001

Notes: Linear probability models with province-times-year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. Wheat shock in respective period included in all regressions. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Sample splits

Table 14: Border districts, 2002-2014 period

	(log) BRD	1 if >0	1 if >10	1 if >25	1 if >100
	(1)	(2)	(3)	(4)	(5)
	Panel A: Year- and district-fixed effects				
Dependent variable	*Border districts*				
Opium shock (t-1)	-4.789***	-1.351***	-1.254***	-0.808***	-0.163*
	(1.324)	(0.438)	(0.402)	(0.286)	(0.084)
Wheat shock (t-1)	-0.739	0.062	-0.295	-0.228	0.000
	(0.752)	(0.240)	(0.218)	(0.176)	(0.073)
Number of observations	1443	1443	1443	1443	1443
Adjusted Within R-Squared	0.018	0.018	0.009	0.006	0.001
Dependent variable	*No border districts*				
Opium shock (t-1)	-1.048	-0.820**	-0.213	0.141	0.186
	(1.296)	(0.386)	(0.363)	(0.300)	(0.157)
Wheat shock (t-1)	0.857	0.222	0.280*	0.154	0.049
	(0.563)	(0.141)	(0.155)	(0.147)	(0.097)
Number of observations	3731	3731	3731	3731	3731
Adjusted Within R-Squared	0.004	0.006	0.003	0.000	0.000
	Panel B: Province×year- and district-fixed effects				
Dependent variable	*Border districts*				
Opium shock (t-1)	-5.751**	-0.698	-1.647**	-1.271*	-0.275
	(2.564)	(0.787)	(0.729)	(0.658)	(0.186)
Wheat shock (t-1)	-0.829	0.410	-0.426	-0.502	0.007
	(1.251)	(0.316)	(0.334)	(0.340)	(0.103)
Number of observations	1430	1430	1430	1430	1430
Adjusted Within R-Squared	0.007	0.003	0.004	0.006	-0.000
Dependent variable	*No border districts*				
Opium shock (t-1)	-4.386***	-0.881*	-1.103**	-1.031**	-0.279
	(1.666)	(0.510)	(0.497)	(0.454)	(0.272)
Wheat shock (t-1)	0.158	0.253	0.099	-0.136	-0.061
	(0.683)	(0.196)	(0.213)	(0.191)	(0.131)
Number of observations	3718	3718	3718	3718	3718
Adjusted Within R-Squared	0.008	0.004	0.005	0.004	0.000

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 15: Southern provinces, 2002-2014 period

	(log) BRD	1 if >0	1 if >10	1 if >25	1 if >100
	(1)	(2)	(3)	(4)	(5)
	Panel A: Year- and district-fixed effects				
Dependent variable	*Nimroz, Kandahar and Hilmand*				
Opium shock (t-1)	-8.468***	-0.592	-1.459***	-2.359***	-1.686***
	(1.387)	(0.437)	(0.364)	(0.351)	(0.452)
Wheat shock (t-1)	-1.862	-0.269	-0.336	-0.304	-0.272
	(1.400)	(0.324)	(0.356)	(0.382)	(0.231)
Number of observations	532	532	532	532	532
Adjusted Within R-Squared	0.063	0.002	0.020	0.064	0.043
Dependent variable	*All other provinces*				
Opium shock (t-1)	-3.573***	-1.293***	-0.963***	-0.392*	0.017
	(0.996)	(0.306)	(0.280)	(0.216)	(0.105)
Wheat shock (t-1)	0.593	0.144	0.138	0.135	0.098
	(0.457)	(0.127)	(0.130)	(0.114)	(0.066)
Number of observations	4732	4732	4732	4732	4732
Adjusted Within R-Squared	0.015	0.013	0.010	0.004	0.002
	Panel B: Province×year- and district-fixed effects				
Dependent variable	*Nimroz, Kandahar and Hilmand*				
Opium shock (t-1)	-8.540***	-0.204	-1.527**	-2.744***	-1.895**
	(2.807)	(0.856)	(0.689)	(0.602)	(0.701)
Wheat shock (t-1)	-0.754	0.033	-0.045	-0.099	-0.269
	(1.444)	(0.353)	(0.366)	(0.403)	(0.266)
Number of observations	532	532	532	532	532
Adjusted Within R-Squared	0.040	-0.004	0.012	0.057	0.033
Dependent variable	*All other provinces*				
Opium shock (t-1)	-4.366***	-1.237***	-1.225***	-0.638*	-0.050
	(1.322)	(0.388)	(0.387)	(0.333)	(0.142)
Wheat shock (t-1)	0.489	0.313*	0.101	0.035	0.044
	(0.575)	(0.165)	(0.167)	(0.157)	(0.083)
Number of observations	4732	4732	4732	4732	4732
Adjusted Within R-Squared	0.011	0.009	0.007	0.002	-0.000

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 16: Taliban territory 1996, 2002-2014 period

	(log) BRD (1)	**1 if >0** (2)	**1 if >10** (3)	**1 if >25** (4)	**1 if >100** (5)
			Panel A: Year- and district-fixed effects		
Dependent variable			*Taliban territory 1996*		
Opium shock (t-1)	-1.364	-0.663*	-0.290	-0.058	0.055
	(1.218)	(0.369)	(0.352)	(0.316)	(0.168)
Wheat shock (t-1)	-0.404	0.039	-0.071	-0.159	-0.028
	(0.709)	(0.179)	(0.188)	(0.190)	(0.126)
Number of observations	2990	2990	2990	2990	2990
Adjusted Within R-squared	0.000	0.003	-0.000	0.000	-0.001
Dependent variable			*No Taliban territory 1996*		
Opium shock (t-1)	-5.102***	-1.684***	-1.355***	-0.675**	-0.059
	(1.325)	(0.413)	(0.376)	(0.264)	(0.053)
Wheat shock (t-1)	-0.570	0.080	-0.262	-0.107	-0.022
	(0.620)	(0.203)	(0.178)	(0.146)	(0.031)
Number of observations	2184	2184	2184	2184	2184
Adjusted Within R-squared	0.022	0.021	0.015	0.006	-0.001
			Panel B: Province×year- and district-fixed effects		
Dependent variable			*Taliban territory 1996*		
Opium shock (t-1)	-7.913***	-0.822	-2.122***	-2.092***	-0.749*
	(2.037)	(0.635)	(0.593)	(0.588)	(0.390)
Wheat shock (t-1)	0.628	0.313	0.289	0.088	0.002
	(0.873)	(0.217)	(0.253)	(0.245)	(0.161)
Number of observations	2990	2990	2990	2990	2990
Adjusted Within R-squared	0.019	0.004	0.014	0.014	0.004
Dependent variable			*No Taliban territory 1996*		
Opium shock (t-1)	-3.170**	-1.281***	-0.747*	-0.125	-0.057
	(1.533)	(0.489)	(0.423)	(0.294)	(0.065)
Wheat shock (t-1)	-0.054	0.297	-0.138	-0.047	-0.042
	(0.571)	(0.223)	(0.151)	(0.131)	(0.036)
Number of observations	2158	2158	2158	2158	2158
Adjusted Within R-squared	0.007	0.014	0.002	-0.001	-0.001

