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Stimulant or depressant?
Resource-related income shocks and conflict

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

JEL Codes: D74, K4, O53, Q1

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1. Introduction

An important strand of the resource-curse literature examines how resource-related income shocks are linked to conflict (e.g., Brückner & Ciccone, 2010; Morelli & Rohner, 2015; Berman *et al.*, 2017). Yet, we've only begun to understand the microfoundations behind the resource-conflict-nexus. After focusing on the aggregate country level for many years, recent contributions at the micro level have discovered large heterogeneities across different commodities and countries (e.g., Dube & Vargas, 2013). Our results show that higher opium prices reduce conflict incidence and intensity in Afghanistan. We explore the mechanisms behind this relationship to understand the role of opium in the Afghan conflict that caused more than 100,000 battle-related deaths since 2002. Although every conflict is distinct, we believe this case provides important lessons for other settings. Many conflict-ridden countries struggle with weak state capacity, have high ethnic diversity, experience difficulties in forming stable coalitions, and feature a weak labor market with heavy reliance on one specific product.

Our paper makes four main contributions, which we explain within the frameworks of the opportunity cost effect and contest effect. The former predicts that higher resource prices improve living conditions and lower conflict, the latter postulates that higher prices intensify conflicts over valuable resources between different groups.

First, we examine and verify one key insight from Dube & Vargas (2013). They show that positive price changes of relatively more labor-intensive goods reduce conflict because they increase the opportunity costs of joining rebel groups and engaging in fighting. Afghanistan, characterized by a weak labor market and a large share of people working in agriculture, provides a good example to cross-validate the external validity of this important hypothesis. There are only two main crops that are feasible to produce across the country; opium, which is very labor-intensive, and wheat, which requires less labor (Mansfield & Fishstein, 2016). Accordingly, a relative decline in opium prices causes marginal producers to shift towards wheat production and decreases labor demand.[1] In the absence of lucrative alternatives, joining a rebel group like the Taliban is one of the few options (e.g., Bove & Elia, 2013). Using survey data, we verify that opium profitability indeed matters for well-being at the household level. We then exploit district level data on opium markets, labs, and trafficking routes to see whether the effect is stronger in districts that can extract a larger share of the value added. Finally, we show that the apparent reliance on opium increases after an exogenous policy shock that deprived people of an important alternative source of income.[2]

[1] According to UNODC (2004) between 80% to 90% of landowners and farmers decide on their own what they plant, which will usually be the most profitable crop.

[2] Our analysis does not explicitly consider other crops. We do not neglect their importance in certain areas, 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, as each individual crop is negligible in importance compared to opium and the cultivation of these alternatives is restricted to certain areas, we assume that shocks to the profitability of these crops are not systematically biasing the effect of the exogenous opium profitability.

Second, we carve out the role of government influence and enforcement. We argue that the degree to which the *de jure* illegality of a drug influences conflict decisively depends on *de facto* government control and enforcement. The enforcement of rules creates an incentive for opium farmers to cooperate with the Taliban, who offer protection against those measures (Clemens, 2013). This can lead to more fights between the Taliban and the government (Peters, 2009). Based on Michalopoulos & Papaioannou (2014) and Lind *et al.* (2014), we use the distance to major cities as a measure of the Afghan government's influence and the strength of state institutions. Our results suggest that government law enforcement is largely confined to districts within a limited radius around Kabul. Officially, the International Security Assistance Forces (ISAF), as expressed in several United Nations Security Council (UNSC) bulletins, claims resolute actions against drug producers and traffickers. Yet, in line with statements by the US military leadership who do not regard "anti-drug enforcement" as part of their agenda, we find no evidence of a heterogeneous effect according to foreign military presence.[3]

Third, we highlight that contest effects depend on the degree of competition between groups that fight for territorial control. Afghanistan is an ideal setting to analyze the role of group competition, as it comprises many ethnic groups, but at the same time, most conflict events since 2001 are best characterized as fights between the Taliban and pro-government groups. We provide evidence that, on average, the conflict-inducing effect of increased intergroup competition over lucrative opium production sites is dominated by the opportunity costs effects of higher prices. Furthermore, we show that the conflict-reducing effect of opium is stronger in districts that are more plausibly dominated by the Taliban. Hence, government enforcement and the intensity of group competition help to explain why our results differ from the existing evidence for Colombia, where rising cocaine prices seem to lead to more conflict (Angrist & Kugler, 2008; Mejia & Restrepo, 2015).

Fourth, we establish causality by combining temporal variation in international drug prices with a new dataset on spatial variation in opium suitability (Kienberger *et al.*, 2017), to measure changes in opium profitability across time and districts. Our strategy exploits the fact that higher prices have a larger effect in districts with a higher suitability, conditional on the overall price level. We also exploit patterns in consumer demand. Specifically, we use the international price of heroin (made of opium), drugs that are complements to heroin, and local opium prices to verify the causal interpretation of our findings in a reduced-form setting. In addition, we make use of the differential effect of international prices as well as of changes in legal opioid prescriptions in the United States in an instrumental variable (IV) setting to

[3] The official views are visible in, for instance, the 2004 UNSC Resolution 1563 stressing "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, accessed June 14, 2018). When asked about the actual approach of the military, Jean-Luc Lemahieu, who was head of the UNODC in Afghanistan from 2009 to 2013, is quoted as saying "drug control wasn't a priority." Other sources at the US government are quoted with an informal bargain that they "would not pursue top Afghan allies who were involved in the drug trade." Source: http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204, accessed June 14, 2018.

assess the size of the effect. All strategies lead to the same result: higher opium profitability consistently reduces both conflict incidence and intensity. An increase of opium revenues by 10% leads to a decrease in the number of battle-related deaths of about 1.5%.

Our data allow us to identify if this effect is indeed driven by changes in opportunity costs. We use different waves of the National Risk and Vulnerability Assessment (NRVA) to show that the gains from higher opium profitability reach the average household. We find that higher prices consistently increase food consumption and living standards, validating that a higher opium profitability increases the opportunity costs of fighting at the individual level. Moreover, we exploit a policy change in the Western military strategy around 2005 to illustrate that the growing reliance of Afghan households on revenues from opium production contributed to the conflict-reducing effect of higher opium prices.

In the next step, we geo-reference data from the United Nations Office for Drugs and Crime (UNODC) on drug markets, labs, and potential trafficking routes (see among other reports, UNODC, 2016). We argue that districts which not only cultivate opium in its raw form, but also process and trade it can capture a larger share of value added along the supply chain. This affects both the intensive margin (higher revenues) as well as the extensive margin (more people benefiting). We conceptualize this by using simple indices and network-based variants of market access (Donaldson & Hornbeck, 2016). If the contest effect based on group competition about territorial control dominates, we would expect more fighting in those districts. The results show, however, that the opportunity cost effects seems to prevail over potential contest effects, and the conflict-reducing effect of higher prices is larger in districts with high value added.

The only area where this relation is clearly different is close to Kabul. Outside a small radius of about 75 km or 2 hours travel time around Kabul, almost all fighting is best characterized as a conflict between Taliban and Taliban-affiliated groups on one side, and pro-government groups on the other side. We use maps on the homelands of Pashtuns and historical Taliban control prior to 2001 as a proxy for whether a district is plausibly controlled by the Taliban. The Taliban were initially a Pashtun ethnic group, making it easier to establish a presence in Pashtun districts (see Trebbi & Weese, 2016). Links from before 2001 should also make it easier to reestablish their hold on a district. In line with our hypothesis, we find that the conflict-reducing effect of higher opium prices is stronger in areas that are more likely controlled by the Taliban after 2001. This supports qualitative evidence about the group acting as a stationary bandit, which maximizes its revenues extracted through taxing opium farmers (Peters, 2009) in the districts it controls. Reports even suggest that the Taliban implement conflict-solving mechanisms to minimize violence that would potentially disturb the profitable production process.[4]

To complement this evidence, we also use the geographical distribution of ethnic homelands (Wei-

[4] See http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204, accessed June 14, 2018.

dmann *et al.*, 2010) to code the number of ethnic groups and classify districts as ethnically mixed. We would expect that if there was strong competition between ethnic groups about territorial control (e.g., Esteban *et al.*, 2012), the conflict-reducing effect would be smaller or non-existent in ethnically heterogeneous districts. Nonetheless, we find no significant evidence in that direction, further supporting our hypothesis of generally limited competition between groups and a mostly bipolar conflict. Although limited in terms of years, evidence from the five years before 2001 suggests that, at times when different groups and warlords were still competing about territorial control of lucrative production grounds, there is no conflict-reducing effect of higher prices.

Section 2 discusses the contributions to the literature and relevant theoretical considerations; Section 3 introduces the data; Section 4 explains the empirical strategy. The main results are then presented in Section 5. We investigate mechanisms and the underlying channels in Section 6; and discuss sensitivity tests in Section 7. Section 8 summarizes and provides policy implications.

2. Literature and theoretical considerations

Contributions to literature: We contribute to different strands of the literature. First, we add to the large literature on resource-related income shocks and conflict. Empirically, income is often found to be one of the strongest correlates of violence (e.g., Fearon & Laitin, 2003; Collier & Hoeffler, 2004; Blattman & Miguel, 2010). Most recent studies exploit income shocks induced by international commodity price changes or rainfall fluctuations that affect local production and income levels, and can in turn also affect the level of conflict. However, studies at the cross-country macro level (e.g., Bazzi & Blattman, 2014; Brückner & Ciccone, 2010; Miguel *et al.*, 2004; Nunn & Qian, 2014) and the subnational level (e.g., Caselli & Michaels, 2013; Dube & Vargas, 2013; Berman & Couttenier, 2015; Berman *et al.*, 2017) are still far from reaching a consensus. One plausible reason is that the majority of these papers do not consider different features of resources and income sources and differences in the degree of competition between groups about territorial control.[5]

Second, our analysis adds to the scarce causal evidence on the effect of illegal commodities. Despite the importance of the illicit economy, particularly in many developing and conflict-ridden societies, the literature provides very limited evidence on the effects of illegal commodity shocks on conflict. Closely related to our paper is the work by Angrist & Kugler (2008) and Mejia & Restrepo (2015), who exploit demand and supply shocks to cocaine and find a positive relationship with conflict in the Colombian context. Mejia & Restrepo (2015) show that, when cocaine production was estimated to be

[5] Lujala (2009) differentiate between various types of resources, Lujala (2009) finds a negative correlation of conflict with drug cultivation, but suggests a conflict-increasing effect of gemstone mining and oil and gas, but does not address endogeneity. La Ferrara & Guidolin (2007) analyze the effect of conflict on diamond production, i.e., the opposite direction of causality. Gehring & Schneider (2018) show that oil shocks do not lead to violent conflict, but their distribution can foster separatist party success in democracies.

more profitable, the number of homicides increases. This effect is stronger in municipalities with a high suitability to grow coca, while a higher profitability of alternative crops such as cocoa, sugar cane, and palm oil tends to reduce violence. We augment these findings by showing that *de jure* illegality does not matter per se, but only when it is actually enforced by the government.