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

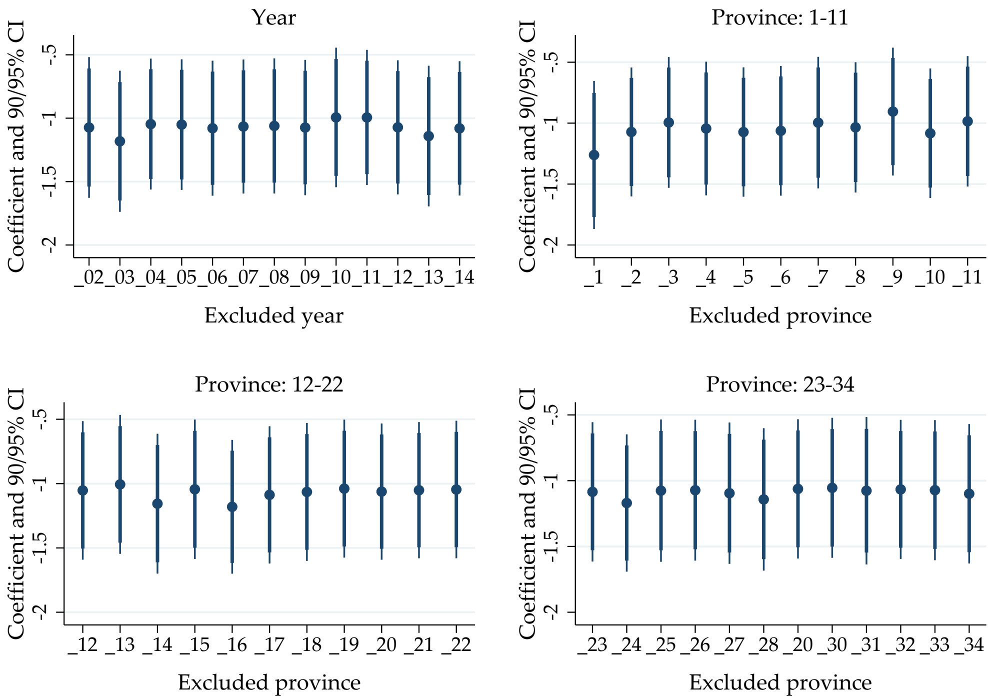


Figure 7: Leave on out - year and province

Alternative outcome measures

Table 17: Types of fighting, 2002-2014 period

	All BRD **BRD: all** (1)	**Taleb.-Civil.** **BRD: a+b** (2)	**Taleb.-Gov.** **BRD: a+b** (3)	**Taleb.-Gov.** **BRD: Taleb.** (4)	**Taleb.-Gov.** **BRD: Gov.** (5)
			Panel A: Year- and district-fixed effects		
Opium shock (t-1)	-2.237**	-0.254	-1.767*	-0.744	-1.080
	(0.958)	(0.183)	(0.965)	(0.602)	(0.859)
Wheat shock (t-1)	0.411	-0.011	0.660	0.445	0.282
	(0.452)	(0.101)	(0.452)	(0.273)	(0.439)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.006	0.000	0.006	0.004	0.002
			Panel B: Province×year- and district-fixed effects		
Opium shock (t-1)	-4.976***	-0.656**	-4.732***	-3.555***	-3.581***
	(1.287)	(0.314)	(1.319)	(0.894)	(1.170)
Wheat shock (t-1)	0.292	-0.029	0.415	0.319	-0.007
	(0.555)	(0.143)	(0.570)	(0.375)	(0.548)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.012	0.001	0.012	0.014	0.006

Notes: Linear probability models with province-times-year- and district-fixed effects. Dependent variable is the log of BRD for a specific type of conflict operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Table 18: Conditional Logit - incidence, onset and ending, 2002-2014 period

	1 if >0 (1)	**1 if >10** (2)	**1 if >25** (3)	**1 if >100** (4)
		Panel A: Incidence		
Opium shock (t-1)	-12.367***	-12.701***	-13.630***	-14.761
	(2.796)	(3.640)	(4.686)	(12.067)
Wheat shock (t-1)	-0.674	-2.679**	-3.873***	-1.607
	(1.183)	(1.184)	(1.430)	(2.553)
Number of observations	4433	3523	2444	806
Pseudo R-Squared	0.354	0.274	0.276	0.217
		Panel B: Onset		
Opium shock (t-1)	-9.301***	-12.029***	-12.764***	-17.941
	(2.487)	(3.219)	(4.066)	(10.945)
Wheat shock (t-1)	-1.222	-2.945**	-2.714*	-1.329
	(1.076)	(1.252)	(1.482)	(2.523)
Number of observations	2976	2750	2006	714
Pseudo R-Squared	0.174	0.139	0.154	0.158
		Panel C: Ending		
Opium shock (t-1)	7.513***	2.530	5.634	19.652
	(2.391)	(3.531)	(3.923)	(19.205)
Wheat shock (t-1)	0.550	0.369	1.948	-0.726
	(1.189)	(1.640)	(2.121)	(4.094)
Number of observations	1931	1195	730	207
Pseudo R-Squared	0.106	0.077	0.104	0.160

Notes: Conditional logit model with year- and district-fixed effects. Dependent variable is conflict onset/ending operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Table 19: Dynamics - lagged dependent, 2002-2014 period

	(log) BRD	1 if >0	1 if >10	1 if >25	1 if >100
	(1)	(2)	(3)	(4)	(5)
			Panel A: Year- and district-fixed effects		
Opium shock (t-1)	-1.973***	-0.928***	-0.469**	-0.156	0.043
	(0.689)	(0.248)	(0.220)	(0.171)	(0.087)
Wheat shock (t-1)	0.189	0.110	0.070	0.051	0.048
	(0.331)	(0.107)	(0.103)	(0.090)	(0.056)
Dependent (t-1)	0.349***	0.180***	0.245***	0.288***	0.253***
	(0.021)	(0.019)	(0.022)	(0.026)	(0.041)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.139	0.043	0.064	0.084	0.065
			Panel B: Province×year- and district-fixed effects		
Opium shock (t-1)	-3.959***	-0.942**	-1.066***	-0.792***	-0.285*
	(1.059)	(0.368)	(0.330)	(0.278)	(0.165)
Wheat shock (t-1)	0.236	0.286*	0.082	-0.009	-0.021
	(0.458)	(0.146)	(0.143)	(0.126)	(0.077)
Dependent (t-1)	0.236***	0.076***	0.154***	0.228***	0.207***
	(0.023)	(0.020)	(0.023)	(0.027)	(0.039)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.071	0.013	0.030	0.056	0.044

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is the log of BRD for a specific type of conflict operationalized as indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01

Table 20: ACLED event conflict data, 2004-2010 period

	(log) All events (1)	(log) Violent events (2)	(log) Against civilians (3)
	Panel A: Clustered at district-level		
Opium shock (t-1)	-4.879**	-4.715*	-1.877*
	(2.447)	(2.458)	(0.972)
Wheat shock (t-1)	1.785**	1.821**	0.373
	(0.751)	(0.749)	(0.258)
Number of observations	2786	2786	2786
Adjusted Within R-Squared	0.020	0.020	0.010
	Panel B: Clustered at province-level		
Opium shock (t-1)	-4.879	-4.715	-1.877*
	(3.157)	(3.145)	(1.045)
Wheat shock (t-1)	1.785**	1.821***	0.373
	(0.658)	(0.658)	(0.250)
Number of observations	2786	2786	2786
Adjusted Within R-Squared	0.020	0.020	0.010
	Panel C: Weighted suitabilities, Clustered at district-level		
Opium shock (t-1)	-7.529***	-7.389***	-2.461***
	(2.141)	(2.147)	(0.799)
Wheat shock (t-1)	-0.531	-0.601	-0.303*
	(0.466)	(0.465)	(0.169)
Number of observations	2772	2772	2772
Adjusted Within R-Squared	0.014	0.014	0.012

Notes: Linear probability models with province-times-year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading accroding to ACLED data. Standard errors are in parentheses (clustered at the district-level) Significance levels: * 0.10 ** 0.05 *** 0.01

D Robustness checks

Definition of shock variable: drug prices

Table 21: International Cocaine price, 2002-2014 period

	(log) BRD (1)	1 if >0 (2)	1 if >10 (3)	1 if >25 (4)	1 if >100 (5)
			Panel A: Year- and district-fixed effects		
Opium shock (t-1)	-2.014**	-0.931***	-0.462*	-0.128	0.075
	(0.878)	(0.266)	(0.251)	(0.205)	(0.101)
Wheat shock (t-1)	0.395	0.142	0.111	0.067	0.057
	(0.455)	(0.122)	(0.127)	(0.117)	(0.070)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.006	0.009	0.003	0.000	0.000
			Panel B: Province×year- and district-fixed effects		
Opium shock (t-1)	-4.449***	-0.934***	-1.069***	-0.882***	-0.294*
	(1.187)	(0.356)	(0.345)	(0.312)	(0.173)
Wheat shock (t-1)	0.270	0.290*	0.093	-0.018	-0.019
	(0.557)	(0.155)	(0.162)	(0.153)	(0.092)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.012	0.007	0.006	0.005	0.001

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Opium shock is defined as the interaction between international cocaine prices and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 22: International price deviations, 2002-2014 period

	(log) BRD (1)	1 if >0 (2)	1 if >10 (3)	1 if >25 (4)	1 if >100 (5)
	Panel A: Year- and district-fixed effects				
Opium shock (t-1)	-0.055**	-0.027***	-0.013*	-0.003	0.002
	(0.025)	(0.008)	(0.007)	(0.006)	(0.003)
Wheat shock (t-1)	0.466	0.165	0.125	0.075	0.056
	(0.447)	(0.120)	(0.125)	(0.115)	(0.069)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.005	0.009	0.003	0.000	0.000
	Panel B: Province×year- and district-fixed effects				
Opium shock (t-1)	-0.130***	-0.027**	-0.032**	-0.026**	-0.009
	(0.042)	(0.011)	(0.013)	(0.012)	(0.006)
Wheat shock (t-1)	0.344	0.310**	0.107	-0.002	-0.019
	(0.404)	(0.132)	(0.128)	(0.145)	(0.075)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.011	0.007	0.006	0.005	0.001

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Opium shock is defined as the interaction between international price deviations (from the mean) and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 23: Normalized drug prices, 2002-2014 period

	(log) BRD (1)	1 if >0 (2)	1 if >10 (3)	1 if >25 (4)	1 if >100 (5)
	Panel A: Year- and district-fixed effects				
Opium shock (t-1)	-0.566***	-0.227***	-0.134**	-0.055	-0.001
	(0.195)	(0.059)	(0.057)	(0.046)	(0.022)
Wheat shock (t-1)	0.296	0.135	0.083	0.039	0.036
	(0.454)	(0.122)	(0.127)	(0.117)	(0.069)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.007	0.010	0.004	0.001	-0.000
	Panel B: Province×year- and district-fixed effects				
Opium shock (t-1)	-1.069***	-0.229***	-0.265***	-0.201***	-0.072*
	(0.269)	(0.081)	(0.081)	(0.072)	(0.039)
Wheat shock (t-1)	0.255	0.283*	0.081	-0.011	-0.021
	(0.559)	(0.156)	(0.161)	(0.153)	(0.091)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.013	0.007	0.007	0.005	0.001

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Opium shock is defined as the interaction between the mean of normalized drug price (cocaine, ecstasy and amphetamines) and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 24: Local prices, 2002-2014 period

	(log) BRD	1 if >0	1 if >10	1 if >25	1 if >100
	(1)	(2)	(3)	(4)	(5)
	Panel A: Year- and district-fixed effects				
Opium shock (t-1)	-0.311**	-0.175***	-0.088**	-0.003	0.027
	(0.154)	(0.050)	(0.043)	(0.035)	(0.018)
Wheat shock (t-1)	0.711*	0.266**	0.171	0.098	0.056
	(0.422)	(0.114)	(0.116)	(0.109)	(0.064)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.004	0.008	0.003	0.000	0.000
	Panel B: Province×year- and district-fixed effects				
Opium shock (t-1)	-0.690***	-0.098	-0.193***	-0.145***	-0.074**
	(0.184)	(0.063)	(0.055)	(0.049)	(0.030)
Wheat shock (t-1)	0.856	0.440***	0.218	0.093	0.003
	(0.535)	(0.146)	(0.152)	(0.144)	(0.082)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.008	0.005	0.005	0.003	0.002

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Opium shock is defined as the interaction between local Afghan prices in const. 2010 EU/kg and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Definition of shock variable: suitability

Table 25: Weighted suitabilities, 2002-2014 period

	(log) BRD (1)	**1 if >0** (2)	**1 if >10** (3)	**1 if >25** (4)	**1 if >100** (5)
			Panel A: Year- and district-fixed effects		
Opium shock (t-1)	-2.965***	-1.119***	-0.684**	-0.342	-0.046
	(0.947)	(0.285)	(0.266)	(0.208)	(0.100)
Wheat shock (t-1)	-0.941**	-0.292**	-0.249**	-0.169*	-0.049
	(0.428)	(0.131)	(0.122)	(0.100)	(0.061)
Number of observations	5148	5148	5148	5148	5148
Adjusted R-squared	0.563	0.480	0.411	0.391	0.264
			Panel B: Province×year- and district-fixed effects		
Opium shock (t-1)	-4.943***	-1.076***	-1.200***	-1.030***	-0.324*
	(1.246)	(0.378)	(0.348)	(0.302)	(0.175)
Wheat shock (t-1)	-0.752	-0.402**	-0.218*	-0.087	0.024
	(0.467)	(0.156)	(0.132)	(0.115)	(0.076)
Number of observations	5148	5148	5148	5148	5148
Adjusted R-squared	0.652	0.551	0.485	0.457	0.310

Notes: Linear probability models with different sets of fixed effects as indicated above the panels. Dependent variable is conflict incidence operationalized as indicated in the column heading. Opium shock is defined as the interaction between international prices and the weighted suitability to grow opium (wheat). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Standard errors

Table 26: Standard errors clustered at different levels, 2002-2014 period

	(log) BRD (1)	1 if >0 (2)	1 if >10 (3)	1 if >25 (4)	1 if >100 (5)
			Panel A: Clustered at province-level		
Opium shock (t-1)	-4.976***	-1.035**	-1.215**	-0.973**	-0.346
	(1.598)	(0.431)	(0.480)	(0.440)	(0.232)
Wheat shock (t-1)	0.292	0.296**	0.095	-0.011	-0.020
	(0.403)	(0.134)	(0.127)	(0.144)	(0.076)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.012	0.007	0.006	0.005	0.001
			Panel B: Clustered at district- and year-level		
Opium shock (t-1)	-4.976***	-1.035**	-1.215***	-0.973***	-0.346
	(1.318)	(0.390)	(0.394)	(0.315)	(0.200)
Wheat shock (t-1)	0.292	0.296**	0.095	-0.011	-0.020
	(0.491)	(0.130)	(0.145)	(0.139)	(0.084)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.012	0.007	0.006	0.005	0.001
			Panel C: Clustered at province- and year-level		
Opium shock (t-1)	-4.976***	-1.035**	-1.215**	-0.973**	-0.346
	(1.592)	(0.435)	(0.477)	(0.409)	(0.238)
Wheat shock (t-1)	0.292	0.296**	0.095	-0.011	-0.020
	(0.322)	(0.114)	(0.106)	(0.120)	(0.067)
Number of observations	5174	5174	5174	5174	5174
Adjusted Within R-Squared	0.012	0.007	0.006	0.005	0.001

Notes: Linear probability models with province-times-year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. Standard errors are clustered as indicated in the Panel heading. Significance levels: * 0.10 ** 0.05 *** 0.01