This connects to studies about the problem of establishing a credible government in a poor and economically constrained environment (Berman *et al.*, 2011a). If law is enforced, this can lead to conflict with the producers, create support for cartels or rebel groups, and increase the likelihood that higher prices foster conflict (Chimeli & Soares, 2017). Moreover, enforcement is usually ineffective and affects cultivation only marginally (Ibanez & Carlsson, 2010; Mejía *et al.*, 2015). Our results suggest that the Afghan government is either unwilling or unable to enforce laws concerning opium production in districts beyond a limited distance from Kabul. Related to the role of the Taliban as stationary bandits, we contribute to the literature on the provision of state-like institutions by non-state actors (e.g., De La Sierra, 2015), also referring to problems of imposing rules upon occupied territory (Acemoglu *et al.*, 2011).

This study also contributes to the strand of literature that emphasizes existing cleavages between ethnic groups as an important driver of conflict (e.g., Esteban & Ray, 2008; Michalopoulos & Papaioannou, 2016; Morelli & Rohner, 2015; Rohner *et al.*, 2013). We show that in Afghanistan the conflict was mostly bipolar between pro-Taliban and pro-government groups. We do not focus on the behavior of individual groups within these two factions (as in König *et al.*, 2017), partly since there are very few recorded fights within alliances after 2001. Prior to 2001, conflicts were apparently more fragmented with generally more competition between groups about resources, and an overall less negative and insignificant effect of opium profitability.

We also add to the emerging literature on conflict and violence in Afghanistan (e.g., Child, 2018; Lyall *et al.*, 2013; Sexton, 2016). Trebbi & Weese (2016) use a new method to study the internal organization of rebel groups in Afghanistan, and support the dominating role of the Taliban as by far the most important rebel group during our sample period. Condra *et al.* (2018) show how the Taliban try to undermine electoral institutions by means of targeted attacks. In contrast, most of the conflicts we capture within our sample period are between the Taliban and pro-government groups rather than against civilians. Wright (2018) argues that the tactics of rebel groups depend on their capacity and the state's capacity, as well as on outside options available to civilians – all potentially affected by income shocks. While rebel tactics are not the focus of our study, we distinguish between different types of violence in robustness tests.

Specific evidence on the relationship between opium and conflict is scarce, despite the fact that opium 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 a higher share 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 2004-2009 period. Our paper augments their findings with a larger sample, over a longer time period, and with more systematic identification strategies.

Lind *et al.* (2014) find a negative impact of Western casualties on opium production over the 2002-2007 period, and no effect in the opposite direction. Compared to the focus on Western casualties, we can provide a more comprehensive measurement of conflict, and our different strategies allow us to carve out the direction of causality more clearly.[6] At first sight, our results seem to be at odds with Berman *et al.* (2011b), who find no positive correlation between unemployment and insurgency attacks for Afghanistan, Iraq and the Philippines. The difference might be explained by their focus on the 2008-2009 period, the use of other outcome variables and potential endogeneity problems. Our household level results over the 2005-2012 period show that a higher opium profitability improves living conditions for average households.

Theoretical considerations: From a theoretical perspective, it is *ex ante* unclear in which direction income shocks in general, and (temporary) resource-related income shocks in particular, affect conflict. Existing literature mainly distinguishes between two channels, the opportunity costs mechanism (e.g., Grossman, 1991), and the contest model (e.g., Hirshleifer, 1988, 1989, 1995). For clarity and simplicity, we frame our paper in terms of these two main theories. The first theory hypothesizes that, with a rise in income, the opportunity costs of fighting increase, leading to, all else equal, less violence. Joining or supporting anti-government troops like the Taliban becomes less attractive for an individual after an increase in the profitability of opium.

In Afghanistan, the main alternative to growing poppies is growing wheat (UNODC, 2013; Lind *et al.*, 2014) but, if neither is sufficiently attractive, joining a rebel group is considered to be a viable alternative.[7] Many studies suggest that growing poppies is generally far more profitable. The gross wheat-to-opium per unit income-ratio ranges between 1:4 to 1:27 (UNODC, 2005, 2013). Nevertheless, Mansfield & Fishstein (2016) criticize this over-simplified approach for focusing on gross instead of net returns, and ignoring differences in the production process. For instance, opium is much more labor

[6] As the ISAF "is not directly involved in the poppy eradication or destruction of processing facilities, or in taking military action against narcotic producers" (see ISAF mandate: http://www.nato.int/isaf/topics/mandate/index.html), the authors argue that Western casualties are more exogenous compared to the total number of casualties. Nevertheless, the 2004 UNSC Resolution 1563, for instance indicates that Western forces were involved in eradication during the 2002-2007 period (see „extending central government authority to all parts of Afghanistan, [...], and of combating narcotics trade and production", http://unscr.com/en/resolutions/doc/1563, accessed June 4,2018).

[7] Bove & Elia (2013, p. 538) write that "in Afghanistan individuals may choose between opium cultivation and joining an anti-government group."

intensive. 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, there is considerable geographical variation in the suitability of a district to produce the two crops.

This leads to two important implications. First, whether opium is profitable (and more profitable than wheat) depends on the prices in the respective year, and differs between districts. Mansfield & Fishstein (2016) report that, based on net returns, there were years where opium was profitable across nearly all locations they examined, and other years where it depended on location. Our empirical strategy exploits this heterogeneous effect of price changes depending on the suitability of soil. Second, we need to control for wheat profitability, to capture the change in opium prices relative to wheat.[8]

These insights highlight how lower opium prices can lead to more conflict through decreasing opportunity costs. If opium becomes relatively less profitable compared to wheat, some marginal landowners will decide to switch to the less labor-intensive wheat production. This will decrease the demand for labor. For those Afghans owning land, it means that they lose 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 groups, who pay a minimal salary, or supporting them with shelter or local expertise, can be the only viable alternative.[9]

In contrast to the opportunity cost mechanism, the contest (or rapacity) effect predicts more fighting in attractive districts when opium prices are high. The reason is that the potential gains from fighting are greater, hence group competition over territorial control intensifies. The importance of the contest effect depends on the degree to which different groups compete about territorial control of lucrative districts. An extreme example like Norway helps to illustrate that. One reason why Norway is able to profit from its oil resources, is that there is very little competitive and hostile spirit between its different regions about the distribution of oil revenues. In cases with existing historical tensions between regions like in the UK (Gehring & Schneider, 2018) or between ethnic groups, changes in resource value affect secessionism and conflict. Hence, the size of the conflict-fueling contest effect depends on the degree of group competition.

Competition over control in Afghanistan after 2001 was between the Taliban and groups supporting it, and pro-government groups. For simplicity, it is helpful to distinguish between two parts of the country. There are areas with a strong presence of the central government, in which the laws concerning

[8] The effect of a price increase for wheat itself is ambiguous. While the income of few exporting farmers increases, most farmers grow wheat only as a staple crop and households who are net buyers of wheat are negatively affected (Mansfield & Fishstein, 2016).

[9] Several sources speak of ten US Dollar per month as the wage offered by the Taliban (more than in the official army), e.g., https://www.wired.com/2010/07/taliban-pays-its-troops-better-than-karzai-pays-his/ and Afghan officials are cited as wanting to turn "ten-dollar-Taliban" around (https://www.cleveland.com/world/index.ssf/2009/08/afghan_leaders_move_-toward_rec.html, accessed June 14, 2018).

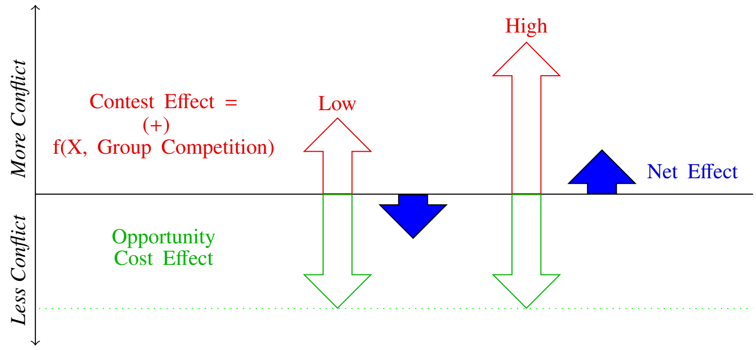

Figure 1: Contest effect as function of violent intergroup competition

opium are enforced to some degree. In these areas, farmers benefit less from higher prices, which can also lead to more conflict when farmers turn to the Taliban in exchange for protection of their crops (Clemens, 2013). Outside this area, government influence is limited and the existing quantitative and qualitative evidence almost unanimously agrees that enforcement is very weak and not effective (e.g., Clemens, 2008). In these areas, the majority of the country, Taliban and pro-government groups could potentially compete over territorial control, especially over lucrative production grounds when prices are high. We provide evidence for this distinction, and show results highlighting that, outside the area of stronger government influence, there is still a difference between contested districts and those dominated by one group.

We visualize the potential effect based on the opportunity cost and contest effects in Figure 1. For fixed opportunity costs, whether the net effect of higher prices is positive or negative depends on the size of the contest effect. We examine both the importance of opportunity costs, as well as the role of differences in group competition empirically.