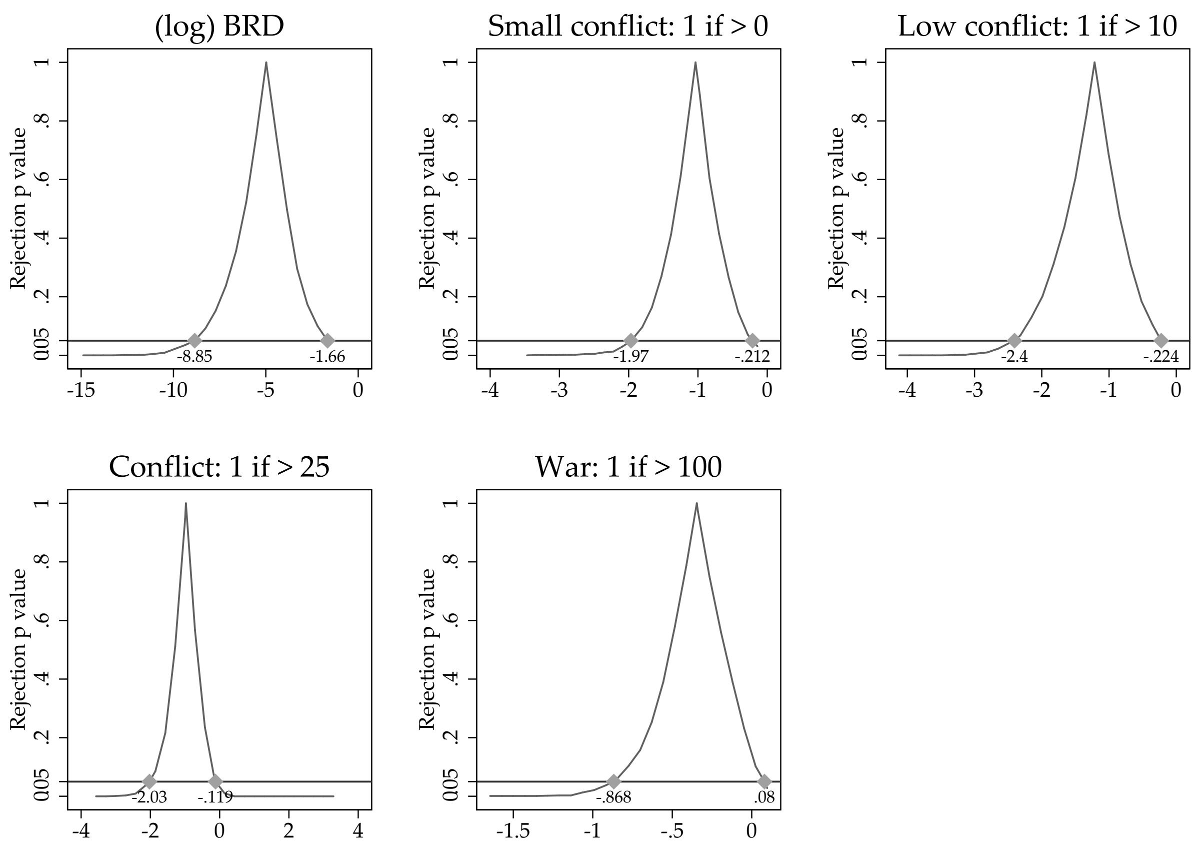


Figure 8: Wild Bootstrap (province-level clustered se)

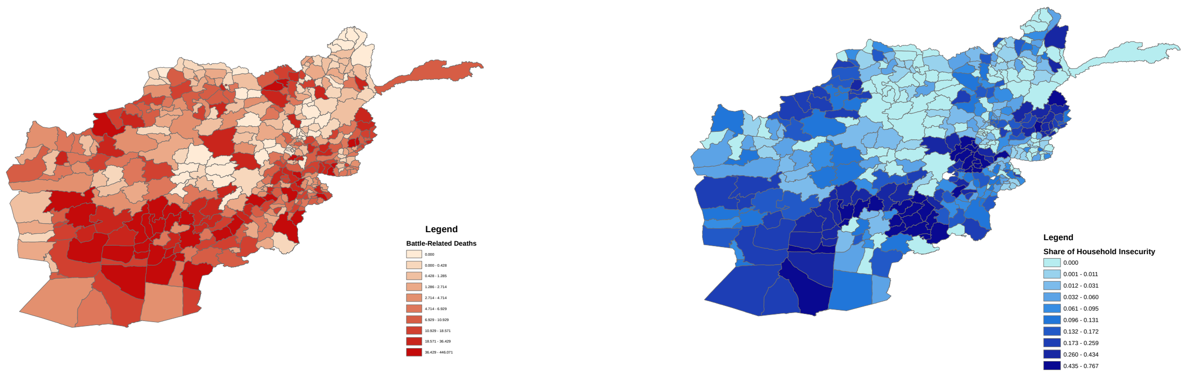
Further covariates and trends

Table 27: Including covariates, 2002-2014 period

	(log) BRD (1)	1 if >0 (2)	1 if >10 (3)	1 if >25 (4)	1 if >100 (5)
			Panel A: Baseline covariates		
Opium shock (t-1)	-4.505***	-0.951**	-1.147***	-0.791**	-0.348*
	(1.363)	(0.424)	(0.402)	(0.349)	(0.188)
(log) Wheat shock (t-1)	0.170	0.319*	0.117	-0.060	-0.126
	(0.535)	(0.169)	(0.163)	(0.145)	(0.094)
VHI	0.000	0.000	-0.000	-0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Luminosity (t-2)	0.015	-0.009	0.010	0.012	0.012**
	(0.037)	(0.006)	(0.011)	(0.012)	(0.006)
(log) Population (t-2)	3.509	-0.047	0.545	1.120	0.928***
	(3.443)	(0.891)	(0.843)	(0.919)	(0.354)
Number of observations	4378	4378	4378	4378	4378
Adjusted Within R-Squared	0.013	0.006	0.008	0.008	0.011
			Panel B: Time-invariant covariates×trend		
Opium shock (t-1)	-4.100***	-0.851*	-1.045***	-0.696**	-0.356*
	(1.310)	(0.433)	(0.396)	(0.328)	(0.182)
(log) Wheat shock (t-1)	0.098	0.276	0.115	-0.065	-0.137
	(0.531)	(0.172)	(0.164)	(0.141)	(0.092)
VHI	0.000	0.000	-0.000	-0.000	0.000
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Luminosity (t-2)	-0.005	-0.010	0.006	0.007	0.008
	(0.034)	(0.006)	(0.010)	(0.012)	(0.006)
(log) Population (t-2)	3.180	0.016	0.436	1.012	0.904***
	(3.362)	(0.948)	(0.851)	(0.866)	(0.333)
Number of observations	4356	4356	4356	4356	4356
Adjusted Within R-Squared	0.036	0.010	0.020	0.029	0.024
			Panel C: Time-invariant covariates×time dummies		
Opium shock (t-1)	-3.950***	-0.817*	-1.022**	-0.696**	-0.344*
	(1.355)	(0.444)	(0.405)	(0.333)	(0.181)
(log) Wheat shock (t-1)	0.078	0.275	0.111	-0.088	-0.135
	(0.579)	(0.186)	(0.181)	(0.157)	(0.106)
VHI	0.001	0.000	0.000	0.000	0.000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Luminosity (t-2)	-0.007	-0.006	0.004	0.008	0.005
	(0.037)	(0.008)	(0.011)	(0.012)	(0.006)
(log) Population (t-2)	2.884	-0.017	0.341	0.971	0.864***
	(3.534)	(1.002)	(0.885)	(0.909)	(0.327)
Number of observations	4356	4356	4356	4356	4356
Adjusted Within R-Squared	0.032	0.002	0.015	0.025	0.034

Notes: Linear probability models with province-times-year- and district-fixed effects. Dependent variable is conflict incidence operationalized as indicated in the column heading. The set of time-invariant covariates includes ruggedness, heroin/morphine lab, major/sub opium markets, main/secondary roads, military camps, proximity to Kabul, unofficial border crossings, Pashtuns, Taliban territory 1996. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

E Additional Maps



Number of battle-related deaths (BRD) from UCDP (GED)   Share of households experiencing insecurity/violence shock from NRVA

Figure 9: Distribution of objective (BRD) and subjective (NRVA) conflict indicators (2002-2014)

The figure below is an excerpt from a book by Dorronsoro (2005). We georeferenced the green area as the area formerly under Taliban control, and the other three polygons as not under Taliban control.

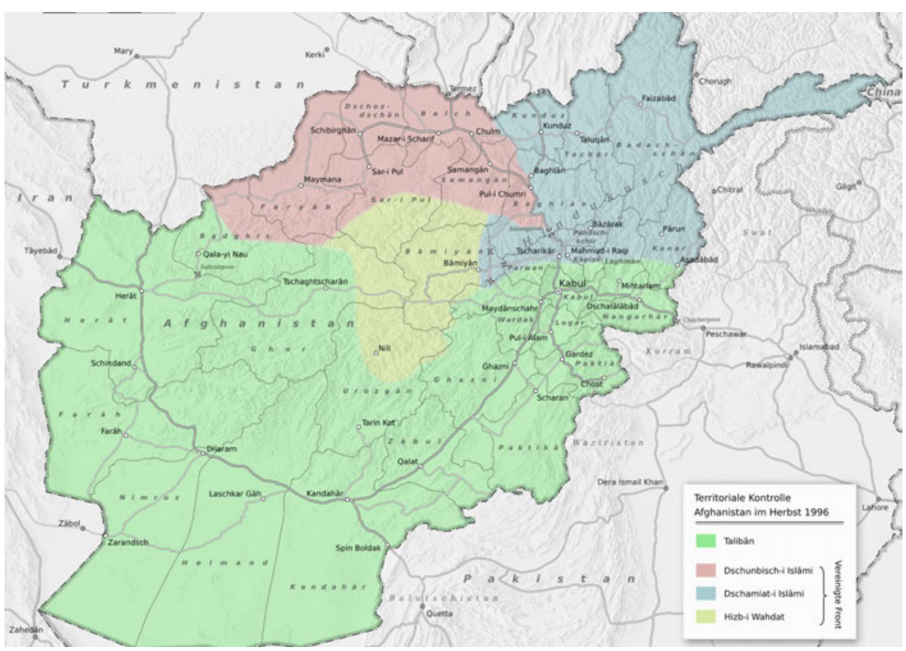


Figure 10: Political control in Afghanistan in the fall of 1996 (Dorronsoro, 2005)

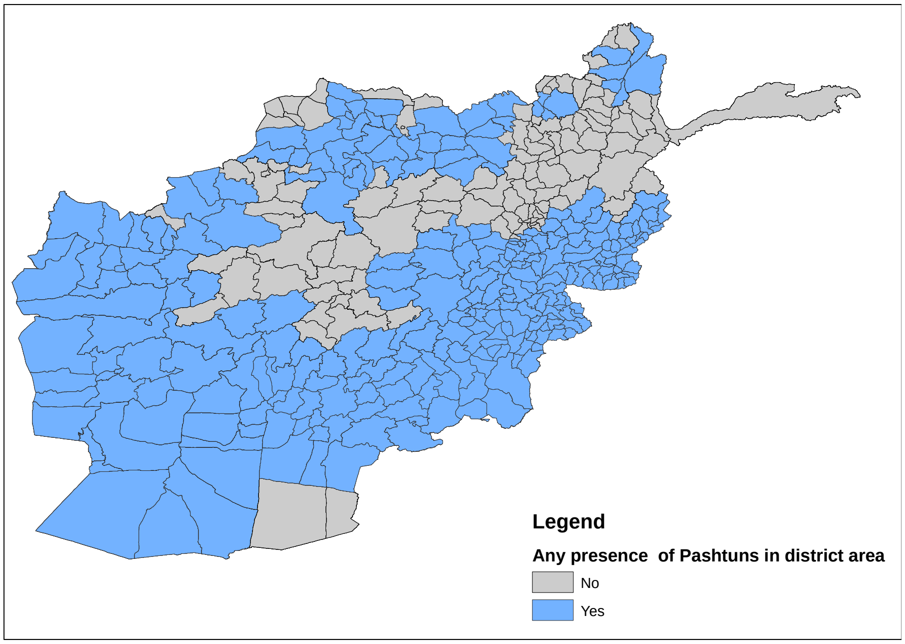
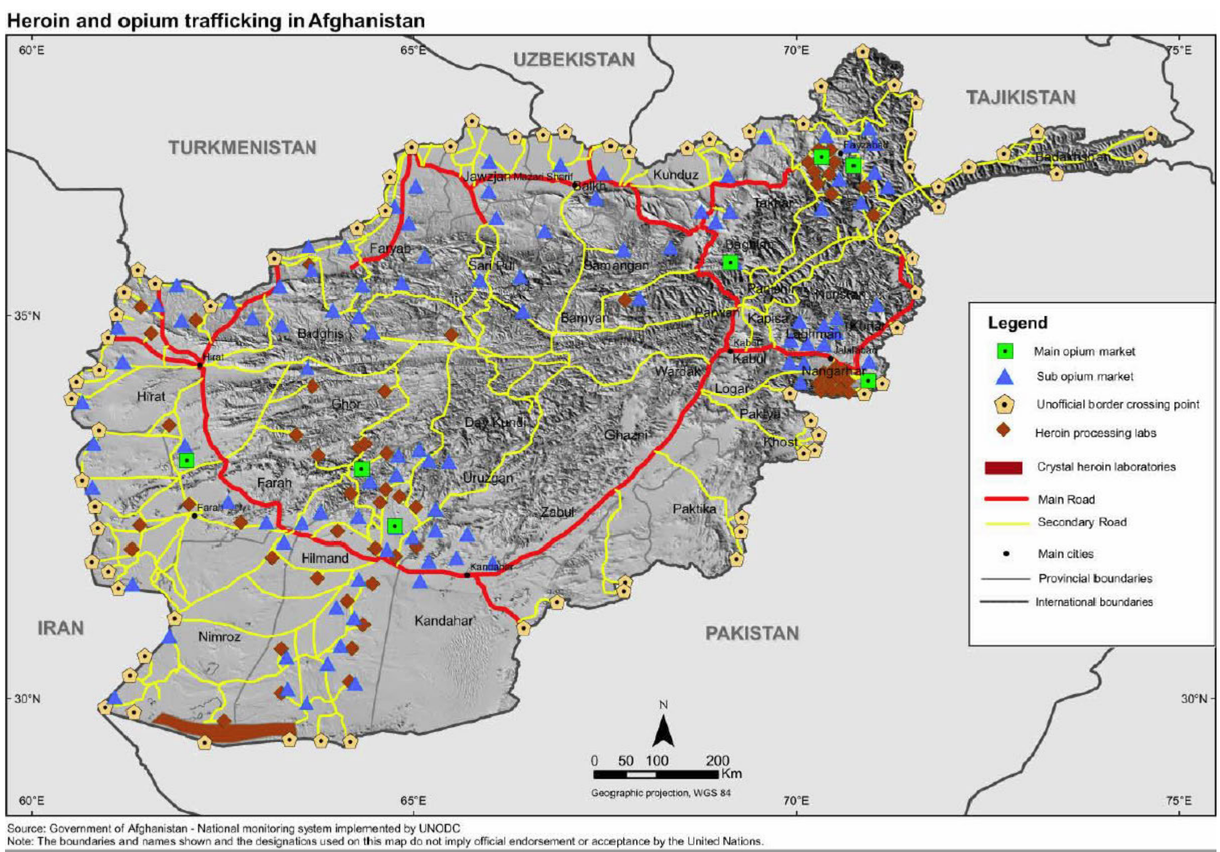


Figure 11: Existence of any significant ethnic Pashtun population share in a district. Source: GREG (Weidmann *et al.*, 2010)

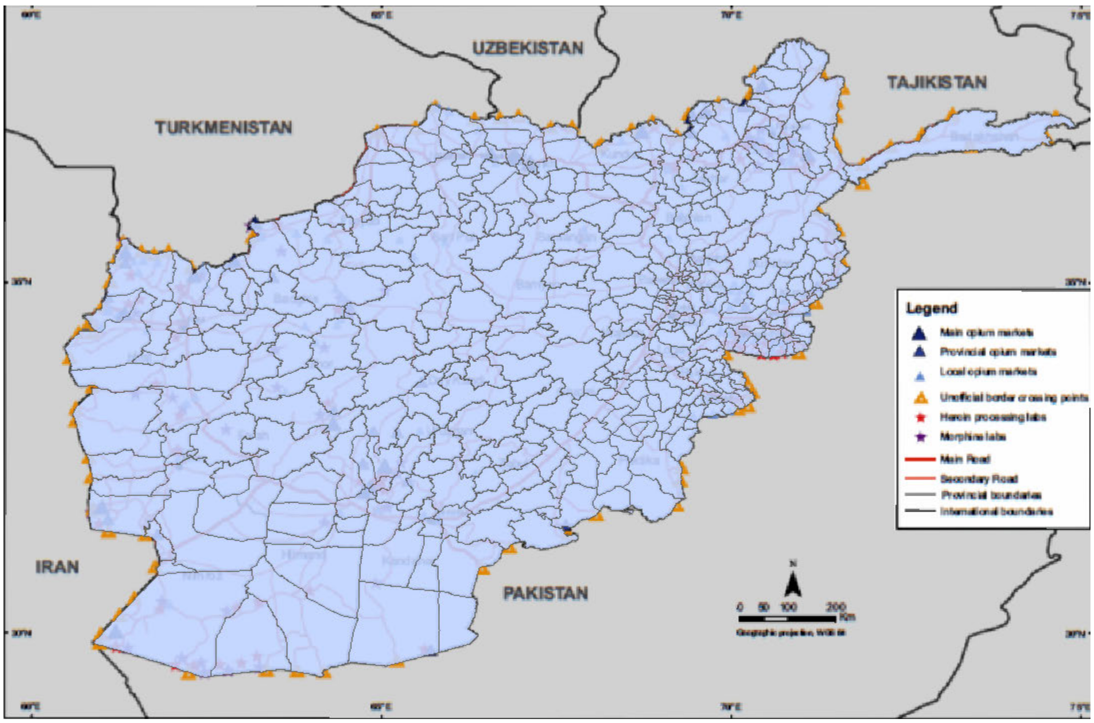
F Data coding and map generation

Processing and trafficking. There is little to no information that is publicly available on trafficking routes that might be used to smuggle opium through and out of the country. Nevertheless, the UN Office on Drugs and Crime creates and contains spatial maps in its public reports. We were able to digitize a UNODC map from 2007 (about the middle of our sample period) by taking image files of the maps themselves and georeferencing specific points on the images (border points) to a geographically accurate projection of Afghanistan. This process was continued until the map and the images matched perfectly. We then digitized the data contained in the image about the important roads used for trafficking, and theother variables such as main opium markets, heroin processing labs.