Furthermore, there might be potential spill-over effects as the taxes the Taliban collect from opium producers could be partly pooled through the Taliban's central finance committee. More than 65% of the farmers and traffickers in southern Afghanistan stated that the Taliban offer to protect opium production and trafficking (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" in the form of a land or road tax. If the group acts as a stationary bandit (De La Sierra, 2015), they could establish monopolies of violence to sustain taxation contracts and try to avoid conflict within the suitable districts that they control when the profitability of the taxable resources is higher. At the same time, a certain share of the revenues might be pooled and send to the group's central financing committee, and help to finance attacks in other areas.[10]

[10] See, e.g., http://www.huffingtonpost.com/joseph-v-micallef/how-the-Taliban-gets-its_b_8551536.html, accessed June 14, 2018.

3. Data description

Conflict data: The UCDP Georeferenced Event Dataset (GED) is our primary source for different conflict indicators.[11] It includes geocoded information (based on media reports) on the "best estimate of total fatalities resulting from an event" (Sundberg & Melander, 2013; Croicu & Sundberg, 2015), with specific information about the types of fighting (one-sided, state-based, non-state) and the actors involved as illustrated in Table 8.[12] In our sample period, 94% of the events covered by UCDP are fights between the Afghan government and the Taliban (so-called state-based violence). Less than 4% of all cases are classified as one-sided with the Taliban as the perpetrator and civilians as the victims. We differentiate between these different types in Section 7. In addition, we use the SIGACTS (Significant Activities) data on the events direct fire, indirect fire, and improvised explosive device (IED) from Shaver & Wright (2016) to verify the reliability of UCDP GED data.

Our analysis is at the district level (ADM2). There are 398 districts, which belong to 34 provinces (ADM1) (see Figure 12 in Appendix C). We report results for thresholds of 5, 25, 50, and 100 battle-related deaths (BRD), and the log of the number of BRD per district-year as a continuous conflict measure.[13] Using different thresholds, each somewhat arbitrary, along with a continuous measure of BRD, alleviates concerns about specifying when a conflict becomes relevant and ensures transparency. To further verify the reliability of the UCDP GED data, Figure 25 in Appendix G shows a high correlation with a subjective conflict indicator derived from the NRVA household survey. We use population-weighted and unweighted suitabilities to test potential differences with regard to population density, a jackknife approach (i.e., dropping one province at a time) to account for the influence of high-conflict areas, and consider different conflict types in robustness tests.

Opium and wheat suitability index: We exploit a novel dataset measuring the suitability to grow opium based on exogenous underlying information about land cover, water availability, climatic suitability, and soil suitability. Conceptually, the index, developed in collaboration with UNODC, is comparable to suitability indices by the Food and Agricultural Organization (FAO) (see Kienberger *et al.*, 2017). The left hand side of Figure 2 plots the distribution of the opium suitability index across Afghan districts.

[11] We prefer this over the Armed Conflict Location & Event Data Project (ACLED). ACLED is only available for the 2004-2010 period, thus reducing the sample by half, and is reported to be less reliable for Afghanistan (e.g., Eck, 2012).

[12] An event is defined as "[a]n incident where armed force was [used] 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" (Sundberg & Melander, 2013; Croicu & Sundberg, 2015). These battle-related deaths include dead civilians and deaths of persons of unknown status. For more details see Appendix A. Weidmann (2015) documents some under-reporting of media-based conflict data in areas with low population density compared to the SIGACTS data, which are based on military reports and not publicly available. Media-based datasets could also be downward biased with regard to the intensity of conflict, especially in high conflict areas.

[13] It is standard at the country level to only use the two thresholds of 25 and 1000, but the latter threshold is evidently not appropriate for an analysis at the district level. Berman & Couttenier (2015), in contrast, use a one-BRD threshold. However, the grid cell level at which they work is of a much smaller size than the ADM2 level. For our size, we consider five BRD a good threshold to detect small conflict, whereas a one-BRD threshold might suffer from misreporting and falsely coding conflict.

An index of one indicates perfect suitability, and an index of zero means a district is least suitable for growing opium. Given that opium is a “renewable” resource, this suitability can also be understood as the actual “resource” that varies across districts. We weight the suitability with the population density, to account for areas that are potentially hard to reach and not populated, but this does not affect our results. Figure 2 also shows the distribution of wheat suitability on the right hand side. There is a positive correlation between the two, but also clear differences.

Opium suitability (based on Kienberger *et al.*, 2017) Wheat suitability (based on FAO GAEZ)

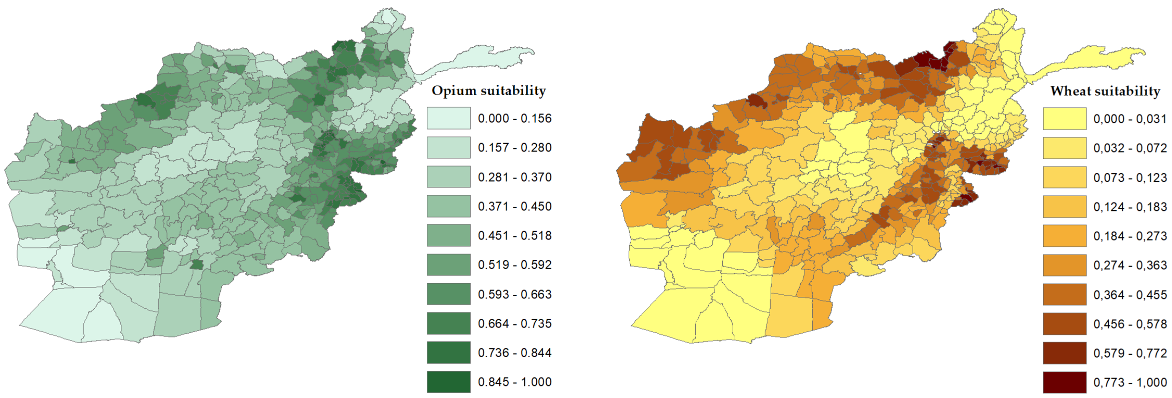

Figure 2: Distribution of opium and wheat suitability across districts (weighted by population)

Drug prices: We use international drug price data on heroin and complement drugs from the European Monitoring Center for Drugs and Drug Addiction (EMCDDA). We take the mean prices for each country-year and then calculate the average across all countries to eliminate the effects of country-specific shocks and to capture global changes in demand. Local price data on opium is derived from the annual Afghanistan Opium Price Monitoring reports by UNODC. The international price is the price for heroin, an opiate derived from morphines that are extracted from the opium poppy.[14] The complementary drugs we consider are cocaine, amphetamine, and ecstasy. We also create the variable complement index which is defined as the average of three complements.

Drug cultivation and drug revenues: 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. We calculate actual opium production at the district-year level from opium cultivation and the respective yields, which vary by year and region. Opium revenues equal opium production in kilograms multiplied with the yearly Afghan farm-gate prices (fresh opium at harvest time, country-average) in constant 2010 Euro/kg. For the regression analysis we take the logarithm of the revenues.

[14] EMCDDA provides data on white and brown heroin. The bulk of heroin consumed in Europe is brown heroin, which is also much cheaper than white heroin. Besides being less common, white heroin is only reported by a small number of European countries and is also likely to be consumed in fewer countries. Both types are products of opium poppies and the correlation between white and brown heroin prices is 0.49.

Survey Data: We use the NRVA survey waves conducted in 2005, 2007/08 and 2011/12 (CSO, 2005, 2007/08, 2011/12) to better test the opportunity cost channel at the household level. They are nationally representative and include between 21,000 and 31,000 households as well as covering from 341 to 388 of the 398 official districts in Afghanistan. We harmonize data from three different waves to construct indicators based on food consumption and expenditures, household assets, and a self-reported measure on the household's economic situation.

All these variables and their sources are described in more detail in Appendix A, where we also describe all remaining variables.

4. Identification strategy

A. Estimating equation and identification

Our baseline specification focuses on the reduced-form intention-to-treat (ITT) effect. We prefer this specification because opium cultivation data are district level estimates by UNODC derived from province level data that might exhibit considerable measurement error.[15] To circumvent these concerns we combine temporal price variation with district level data on the suitability to grow opium to compute the reduced-form effect. In addition, we use actual opium revenues (and cultivation) to assess the size of our effect in an IV setting. This approach resembles Bartik or shift-share instruments that combine cross-sectional variation with variation in a times series (e.g., Nunn & Qian, 2014). Our baseline equation at the district-year level over the 2002 to 2014 period is:

$$conflict_{d,t} = \beta opium\, profitability_{d,t-1} + \zeta wheat\, profitability_{d,t-1} + \tau_t + \delta_d + \tau_t \delta_p + \varepsilon_{d,t}. \quad (1)$$

Standard errors are clustered at the district level, but results are robust to different choices including the use of province level clusters and a wild-cluster bootstrap approach (Appendix F, Figure 15). The outcome variable, $conflict_{d,t}$, is the incidence or the intensity of conflict in district d in year t based on the different thresholds. Our "treatment" variable $opium\, profitability_{d,t-1}$ measures the relative extent of the shock induced by world market price changes in *t-1* conditional on the exogenous district-specific suitability to grow opium in district d. More specifically, $opium\, profitability_{d,t-1}$, and analogously $wheat\, profitability_{d,t-1}$, are defined as:

$$opium\, profitability_{d,t-1} = drug\, price_{t-1} \times opium\, suitability_d,$$

$$wheat\, profitability_{d,t-1} = wheat\, price_{t-1} \times wheat\, suitability_d.$$

We include wheat-related income shocks ($wheat\, profitability_{d,t-1}$), since wheat is the main (legal)

[15] As stated by the UNODC (2015, 63) "[d]istrict 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." Assuming the measurement error is normal, this would bias our estimations towards zero. In case the precision of estimates is also affected by conflict and suitability, however, the bias is hard to predict.

alternative crop that farmers grow throughout Afghanistan. The effect of wheat price shocks on income is ambiguous, as Afghanistan also imports large amounts of wheat. In fact, Afghanistan contributes less than 1% to the global wheat supply, which is why we follow the literature and consider the international price as exogenous (e.g., Berman & Couttenier, 2015). Note, that our main results regarding $opium\ profitability$ all hold without including this variable. Our baseline equation includes year-fixed effects τ_t, district-fixed effects δ_d, and province-times-year-fixed effects $\tau_t\delta_p$.