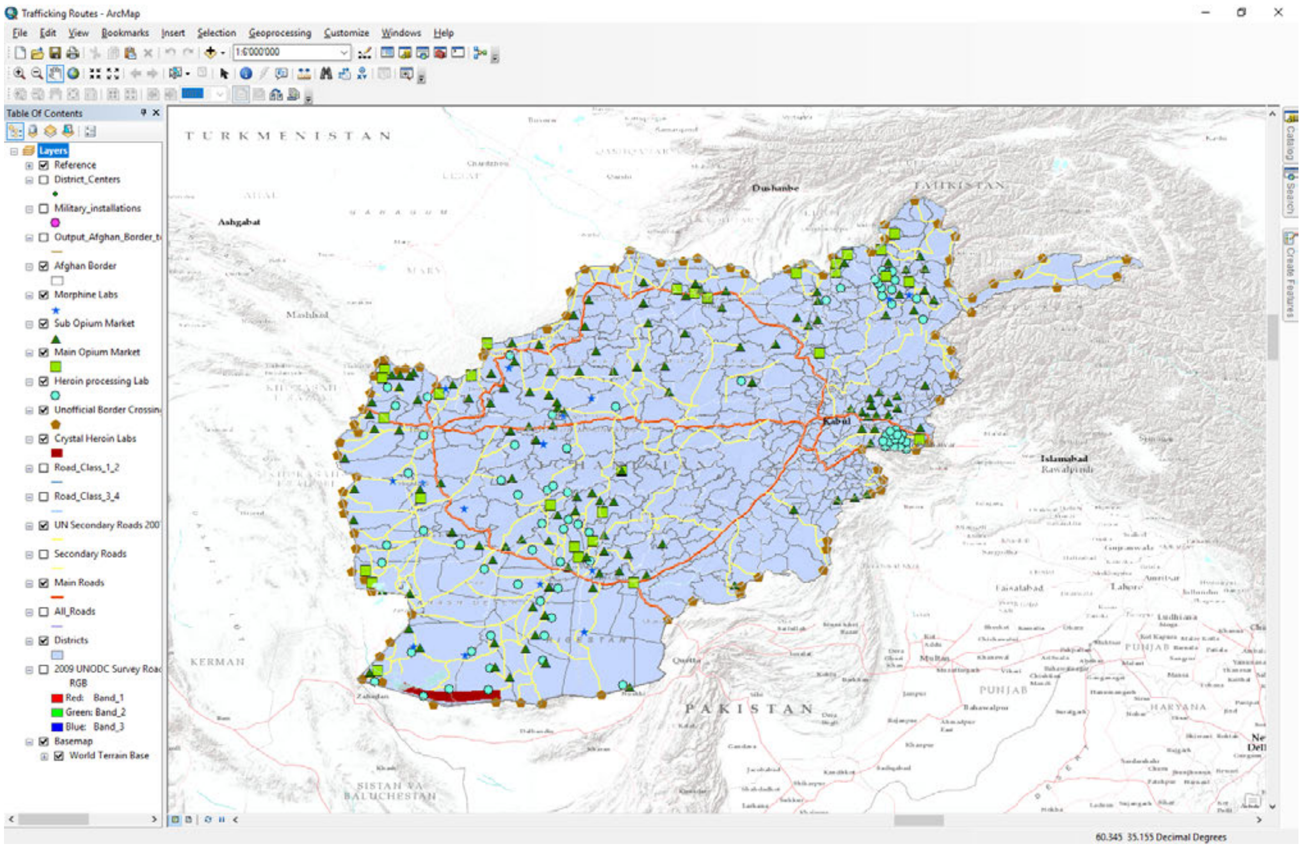
Original UNODC Map (2007)

Map making process. The source of the original map comes is the UNODC's 2007 Afghanistan Opium Survey. The map depicts major and secondary roads, main cities, opium markets, border crossing points, and processing labs. We also used the 2009 Afghanistan Opium Survey to cross-validate the data points. In almost all cases, there were no changes between the two years. In case the 2009 map identifies additional markets or labs we added these as data points. Given that the location of illegal markets and labs will always contain some measurement error and could be moved over time, our aim is to code variables that measure the potential for a trafficking route, border crossing, market or lab. This means that also due to the availability of data the indicators that we create are time-invarying. We interact the binary indicators extracted from the map with an exogenous variable, so that the interaction term can be interpreted as causal under relatively mild circumstances.



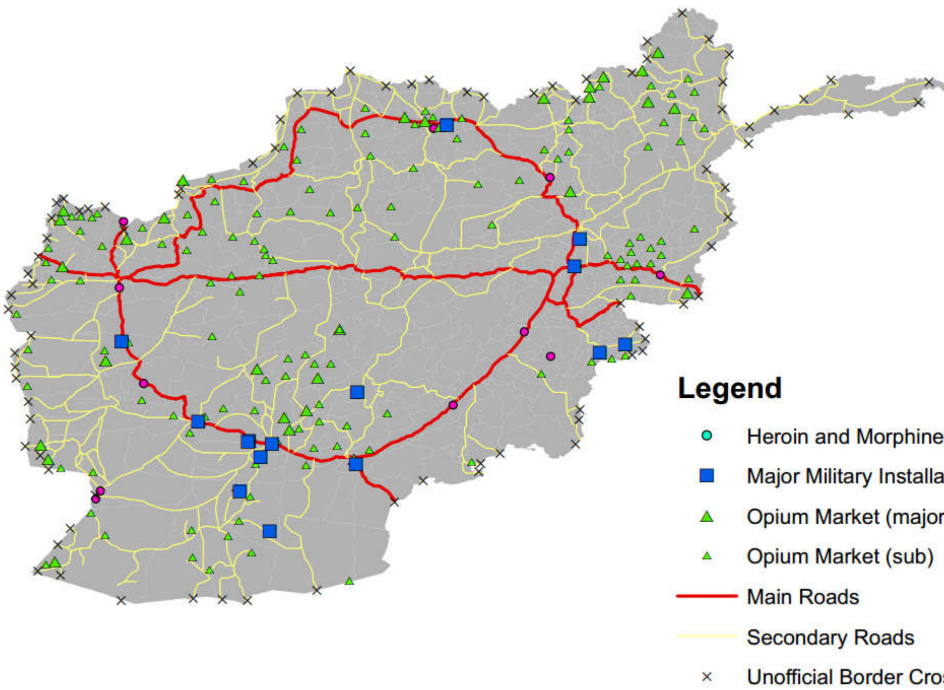
Superimposed Maps

In the next step of the process, we match the borders of the image and the georeferenced (GCS WGS 1984) shapefile from the Afghan authorities. This way, we are accurately overlaying the data points and not simply making an educated guess as to where to place the points.



The final digitized version of the UN Maps (2007 and 2009 combined)

This is the final digitized version of the map based on the UNODC data, overlaid with the district data. The binary indicators that we use in Section 4 on heterogeneous effects are coded as one if the respective feature is present within the boundaries of the district polygon at least once. Some districts feature more than one border crossing or market, but we think that the data contained too much measurement error for a precise count to yield useful information.



Final Map

This is the final map combining data from the UNODC Afghanistan Opium Surveys with the existence of major military bases in their geographic locations. We go into further detail below as to how we identified military bases.

Major military bases. This section describes how we determine the locations of major known military bases in Afghanistan. There are nearly 400 foreign military bases in Afghanistan, but none of these bases release information as to their geographic location for security reasons. In order to find this information, we compiled what data we could to determine which bases were most important to include, where exactly (latitude and longitude coordinates) these bases are (or were; many are now closed) and a number of other important variables (see tables below). We ended up relying on information from Wikipedia's GeoHack program for the more well-known bases and on news articles, and Wikimapia and Google Maps satellite data for the less well-documented ones. News articles were useful in this case because they are often allowed to publish the district in which these bases are located; from there, we were able to look for these bases by referencing photos of hte bases (if available) with available satelite data. Below, we show where and how we got the locations of 54 important bases and where the latitude and longitude coordinates lead to on a map.

OBJECTID *	Base Name	Installation Type	Militaries Present	Lat	Lon	District	Opened	Closed	Field9	Notes	Shape *
1	Delaram	FOB	USMC	32.163889	63.430833	Delaram	2009	2014	<Null>	<Null>	Point
2	Leatherneck	Camp	USMC	31.863889	64.208056	Nahri Saraj	2008	2014	<Null>	Regional Command Southwest Headquarters	Point
3	Kabul International Airport	Camp	ISAF, Turkish Army, US Army, USMC, USAF, Mongolian Armed Forces	31.505833	65.847778	Kabul	2001	.	Open	ISAF Headquarters, ISAF Joint Command Headquarters, Headquarters for RC-Capital	Point
4	Kandahar Airfield	Airfield	RAF, USAF, US Army	31.505833	65.847778	Kandahar	2001	.	Open	RC-S headquarters	Point
5	Shindand Airbase	Airbase	USAF, AAF	33.391331	62.260975	Shindand	2004	2014	<Null>	<Null>	Point
6	Bagram Airfield	Airfield	US Army, USAF	34.946111	69.265001	Bagram	2001	.	Open	Largest US base in Afghanistan, RC-East Headquarters	Point
7	Bastion	Camp	British Army, RAF, Royal Navy (RN), Royal Marines (RM), USMC, Estonian Land Forces, Danish Defence, Tonga Defence Services	31.859329	64.190499	Nahri Saraj	2006	2014	<Null>	Main British base and formerly home to Task Force Helmand	Point
8	Price	MOB	RM, British Army, Danish Defence, US Army, USMC	31.818889	64.557778	Nahri Saraj	2006	2014	<Null>	<Null>	Point
9	Lashkar Gah	MOB	British Army, RM	31.623056	64.381389	Lashkargah	2006	2014	<Null>	<Null>	Point
10	Eggers	Camp	NATO, US Army, USMC, US Air Force, Australian Army, New Zealand Army, French Army, Turkish Army, Mongolian Armed Forces	34.530559	69.179731	Kabul	2006	2014	<Null>	NATO Training Mission – Afghanistan Headquarters	Point
11	Salerno	FOB	US Army, USAF, US Navy	33.210001	69.570001	Khost (Matun)	2003	2013	<Null>	<Null>	Point
12	Chapman	FOB	US Special Operation Command, US Army, CIA	33.339001	69.955001	Khost (Matun)	2001	.	Open	Major CIA and Special Operations counter-insurgency outpost	Point
13	Marmal	Camp	German Army, German Navy, German Air Force, Royal Netherlands AF, Swedish Air Force, US Army, Mongolian Armed Forces	36.702101	67.228201	Mazar-e Sharif	2005	.	Open	<Null>	Point
14	Dwyer	Camp	USMC, British Army, RM	31.101111	64.067222	Garmsir	2007	2009	<Null>	<Null>	Point
15	Rhino	Camp	USMC, US Navy, US Army, USAF, SASR	30.486667	64.525556	Garmsir	2001	2002	<Null>	First Marine land base in Afghanistan	Point
16	Holland	Camp	Australian Army, New Zealand Army, US Army, Royal Netherlands Army, ANA	32.613889	65.866667	Tarin Kot	2006	2013	<Null>	<Null>	Point
17	Black Horse	Camp	US Army, Canadian Army	34.577222	69.287778	Kabul	2008	2013	<Null>	<Null>	Point
18	Dogan	Camp	<Null>	34.548439	69.261574	Kabul	2002	2015	<Null>	<Null>	Point
19	Invicta	Camp	Italian Army	34.544722	69.301944	Kabul	2006	2012	Close unk, camp was open in 2012	<Null>	Point
20	Julien	Camp	Canadian Army	34.460278	69.118333	Kabul	2003	2005	<Null>	Reopened as a Counterinsurgency Academy in April 2007	Point
21	Julien	Camp	Canadian Army	34.460278	69.118333	Kabul	2007	.	Open	Reopened as a Counterinsurgency Academy in April 2008	Point
22	Phoenix (Qargha)	Camp	US Army	34.54694	69.258333	Kabul	.	.	Open	Opening unknown	Point
23	Souter	Camp	British Army	34.533333	69.166667	Kabul	2007	2014	Slated to close in 2014	<Null>	Point
24	Warehouse	Camp	Canadian Army	34.541389	69.304444	Kabul	2002	2014	Slated to close in 2014, Canada withdrew all troops at this time	<Null>	Point
25	Pucino	Camp	USSOCOM	33.210001	69.570001	Khost (Matun)	2002	2013	<Null>	<Null>	Point
26	Clark	Camp	US Army	33.340564	69.736539	Mandozayi	.	.	Open unk, close unk	<Null>	Point
27	Blessing	Camp	US Army, USMC	34.985833	70.903611	Waygal	2002	2011	<Null>	<Null>	Point
28	Bostick	FOB	US Army	35.423	71.33	Nari	2006	2012	<Null>	<Null>	Point
29	Joyce	FOB	US Army	34.780113	71.11345	Sarkani	2002	2013	Close unk, camp was open in 2013	<Null>	Point
30	Wright	Camp	US Army	34.8525	71.135278	Asadabad	2001	.	Close unk	<Null>	Point
31	Albert	Camp	US Army	34.946111	69.265	Bagram	2004	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
32	Blackjack	Camp	US	34.946111	69.265	Bagram	.	2012	Open unk, close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
33	Bulldog	Camp	US	34.946111	69.265	Bagram	.	2012	Open unk, close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
34	Civilian	Camp	US	34.946111	69.265	Bagram	2003	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
35	Cunningham	Camp	US	34.946111	69.265	Bagram	2004	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
36	Gibraltar	Camp	US	34.946111	69.265	Bagram	2002	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
37	Warrior	Camp	US	34.946111	69.265	Bagram	.	.	Open	Located in/related to Bagram Airfield, opening date unknown	Point
38	Pratt	Camp	US Army	36.692616	67.117951	Mazar-e-Sharif	.	2014	Open unk	<Null>	Point
39	Spann	Camp	US Army	36.692616	67.117951	Mazar-e-Sharif	.	2014	Open unk, between 2001 and 2004	<Null>	Point
40	Baker	Camp	Australian Army	31.505833	65.847778	Daman	2006	2015	<Null>	Located in/related to Kandahar Airfield	Point
41	Nathan Smith	Camp	Canadian Army, US Army	31.65	65.666667	Kandahar	2003	2013	<Null>	<Null>	Point
42	Hadrian	Camp	Royal Netherlands Army	32.6325	65.495833	Deh Rawod	.	2013	Open unk, task force Uruzgan started 2006	<Null>	Point
43	Russell	Camp	Australian Army	32.603889	65.866389	Tarin Kot	2005	2013	<Null>	<Null>	Point
44	Hamidullah	FOB	USMC, British Army, RM	32.032778	64.833333	Sangin	2007	2014	<Null>	<Null>	Point
45	Arena	Camp	Italian Army, Italian Air Force, US Army	34.209444	62.227222	Hirat	2012	.	Open	<Null>	Point
46	Stone	Camp	Carabinieri, US Army	34.125278	62.235833	Hirat	Before/in 2008	2014	<Null>	<Null>	Point
47	Vianini	Camp	Italian Army	34.38	62.181944	Hirat	Before/in 2006	2012	<Null>	<Null>	Point
48	Losano	Camp	RNLAF, US Army, USAF	31.505833	65.847778	Kandahar	.	.	Open unk, close unk	Located in/related to Kandahar Airfield	Point
49	Lagman	FOB	US Army, US Navy, Romanian Army, ANA	32.13	66.929722	Qalat	2004	2014	<Null>	<Null>	Point
50	Shorabak	Camp	ISAF, US, Britain, Denmark, Estonia, Tonga	31.856667	64.220833	Lashkargah	2005	.	Open	ISAF logistics hub	Point
51	Pasab (Wilson)	FOB	US Army	31.485278	65.351944	Panjwayi	.	2014	Open unk, slated to close in 2014	<Null>	Point

Main Bases and Relevant Information

This table shows the available data for 51 bases that we deemed to be the most important foreign bases in Afghanistan over the last 15 years. We list the name, type, location (CGS WGS 1984 coordinates), militaries present, district in which the base is located, date opened and closed (a "." in the opened or closed section means there is either no data for these times or that the base is still open. See Field9 for explanatory notes in these cases), and general notes of interest.