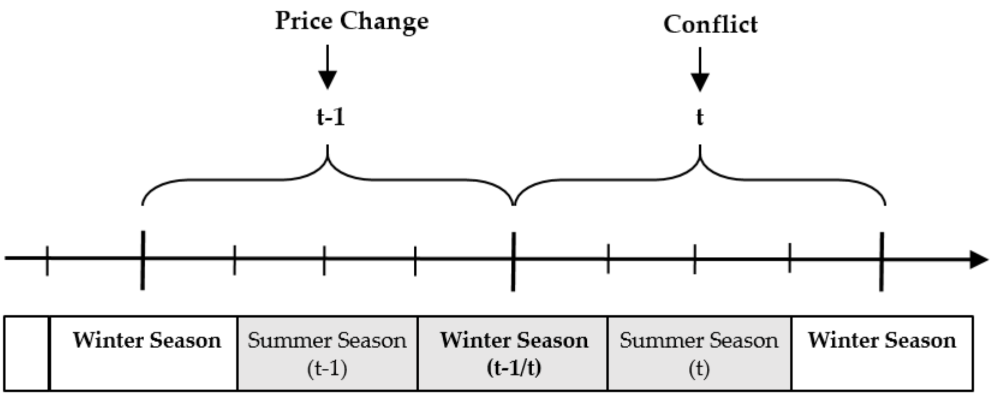

Figure 3: Price changes in year t affect production and revenues in $t-1/t$, and conflict in year t

Market price changes can plausibly influence opium cultivation and revenues in both that year and the following year, as Figure 3 illustrates. There are two main growing seasons for opium in Afghanistan, the winter season starting in fall and the summer season starting around March (Mansfield & Fishstein, 2016). Our preferred specification assumes the largest effect of $opium\ profitability$ on conflict one year later. Price changes in (*t-1*) are most likely to affect cultivation decisions in summer(*t-1*), winter(*t-1*/*t*) and summer(*t*), as well as affecting labor demand and revenues in both (*t-1*) and (*t*). Using prices in (*t-1*) accounts for the fact that producers require time to update their information set and adjust production. Moreover, they often receive their remuneration in advance (Mansfield & Fishstein, 2016).[16] The next section shows the changes in prices over our sample period.

B. Changes in international prices, local prices, and local revenues

In the following, we (i) discuss that the movements of prices over our sample period is mostly driven by changes in demand, (ii) show that international prices of complement drugs correlate positively with the international heroin price, (iii) demonstrate that international prices translate into economically relevant changes in the local price in Afghanistan and, (iv) establish that they affect opium revenues at the district

[16] Caulkins *et al.* (2010, p. 9) also suggest that "the largest driver of changes in hectares under poppy cultivation is not eradication or enforcement risk, but rather last year's opium prices." Taking contemporaneous prices in (*t*) is conceptually difficult with yearly price and conflict averages. Using the price in (*t*) would introduce reverse causality, as price changes later in the year can be affected by conflict earlier in the year. Moreover, it is unclear how quickly changes in world market prices transmit into changes at the local Afghan level. For these reasons, we prefer the lagged value, however, using prices in (*t*) yields comparable results as shown in Appendix E.

level in Afghanistan. Figure 4 displays the variation in the international prices of heroin, cocaine, a complement drug index, as well as the Afghan opium price (in constant 2010 Euro/gram). The local opium farm-gate price at harvest time in Afghanistan is the most direct measure, but also most likely to be driven by opium supply-side effects in Afghanistan. We will explain below how we use cocaine prices and a complement index for three complementary drugs to validate the causal interpretation of our results.

The graph provides several important insights. First, there are variations between the years, but the most important insight is that overall all prices decline over time. This common pattern suggests that prices are, on average, more strongly driven by common demand factors. Interviews with experts at EMCDDA support this view; there is no agreement on the reasons, but the emergence of new synthetic or legal alternatives might be a factor, rather than changes in the supply of an individual drug. Second, there is an overall positive correlation between the international heroin price, the complement index, and the international cocaine price (significant at the 1% level). As expected, the index, which eliminates the influence of drug-specific supply shocks, exhibits less variation than the cocaine price, but is also decreasing. If supply changes for one of the established drugs would be the decisive influencing factors for the price changes we exploit, we should not observe this co-movement of prices between complements and opium. Appendix F shows that we can replicate our results using de-trended opium prices, but this eliminates a large share of the economically relevant variation over time.

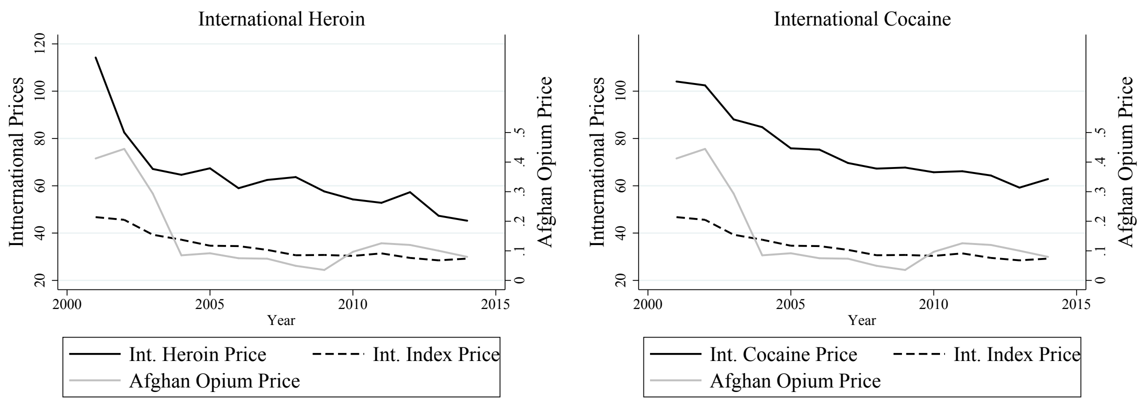

Figure 4: Variation in international and local prices over time

Third, local Afghan prices are also positively correlated with the international heroin price. This indicates that, despite end-customer market prices being multitudes higher than local prices, international price changes also translate into economically meaningful changes in actual opium revenues at the district level.[17] We can also test directly whether international consumer price changes have statistically and economically significant effects at the local Afghan level. We use the empirical model as defined in Equation 1, but with the revenues from opium cultivation as the dependent variable. Opium revenues are defined as the estimated production in kilogram multiplied with the Afghan opium farm-gate price at harvest in constant 2010 EU/kg. Corresponding to Figure 3, Table 1 considers lagged effects in column 1, as well as the moving average over (t) and (t-1) in column 2.

Table 1: Effect of international price changes on opium revenues, 2002-2014 period

	Outcome: (t)	**Outcome: (t) + (t-1)**
	(1)	(2)
Opium Profitability (t-1)	2.336***	2.489***
	(0.827)	(0.749)
Number of observations	5149	5085
Adjusted R-Squared	0.482	0.565

Notes: The dependent variable opium revenues is in logarithms. Column (1) presents lagged effects. Column (2) reports lagged and contemporaneous effects by defining the outcome as the moving average, i.e. (revenues(t)+revenues(t-1))/2. Opium Profitability is defined as the interaction between the normalized drug prices (in logarithms) and the suitability to grow opium. Standard errors clustered at the district-level are displayed in parentheses. Significance levels: * 0.10 ** 0.05 *** 0.01.

In line with our proposed mechanism, external price changes, measured by the interaction of the international heroin price with the suitability to grow opium, lead to an increase in local opium revenues in the same and following year. The results are significant at the 1% level in both columns. Quantitatively, a 1% increase in the international heroin price leads to about a 2.4% increase in revenues for those districts where opium suitability reaches one (perfect suitability). For districts characterized by the mean suitability (0.53) the effect would roughly decrease by half (0.53*2.40=1.27), but the elasticity is still bigger than one.

C. Potential biases

The international opium (heroin) price p^O_{t-1} is of course influenced by overall opium supply in Afghanistan, which contributes a large share of the global opium production (UNODC, 2013). Still, in our setting, we are less worried about overall supply shocks, which are fully captured by the year-fixed effects τ_t. They capture, for instance, yearly changes in crop diseases, shifts in anti-drug policies, or intensifying conflict, to the degree that these affect all districts in Afghanistan in the same way. District-fixed effects δ_d account for time-invariant unobservable district level characteristics and the time lag makes reverse causality less of an issue.

[17] To put this into perspective, some reports indicate that an amount of opium worth 600 US Dollar can have a street value of more than 150,000 US Dollar. See http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204, accessed June 14, 2018. In Appendix F in Table 27 we replace revenues with opium cultivation in hectares. The estimations do not include province-times-year-fixed effects, as the actual district level cultivation data from which revenues are calculated is gathered at the province level.

This does not imply, however, that there are no potentially problematic omitted variables. More specifically, we would be worried about omitted variables OV_{t-1} that affect both opium supply and hence p^O_{t-1}, as well as $conflict_{d,t}$, and have an effect that differs between districts according to the time-invariant $opium\ suitability_d$. Considering Figure 4 helps to understand that these omitted variables, in addition to affecting high and low suitability districts differently, would also have to follow a similar pattern over time to the drug prices to cause a systematic bias.

We are most concerned about a downward bias. One example of a problematic omitted variable are changes in district-specific institutions or policies. Eradication campaigns can decrease supply and hence increase the heroin price, and at the same time raise the likelihood of conflict with farmers. If eradications would also be more likely to take place in low suitability areas, we would observe a spurious negative correlation between higher prices and more conflict in low suitability areas. As a result, the coefficient $opium\ profitability_{d,t-1}$ would be biased downwards. Based on the notorious ineffectiveness of eradication policies (see, Felbab-Brown, 2013; Mejía *et al.*, 2015), this possibility seems rather unlikely, but there could be other unobserved factors that have a similar effect.

District-fixed effects ensure that our main estimations are not affected by cross-sectional differences in factors like population size. Still, as a large share of the drug trade is organized at the ethnic or provincial level (Giustozzi, 2009), ethnic leadership or warlords might change over time and can plausibly affect both conflict and opium production. To the degree that these changes are at the province level, the province-times-year-fixed effects $\tau_t\delta_p$ account flexibly for any differences in unobservables over time. Identification in our setting relies only on within-province variation in a particular year due to differences in how the price affects opium profitability depending on opium suitability.

Hence, time-varying omitted variables would affect opium prices and conflict differentially depending on factors that differ within provinces based on suitability. Table 9 in Appendix B shows that low and high suitability districts indeed differ in some covariates X_d, for instance in the distance to Kabul, or with regard to elevation and ruggedness. A problematic case would be if, along with declining prices, conflict would increase over time; yet, low suitability districts, for reasons unrelated to opium like being more rugged or remote, would experience a smaller increase in conflict. By interacting the complete set of time-invariant covariates X_d, both with a linear time trend or flexibly with time-fixed effects τ_t, we capture any such bias to the extent that it is based on observable differences (see, Appendix F).

Moreover, Appendix F shows that the results hold when using $X_{d,t}$ and $X_{d,t-2}$, vectors of district level time-varying covariates, including climate conditions and other baseline covariates frequently used in other conflict regressions such as luminosity (as a proxy for development) and population. Climate conditions are exogenous to conflict and used as contemporaneous values. We lag luminosity and population twice, with the aim of using a pre-determined value and mitigating the bad control problem.

Finally, we would be concerned if by coincidence long-term trends in prices correlate with long-term trends in conflict that are driven by omitted variables and differ between low and high suitability districts for reasons unrelated to opium (see e.g. Christian & Barrett, 2017). We alleviate this concern in five different ways.

First, Appendix F shows the results with de-trended opium prices, which exhibit less variation, but support the main finding. Second, we randomize prices across years and find that random assignment yields no significant relationship with coefficients being distributed around zero. Third, Section 6B shows that trends between low and high suitability districts begin to diverge more after an exogenous change in Western policy around 2005 increased the reliance of the local population on opium revenues. Fourth, Section 7 uses the increase in legal opioids prescriptions in the USA, which affect heroin prices in a plausibly exogenous way, in an IV setting. Fifth,the next subsection explains how, for our main reduced-form specification, we can exploit the relationship of opium with complement drugs to alleviate remaining concerns about the direction of causality.

D. Identification using changes in complement prices

In order to assess the direction of any remaining potential bias, we gather price data for a variety of drugs that are used as complements to heroin. We exploit the fact that prices of complements depend on the same demand shifters (DS), but the biasing effect of a district level change in opium supply q^O_{t-1} (potentially caused by an omitted variable) points in the opposite direction for the complement price than for the heroin price because of the negative cross-price elasticity. More formally,

$$p^O_{t-1} = f(\overset{(+)}{DS'_{t-1}}, \overset{(-)}{q^O_{t-1}}, \overset{(+)}{q^C_{t-1}}),$$

$$p^C_{t-1} = f(\overset{(+)}{DS'_{t-1}}, \overset{(+)}{q^O_{t-1}}, \overset{(-)}{q^C_{t-1}}).$$

Accordingly, a bias resulting from problematic omitted variables that affect opium supply would distort the estimated coefficient b in different directions for the opium and complement prices. Formally, the expectations for a coefficient estimate from a regression on conflict in the presence of a bias become:

$$E[b^O] = \beta + \gamma \times \frac{\rho(opiumprice_{t-1} \times suit_d, OV_{t-1} \times suit_d)}{\mathrm{Var}(opium\ price_{t-1} \times suit_d)}, \tag{2}$$

$$E[b^C] = \beta \times \frac{\sigma^O}{\sigma^{\epsilon^C} + \sigma^O} + (-\varpi) \times \gamma \times \frac{\rho(complement\ price_{t-1} \times suit_d, OV_{t-1} \times suit_d)}{\mathrm{Var}(complement\ price_{t-1} \times suit_d)}. \tag{3}$$

b^O and b^C are the estimates using the opium and complement price, whereas β is the "true" parameter. σ^O is the standard deviation of the opium price, and ϵ^C indicates the influence of exogenous supply side shocks on the complement price. ϖ is a parameter that is positive if the cross-price elasticity is negative, i.e., if two goods are complements $(-\varpi) \leq 0$. Hence, the equations show two things. Attenuation bias moves the complement estimate towards zero, as $\frac{\sigma^O}{\sigma^{\epsilon^C}+\sigma^O} \leq 1$. At the same time an omitted variable would bias the complement coefficient in the opposite direction as compared to the opium coefficient. Appendix D provides the derivation and explains the necessary assumptions. Three main criteria need to be fulfilled.

1. We need to be able to identify complements for which the negative cross-price elasticity with opium is sufficiently high.
2. We require complements for which large supply-side shocks are unrelated to district level supply-side shocks for opium in Afghanistan. This enables us to treat supply side shocks as random noise (ϵ^C), which only attenuates the coefficient towards zero.
3. The degree to which drug prices are affected by common demand shifters must be sufficiently high relative to ϵ^C. Demand shifters include a change in overall income of consumers, a shift in consumers' preferences about drugs, or the number of buyers in the drug market.

To the extent that these criteria are fulfilled, we can derive the following: If both estimates have the same sign, this strongly signals that the true effect also points in the same direction due to the opposing directions of the omitted variable bias. If both exhibit a negative coefficient, then we can distinguish between two scenarios, a) a downward or b) an upward bias in the opium estimate. In case a) the complement coefficient is more positive than the opium coefficient, because both attenuation bias and OVB move it towards zero. If the complement coefficient is more negative than the opium price, this suggests that the opium coefficient is upward biased (scenario b). In this case, the opium estimate can be interpreted as an upper bound of the true negative effect. Although the intuition is provided in Equations 2 and 3, we also validate this strategy using a Monte Carlo simulation, described in detail in Appendix D.

We make use of the fact that drugs are classified as stimulants (uppers) or depressants (downers), with heroin being in the latter category, to identify complements. Experts agree that there is a high share of polydrug users, particularly users that combine a stimulant and a depressant (EMCDDA, 2016). We gather data on changes in the prices of three depressants that are regarded as complements to opium: cocaine, amphetamine, and ecstasy (EMCDDA, 2016). Leri *et al.* (2003, p. 8) conclude that the "prevalence of cocaine use among heroin addicts not in treatment ranges from 30% to 80%," making it a "strong" complement. This can take place in form of "speed-balling" (mixing heroin and cocaine), consuming the two jointly or with a time lag (e.g., weekend versus workday drug consumption). Cocaine supply is also most clearly exogenous to supply shocks in Afghanistan, with production exclusively taking place in South America and no overlap with regard to trafficking routes (suggested by low cocaine seizures in Asia, see, UNODC, 2013).[18] Thus, cocaine most clearly fulfills conditions 1 and 2.

[18] There is also no evidence suggesting that ecstasy and amphetamines are produced in Afghanistan, but there is vague evidence on amphetamine-type stimulants (ATS) being seized in the Middle East (UNODC, 2013). Afghanistan is never mentioned in this regard and not included in the list of countries of provenance (UNODC, 2013).

One disadvantage of focusing on one complement is that supply side shocks for any individual complement ϵ^C could have a relatively large influence compared to common demands shifters. Using an index of the average normalized prices of the three upper drugs instead has the advantage of reducing the influence of individual supply side shocks, making it more likely that condition 3 is fulfilled. Hence, we use the cocaine price alone as well as a complement index. We find comparable results using either the cocaine price or the index. The movement of prices (and expert opinions) indicates that long term price changes are more strongly driven by common demand-side factors, but this approach helps us to alleviate remaining concerns about omitted variables and their suitability-specific effect on opium supply and conflict.[19]

E. Visualizing the identification strategy

As our identification relies on the interaction term $opium\ profitability_{d,t-1} = drugprice_{t-1} \times suitability_d$, our setting resembles a difference-in-difference approach. The main effects of the two levels of the interaction term ($drug\ price_{t-1}$, $opium\ suitability_d$) are captured by the district-fixed and time-fixed effects in our model. We expect the effect of international price shocks on opium cultivation and revenue to be larger in districts that are more suitable to grow opium compared to districts with a low suitability. Table 14 shows that there are no problematic pre-trend differences.

Figure 5 illustrates our approach with two maps showing the district level opium suitability overlaid with the distribution of conflict across Afghanistan for two selected years. 2004 followed a year of high prices and opium profitability was higher (left graph). 2009, in contrast, was a year of lower prices (right graph). It becomes immediately clear that lower prices are associated with more widespread and more intense conflict, whereas higher prices are associated with less conflict. This indicates support for the importance of opportunity cost effects at the country level. Our identification, however, relies on within-district variation over time conditional on suitability. This intuition becomes clear when comparing the relative change in conflict for 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 most evident in the north, northeast, and east. Although these are only correlations, they help to understand the variation that we exploit in our analysis in the next section.

[19] The price of substitutes can also be positively correlated with the opium price as both prices increase if general demand, preferences or the number of buyers increases. However, when opium supply decreases, the opium price would increase and the price of the substitute would also increase. Hence, we cannot distinguish the demand shock from the second, potentially endogenous, relationship with Afghan opium supply, as both point in the same direction.