Confirming the Location of these Districts using Satellite Imagery

Example - Camp Blackhorse

This is an example of what the Wikimapia satellite imagery we used to locate bases looks like. This is an image of Camp Blackhorse, now closed. We were able to locate this as Camp Blackhorse by first searching for the camp on wikimapia which offered two possible locations (approximately 9 miles away from each other) where the camp could be. After we discovered in a news report that the camp was located next to an Afghan National Army base which was itself located on the site of the Pul-e-Charkhi-Prison, we were able to determined the definitive location of the prison and thus the location of the base.

Definitions and explanation of how each base was found. Below, we have laid out the definitions for what each type of base exists in Afghanistan and explained how we determined the specific locations for each base we included. The base definitions are important to know because the type of base is a good indicator of its size. Though this was of course not the only criteria we used to determine whether or not a specific base should be represented on the map, it was important for weeding out those that are ot included (for example, we included no firebases on account of their temporary and generally small size. Below this, we go into detail about specific bases whose locations we were not able to get from the GeoHack database, in which bases are supposed to have had multiple confirmations. These bases were found using satelite data and through confirming guesses that some people have made on Wikimapia using any available news reports, photos and satelite imagery.

- Definition FOB - A forward operating base (FOB) is any secured forward military position, commonly a military base, that is used to support tactical operations. A FOB may or may not contain an airfield, hospital, or other facilities. The base may be used for an extended period of time. FOBs are traditionally supported by Main Operating Bases that are required to provide backup support to them. A FOB also improves reaction time to local areas as opposed to having all troops on the main operating base.

- Definition MOB - is a term used by the United States military defined as a "permanently manned, well protected base, used to support permanently deployed forces, and with robust sea and/or air access." Not so significant,

- Definition COP - a combat outpost is a detachment of troops stationed at a distance from the main force or formation, usually at a station in a remote or sparsely populated location, positioned to stand guard against unauthorized intrusions and surprise attacks; and the station occupied by such troops, usually a small military base or settlement in an outlying frontier, limit, political boundary or in another country. (Small, about 32 guys. People walking not driving, very small reach, 20km

- Definition Firebase - a temporary military encampment to provide artillery fire support to infantry operating in areas beyond the normal range of fire support from their own base camps.

- Definition Camp - a semi-permanent facility for the lodging of an army. Camps are erected when a military force travels away from a major installation or fort during training or operations, and often have the form of large campsites. Weird definition.

- Definition Base - a facility directly owned and operated by or for the military or one of its branches that shelters military equipment and personnel, and facilitates training and operations. In general, a military base provides accommodations for one or more units, but it may also be used as a command center, a training ground, or a proving ground. In most cases, a military base relies on some outside help in order to operate. However, certain complex bases are able to endure by themselves for long periods because they are able to provide food, water and other life support necessities for their inhabitants while under siege. *All definitions from Wikipedia

All locations taken from Wikimedia's GeoHack program unless referenced as otherwise below:

1. COP/FOB Zangabad has been coded as FOB Pasab. This was the most likely location for a forward operating base close the Zhari/Panjwayi district border. Exact location determined as such using Wikimapia satelite imagery. It is coded as being in the district of Panjwayi.

2. Camp/FOB Hadrian location determined using Wikimapia satelite imagery.

3. Camp Russell location determined using Wikimapia satelite imagery in relation to Camp Holland.

4. Camp Arena, Camp Vianini, and Camp Stone are each in roughly the same area. Using Wikimapia imagery, we assume that Camp Arena, the only camp with an Italian Air Force presence, is located at the airfield in Hirat. Camp Vianini and Camp Stone were assigned their locations using Wikimapia imagery as well. We believe Camp Vianini to be at the location we chose based on the fact that an Italian artillery regiment was attacked at that location and we believe the Italian Army was the only major force at Camp Vianini. Camp Stone, which has multiple country forces at its location, is expected to be south of the airport and Camp Arena, according to Wikimapia data.

5. Camp Blackhorse determined using Wikimapia and various sources citing the camp to be adjacent to the Pul-e-Charkhi ANA compound.

6. Camp Clark determined using Wikimapia satelite imagery.

7. Camp Warehouse determined using Wikimapia stelite imagery.

8. Camp Phoenix lcoation determined using google maps and Wikimapia satelite data.

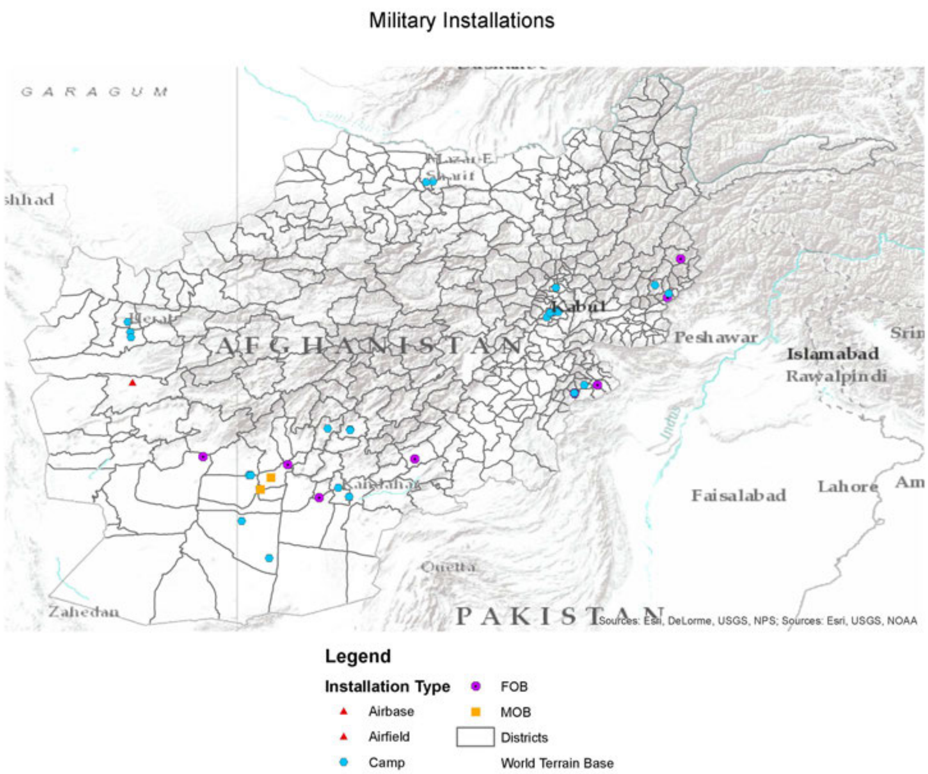
9. Camp Invicta located using Wikimapia satelite data.

10. FOB Hamidullah located using Wikimapia satelite data. In Wikimapia, the location is described as FOB Nolay, the previous name of the base.

11. Camp Blessing located using Wikimapia satelite data.

12. FOB Joyce located using satelite data and with news articles stating that FOB Joyce is within/very close to the village of Serkanay.

13. Camp Wright located using Wikimapia and Google Maps satelite data; it is listed as ’USA Army Base" on the Wikimapia site.



Final Map of Located Military Installations

This map shows the output of the variables in the table above. The latitude and longitude coordinates listed provide the specific location in which these bases have been placed. Some bases are not visible in this view as a result of overlapping with other bases, , in which case the map displays only one dot**.**