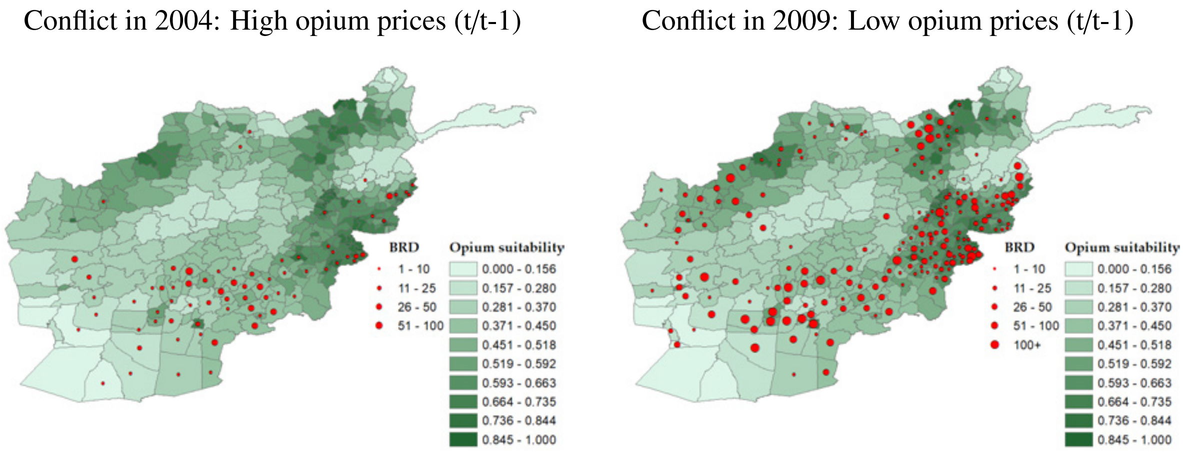

Figure 5: Intensity of conflict in districts with high and low suitability to grow opium

5. Results

A. Main results

We now turn to our main results in Table 2. We report results for different dependent variables, where column 1 uses the continuous measure (log BRD) and columns 2 to 5 define conflict as a binary indicator with increasing thresholds of battle-related deaths. Panel A reports results using the interaction of the local opium price with the suitability to grow opium as the measure for opium profitability. In panel B we replace the local price with the international heroin price (our baseline specification). Panels C and D report results using the complement price index and for robustness the international cocaine price. All regressions include only wheat profitability and province-times-year-fixed effects as control variables. Our results do not rely on the inclusion of control variables as can be seen in Appendix F, where we show that inferences are robust across various specifications.

Turning to the results, the regression coefficients are very much in line with our graphical inspection in Figure 5. Already when using the local opium prices, which introduce endogeneity, we find constantly negative coefficients. When turning to our baseline specification in panel B, the negative effect of the opium profitability on conflict intensity and incidence is more pronounced than in panel A. The coefficients are significant at the 5% to 10% level for the first four specifications. They turn insignificant when considering only conflict events with more than 100 deaths, which is what we expect given the low number of such high scale events and the higher degree of state dependence. A 10% increase in the international heroin price translates into 7% fewer battle-related deaths in perfectly suitable districts. Such a price increase of 10% is only slightly above the average annual price change of 8.8%.

To verify whether this negative effect can be causally interpreted, we now turn to the results using our complement prices. In panels C and D we find that the point estimates using the complement price index and the cocaine price are both negative. The fact that both estimates are negative reassures us that the true effect is also negative. Furthermore, the fact that the estimates using the complement prices are always more negative – and statistically significant at the 1% level in columns 1 to 4 – indicates that the coefficients using the heroin price are (marginally) upward biased and provide an upper bound of the true negative effect. Accordingly, the true effect might be more negative than the coefficients using the heroin price. For all further computations we proceed with this more "conservative" specification.

When turning to wheat, the main legal alternative crop, we observe a positive coefficient in most regressions. Though, contrary to opium price-related shocks, the point estimates of wheat price-related shocks sometimes switch signs and turn negative. Bearing in mind that contrary to opium, wheat is relatively less labor intensive and often also imported from abroad. The fact that most households are net buyers of wheat (Mansfield & Fishstein, 2016), and are thus negatively affected by price increases, could explain the positive coefficients.[20]

Table 2: Main results using normalized drug prices, 2002-2014 period

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: Local Opium Price		
Opium Profitability (t-1)	-0.346***	-0.096***	-0.094***	-0.076**	-0.042**
	(0.107)	(0.033)	(0.032)	(0.029)	(0.018)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.502	0.484	0.454	0.311
			Panel B: International Heroin Price (Baseline)		
Opium Profitability (t-1)	-0.675**	-0.167*	-0.191**	-0.147*	-0.040
	(0.296)	(0.090)	(0.085)	(0.075)	(0.037)
Adjusted R-Squared	0.649	0.501	0.484	0.454	0.310
			Panel C: International Complement Price		
Opium Profitability (t-1)	-0.947***	-0.249***	-0.237***	-0.203***	-0.086**
	(0.308)	(0.094)	(0.086)	(0.076)	(0.041)
Adjusted R-Squared	0.651	0.502	0.484	0.455	0.311
			Panel D: International Cocaine Price		
Opium Profitability (t-1)	-0.461**	-0.116*	-0.124**	-0.102**	-0.026
	(0.199)	(0.059)	(0.057)	(0.051)	(0.025)
Adjusted R-Squared	0.650	0.502	0.484	0.454	0.310

Notes: Linear probability models with with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the normalized drug prices (in logarithms) and the suitability to grow opium. The number of observations is equal across all panels. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

[20] 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 pointing to the high reliance on this crop.

B. Instrumental variable

In the next step, we use IV regressions, where we instrument the endogenous variable (opium revenues) with opium profitability. While the reduced form approach in Table 2 presents the ITT effect, we identify the LATE for compliers in Table 3. For robustness, we introduce a second IV which is the interaction of legal opioid prescriptions with the suitability to grow opium. We discuss this in detail in Section 7. Having an alternative source of exogenous variation enables us to compare the LATE of the different instrumental variables. This step also allows us to quantify the size of the effect in an economically meaningful way. Note that we still prefer the reduced form results presented in Table 2, since the opium cultivation data used to compute revenues are estimates only, and there thus might be non-random measurement error in the data. As in Table 1, we do not include province-times-year-fixed effects as district level opium revenue data are estimates from province level data.

Panel A of Table 3 reports the corresponding Ordinary Least Squares (OLS) results, which point to a conflict-reducing link between revenues and conflict. Panel B turns to the second stage IV results where we instrument opium revenues with opium profitability measured by the interaction of the international heroin price with the suitability to grow opium. We find a negative coefficient for opium revenues in all columns in Panel B, which are significant at the 10% level in columns 1 and 2, and close to conventional significance levels in column 3. The IV results reveal that the opium profitability is a strong instrument as indicated by the Kleibergen-Paap F-statistic, which clearly exceeds the critical threshold of ten, proposed by Staiger & Stock (1997). The estimate reported in column 1 shows that an increase of opium revenues by 10% leads to a decrease in the number of battle-related deaths of about 1.5%.

To preview the findings discussed in Section 7 and in Appendix E, we get very similar results using legal opioid prescriptions as a second IV. This is reassuring regarding the quantitative size of the IV estimates, as well as for the validity of our main identification strategy. We also show IV results for a different timing in Appendix F.

Table 3: 1st and 2nd stage IV results for opium revenue (t-1), 2002-2014 period

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: OLS		
(log) Revenue (t-1)	-0.011**	-0.004***	-0.001	0.001	0.001
	(0.005)	(0.001)	(0.001)	(0.001)	(0.000)
Number of observations	5104	5104	5104	5104	5104
			Panel B: Opium Profitability (t-1) as IV		
(log) Revenue (t-1)	-0.153*	-0.044*	-0.040	-0.018	-0.004
	(0.083)	(0.025)	(0.025)	(0.019)	(0.008)
Number of observations	5104	5104	5104	5104	5104
Kleibergen-Paap F stat.	16.382	16.382	16.382	16.382	16.382

Notes: Linear probability models with year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium profitability is defined as the interaction between the normalized international heroin price (in logarithms) and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Taken together, we find that opium profitability is an important determinant of conflict incidence and intensity in the ITT and IV estimation. Our findings are in line with the results for positive income shocks in Berman & Couttenier (2015) and they support the conclusions in Dube & Vargas (2013) that the labor intensity of a resource compared to alternatives is a decisive factor. However, our results seem to be at odds with the conclusion in Mejia & Restrepo (2015) that an income shock for an illegal resource is related to more conflict. While growing coca has a similar labor intensity to alternative crops like cacao, palm oil, and sugar cane in Colombia (Mejia & Restrepo, 2015), opium cultivation is much more labor-intensive than all alternative crops in Afghanistan. The next section will further elaborate on the role of local monopolies of violence and the absence of group competition as potential explanations for the differences, suggesting that illegality per se is not the decisive factor moderating the effect on conflict. We will also dig deeper into identifying whether the effect is driven by increased opportunity costs of fighting by looking at household level survey data.

6. Mechanisms and transmission channels

A. Opportunity costs at the household level

Whereas the tests above provide an indication of the potential profits in a particular district, an important question remaining is to what degree individual households and farmers actually benefit from a higher opium profitability. To examine this individual dimension, we use different waves of an Afghan nationally-representative household survey, the National Risk and Vulnerability Assessment (NRVA). We construct several indicators of household living standards, in accordance with the literature. This allows us to analyze whether opium profitability translates into better living standards, which would provide evidence for the opportunity cost hypothesis. Figure 6 plots the coefficients for opium profitability for six different regression models with the outcome variable indicated in the legends. We find evidence that dietary diversity and food expenditures increase when households experience a positive opium profitability.[21]

We turn to indicators that are not as volatile as food consumption. In years following high opium prices, households in districts with a higher opium suitability benefit more from the price increases in terms of assets that they hold. The last indicator "Economically Improved" is a self-reported measure, which turns out to be affected in the same direction as the other indicators of living standards. If households are better off economically, there is less need to fight, as the opportunity costs of fighting do indeed increase with a higher opium profitability. The corresponding regression results are presented in Table 36.[22]

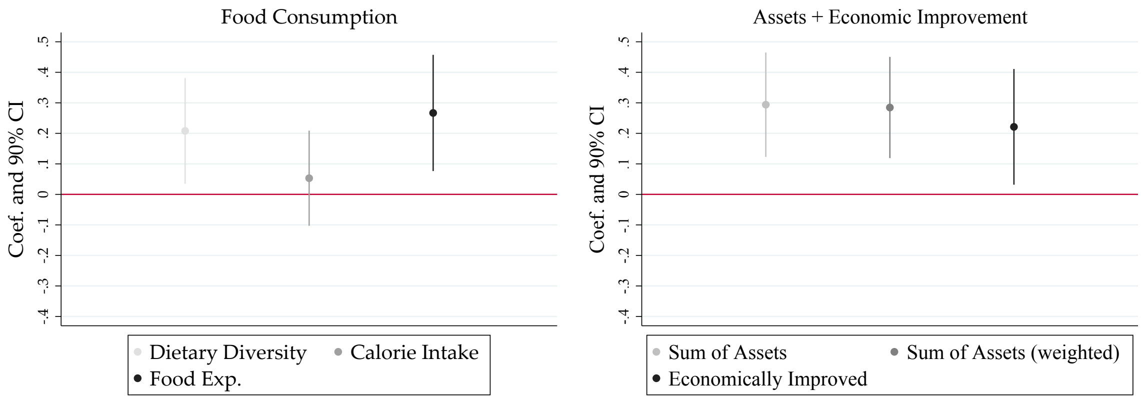

Figure 6: Effect of Opium Profitability (t-1) on standard of living indicators in (t)

B. Opportunity costs and contest effect as share of value added increases

If there was competition among producers (between cartels or rival groups), we would expect that in districts which feature not only raw production but also intermediate steps along the value-chain (like processing, trading or trafficking), rents associated with opium, and thus the gains from fighting, are higher. In line with contest theory, the conflict-decreasing effect of positive income shocks would be relatively smaller in these districts. In contrast, if there was no or little violent group competition, higher profits would increase the opportunity costs of fighting even more in those districts that can extract a larger share of the value added. To be able to test this formally, we require proxies for the potential share of value added per district.

[21] This suggests that quality of food consumption improves. We also construct food expenditure adjusted for spatial price differences using the Paasche or Laspeyres price indexes, since households in different districts face different prices. The results are robust to this choice as can be seen in Table 36.

[22] Results are also robust when accounting for household survey weights as presented in Figure 18.

For this and the two next sections, we georeference data on whether a district contains a heroin or morphine lab, an opium market (major or sub-market), or whether it is crossed by potential drug trafficking routes. Figure 7 shows some of the data. Appendices A and H provide all sources. The information is to a large extent based on UNODC reports. While it is important to keep in mind that there is no reliable information about yearly changes in trafficking routes and opium markets or labs, it is more precise to think of these variables as proxies. Nevertheless, we find it plausible that with little eradication efforts and limited state capacity, most of the locations and trafficking routes would remain relevant throughout the sample period. In particular, we create four indicators measuring the existence or sum of markets and processing labs in a district and whether a district is on a plausible trafficking route that would not need to cross areas of other ethnic groups.

Market access using opium markets   Ethnic groups, military and Taliban territory (1996)

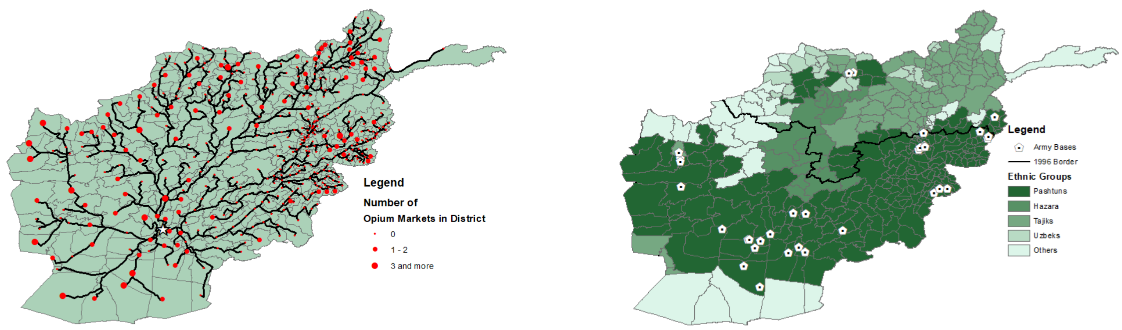

Figure 7: Data used in Mechanisms and Transmission Channels

Notes: Left side: Dots indicate district-specific centroids, black lines are the shortest road connections to the other centroids in the network. Market access is computed for every centroid in the district, leading to individual optimal road connections. Distances are used as weights and multiplied with the importance of the respective network members, e.g. the number of drug markets. Sources: UNODC (2016), Open Street Map and Afghanistan Information Management Service (AIMS).
Right side: Four major ethnic groups in Afghanistan in different shades of green (Source: GREG). White symbols with black dots indicate the location of a foreign military base, for which we could track location, opening and closing date (sources in detail in the Appendix). The area south of the thick black line was controlled by the Taliban prior to 2001 (Dorronsoro, 2005).

As a second group of measures, we proxy for the role and connectivity of a district in the whole drug production and trafficking network using a market access approach adapted from Donaldson & Hornbeck (2016). The assumption is that in addition to capturing a larger share of value added, when a district itself features more markets, being surrounded by other districts with many markets increases the district's probability to extract rents (i) when transporting the raw product to markets, (ii) when processing it in laboratories, and (iii) when trafficking the final product out of the country. This measure takes account of production chains and the interconnectedness of the production network, which should provide a more precise measure of potential profit opportunities and extractable rents related to the opium economy.

We also compute more common market access variables using economic development and population as proxies for the economic importance of districts as consumer markets. As the importance of Afghan consumers for opium-related profits is negligible, a significant interaction with these placebo measures could indicate that our drug market access captures a spurious relationship and not meaningful variation in the share of extractable rents from the opium economy. Market access for a district i is computed as $MA_i = \sum_{j=1}^{N} dist_{i,j}^{-\theta} W_j$. W_j is the importance of district j proxied using either the number of drug markets or mean luminosity. $dist_{i,j}$ are the distances between the district and the other districts and θ is the factor discounting other districts that are further away. We use a factor of 1 as in Donaldson & Hornbeck (2016). To take account of the topography and mountainous terrain in Afghanistan, we compute distances using the two-dimensional road network (Market Access 2D) as well as a three-dimensional road network when adjusting for elevation (Market Access 3D).

Table 4 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. The results in panel A indicate that the link between the 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. All coefficients are negative, and with the exception of the indicator focusing only on laboratories, significant at the 5% or 1% level.

Panel B presents interaction results using the market access measures. In line with our hypothesis, we find a negative interaction effect when using the proxy computed specifically for the drug market, but no relationship when computing the indicator based on luminosity as a proxy for general economic development. Although the measures employed might contain measurement error, the consistent results across all indicators suggest that the conflict-reducing effect is indeed driven by opportunity costs.

Table 4: Opportunity costs proxied by share of value added, 2002-2014 period

	(1)	(2)	(3)	(4)
	Panel A: Opium Markets, Labs, Smuggling			
	Major/Sub Market	**Sum of All Markets**	**Any Lab**	**Ethnic Traff. Route**
Opium Profitability (t-1)	-0.472	-0.480	-0.590*	0.105
	(0.314)	(0.306)	(0.312)	(0.358)
Opium Profitability (t-1)*X	-0.845**	-0.521**	-0.502	-1.734***
	(0.415)	(0.255)	(0.557)	(0.487)
	Panel B: Market Access (Network Approach)			
	Opium Market 2D	**Opium Market 3D**	**Luminosity 2D**	**Luminosity 3D**
Opium Profitability (t-1)	1.489	1.496	-0.902**	-0.899**
	(1.140)	(1.130)	(0.434)	(0.433)
Opium Profitability (t-1)*X	-0.470**	-0.474**	0.035	0.035
	(0.232)	(0.231)	(0.041)	(0.041)

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is the log of battle-related deaths in (t). Opium Profitability is defined as the interaction between the normalized international heroin price (in logarithms) and the suitability to grow opium. Opium Market 2D and 3D range between [2.24,11.23] and [2.21,11.22], so the marginal effects are always negative as well. Regressions include interactions of the opium profitability with a variable X as indicated in in the column heading. For definitions of the variables X please see Appendix A. The number of observations is 5174 in every regression, the adjusted R-squared varies between 0.649 and 0.652. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

There are at least two possible explanations for this result. First, the incentive structure at the group level. 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 Afghan government or Western forces. Fighting or attacks in the same district are harmful for production by impeding works in the field, destroying production sites or drawing attention and thus increasing the likelihood of eradication measures. It is not feasible to precisely compute the respective influence of factors at the household or the group level, but both seem important. 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).

Figure 8 visualizes these results. Panel A indicates that, on average, contest effects relying on violent group competition over lucrative production grounds are lower or of less importance than the opportunity cost effects given higher opium prices. Panel B illustrates the findings of Table 4, panel A, column 1. In Afghanistan, when the share of value added is greater, the change in opportunity cost effects is larger, in absolute terms, relative to the change in contest effects.

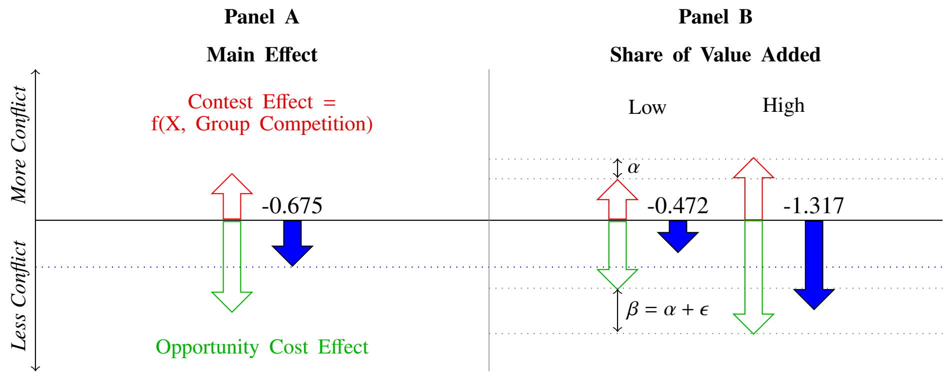

Figure 8: Opportunity cost effects dominate conflict effect (2002-2014)

Notes: Panel A: Opportunity cost effects dominate contest effects on average. Refers to Table 2, panel B, column 1. Panel B: Opportunity costs effects increase more in the share of value added than contest effects. Refers to Table 4, panel A, column 1.

We can further validate the importance of opportunity costs by using an important policy change in the foreign coalition's military strategy. This helps us to verify the importance of the opium economy in providing jobs. More importantly, this sheds some light on the effectiveness of nation-building efforts and foreign military interventions, linking our study to the literature on nation building, as for instance Berman *et al.* (2011a) for Iraq and Dell & Querubin (2018) for Vietnam. These studies often consider a distinction between strategies focusing on the use of firepower and military force, and strategies based on winning "hearts and minds" by investing money and providing services and public goods like security. Obviously, each conflict is different, but nonetheless studying the successes and failures often can provide important lessons for the future and other contexts.

In Afghanistan, the coalition forces initially provided strong financial support to existing warlords and local strongholds from roughly 2001 to 2005 to build a strong anti-Taliban coalition. Rough estimates speak of several "hundred thousands of men" being armed as part of local militias, and more than 60% of provincial governors being "leaders of armed groups and most of the remaining ones had links to the latter" (Giustozzi, 2009, p. 91). Around 2005, the coalition switched their strategy towards a nation-building approach that attempted to pacify and "clean" Afghan politics. In this process, intense pressure on the Afghan government forced political leaders and governors to abandon their connection, as well as their support for militias, causing many trained and armed men to lose their main source of income (Giustozzi, 2009, p. 94 ff.). This change in strategy also coincides with the resurgence of the Taliban.

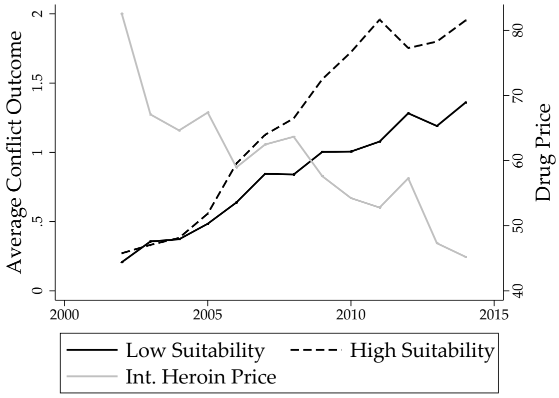

Figure 9: Variation of conflict across high and low suitability districts over time

Notes: To assign a districts to low or high suitability, we use a cut-off of 0.4. See Appendix F Figure 20 for an alternative cut-off of 0.3. Inferences do not depend on this choice.

There is an analogy to the order of events in Iraq, where the de-Baathification process dissolved the Iraqi army and stopped all senior and mid-level party officials from joining the new army and security services. Various experts assess that this "drove many of the suddenly out-of-work Sunni warriors into alliances with a Sunni/anti-American insurgency" that later joined forces like ISIS. They speak of the "pervasive role played by members of Iraq's former Baathist army" and estimate that "25 of ISIS's top 40 leaders once served in the Iraqi military."[23] Figure 9 shows the correlation between prices and conflict in low and high suitability areas. It is clearly visible that, around the approximate timing of this change, the relationship between drug profitability and conflict becomes much stronger in high suitability districts. Dissolving the militias eliminates many reasonably paid jobs, which increases the reliance on income from the opium economy. Hence, the results contrast Berman *et al.* (2011b), who use survey results for two years and find no effect of unemployment. It provides further evidence for the importance of the opportunity cost mechanism in Afghanistan. This also highlights an important trade-off between "cleaning" the state and non-state armed groups as well as fighting the production of an illegal resource at the same time.

[23] See http://time.com/3900753/isis-iraq-syria-army-united-states-military/, https://www.reuters.com/investigates/special-report/mideast-crisis-iraq-islamicstate/, https://www.independent.co.uk/news/world/middle-east/how-saddam-husseins-former-military-officers-and-spies-are-controlling-isis-10156610.html and http://nationalpost.com/news/world/how-the-catastrophic-american-decision-to-disband-saddams-military-helped-fuel-the-rise-of-isil, accessed June 14, 2018. A detailed report about "Lessons of De-Baathification in Iraq" is by Sissons and Al-Saiedi, available at https://www.ictj.org/publication/bitter-legacy-lessons-de-baathification-iraq, accessed June 14, 2018.

C. Government control and enforcement

Drug producing countries often feature weak governments which control limited areas of the country. Differences in the degree of government influence, for instance when comparing Afghanistan to Colombia, could help to explain the heterogeneity in results (Angrist & Kugler, 2008; Mejia & Restrepo, 2015). Less government influence and fewer areas under the government's monopoly of violence should correlate with a lower ability (and/or willingness) to enforce the laws regarding illegal crops.

Drug producers often seem to have little to fear from the Afghan government and Western forces. Researchers describing their fieldwork in Badakhshan "observed neither restrictions to poppy farmers nor any repercussions or a need to hide the fields from outsiders," and in areas supposedly controlled by the government "officials at all levels are benefiting from the proceeds from drug trafficking" (Kreutzmann, 2007, p. 616). Despite the official government claims that "poppy cultivation only takes place in areas controlled by the Taliban," a US counter-narcotics official in Afghanistan reports that "(president) Karzai had Taliban enemies who profited from drugs, but he had even more supporters who did."[24] This suggests that, in the average district, the government has little power or interest to enforce the *de jure* laws against opium production and trafficking.

We assume that government control and enforcement lead to a higher risk of opium seizure, and hence a lower overall expected value of higher prices for households (even though enforcement might have little effect on cultivation, see Ibanez & Carlsson, 2010). We would also expect that higher prices make it more likely that farmers turn to the Taliban for protection against those measures, which could in turn prompt counter-attacks by the government. Furthermore, a lower opportunity costs effect along with a higher contest effect would results in an overall smaller negative, or even a positive, effect of higher opium prices when government control is high. Table 5, panel A shows the corresponding results. We interact *opium profitability* with proxies for influence of the central Afghan government or the Western forces backing it. We employ a dummy variable for identifiable foreign military bases in a district, and approximations for government influence using several measures for the distance to Kabul. None of the interaction coefficients in panel A turns out to be significant. This supports that the Afghan government and Western forces, on average, abstain from becoming too involved in a drug war.

Still, this does not rule out that the government has no influence at all, or does not engage in any anti-drug measures; there could also be a non-linear relationship. In panel B, we dig deeper into the influence of the government by constructing binary indicators for whether a district is within a specific proximity to Kabul or other main cities. Michalopoulos & Papaioannou (2014) also use distance as a measure of government influence, and Lind *et al.* (2014) use it as an indicator for low law enforcement and weak

[24] See, http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204, accessed June 14, 2018. The same source also 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.

state institutions. The results suggests that the influence of the Afghan government seems indeed to be confined to districts within a limited radius around Kabul. The interactions remain significantly positive for a radius of about 75 km or two hours driving distance. The net effect of higher opium prices turns negative around a distance of 100 kms. This differences is confined, however, to Kabul as being close to any of the five other main cities makes no difference.[25]

Figure 19 in Appendix E also validates that, in contrast to the results in Section 6A for the average Afghan household, the effect of a higher opium profitability on households is more negative and exhibits a much higher variance within the area surrounding Kabul. This links our paper to the results in Mejia & Restrepo (2015). In Colombia, there are also areas with limited government enforcement, but overall government influence is much stronger, which diminishes a conflict-reducing opportunity cost effect. It supports the importance of the legal status (Chimeli & Soares, 2017), but emphasizes *de facto* versus *de jure* illegality. The next section shows that, in addition to those differences, the degree of group competition over controlling valuable resources is another important explanatory factor.

Table 5: Government control and rule enforcement, 2002-2014 period

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Potential control of government and Western forces					
	Any Military	**Distance to Kabul**			**Travel Time to Kabul**	
	Base	**Linear**	**Road 2D**	**Road 3D**	**Road 2D**	**Road 3D**
Opium Profitability (t-1)	-0.6669**	-0.2858	-0.5448	-0.5484	-0.6578	-0.6589
	(0.2977)	(0.4923)	(0.5009)	(0.5020)	(0.4383)	(0.4385)
Opium Profitability (t-1)*X	-0.1872	-0.0012	-0.0002	-0.0002	0.0037	0.0038
	(0.5553)	(0.0013)	(0.0012)	(0.0011)	(0.0432)	(0.0430)
	Panel B: Area of control					
	Linear Distance			**Travel Time 3D**		
	1 if < 50	**1 if < 75**	**1 if < 100**	**1 if < 1**	**1 if < 2**	**1 if < 3**
	Proximity to Kabul					
Opium Profitability (t-1)	-0.732**	-0.826***	-0.782**	-0.831***	-0.893***	-0.826**
	(0.304)	(0.308)	(0.313)	(0.308)	(0.314)	(0.325)
Opium Profitability (t-1)*X	1.621***	1.693**	0.712	2.510***	1.685**	0.588
	(0.606)	(0.800)	(0.667)	(0.892)	(0.671)	(0.508)
	Proximity to other main cities					
Opium Profitability (t-1)	-0.706**	-0.685**	-0.535	-0.698**	-0.616**	-0.612*
	(0.312)	(0.327)	(0.345)	(0.301)	(0.309)	(0.330)
Opium Profitability (t-1)*X	0.412	-0.014	-0.463	0.731	-0.389	-0.207
	(0.639)	(0.527)	(0.456)	(1.080)	(0.579)	(0.502)

Notes: Linear probability model with province-times-year- and district-fixed effects. The dependent variable is the log of battle-related deaths in (t). Opium Profitability is defined as the interaction between the normalized international heroin price (in logarithms) and the suitability to grow opium. Regressions include interactions of the opium profitability with a variable X as indicated in in the column heading. Detailed definitions of the X variables are in Appendix A. The other main cities are Kandahar, Kunduz, Jalalabad, Hirat, and Mazari Sharif (next five largest cities). The number of observations is 5174 in every regression with the exception of column 6 in panel A, the adjusted R-squared varies between 0.649-0.653 (column 6, panel A it is 0.437). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

[25] More alternative employment opportunities in and around Kabul might contribute to that.

D. Contest effect conditional on intergroup competition

Qualitative evidence as well as reports and newspaper articles suggest that, in the average Afghan district, contest effects related to violent competition between groups about controlling lucrative territories are limited, and our results show that they are dominated by the opportunity cost effects. In Afghanistan after 2001, drug production as well as the trafficking processes were largely controlled by one of two alliances: the Taliban and local elites cooperating with the Taliban, or the government along with pro-government groups. Two scenarios are plausible. First, Taliban and pro-government groups fight for control, but only the Taliban engage in drug production. Second, both engage in production and extract rents from it, and both are interested in controlling lucrative production grounds. Further away from Kabul, the second scenario seems to be more realistic.

We hypothesize that the degree of violent competition between groups is decisive in moderating the relationship between resource profitability and instability. We want to test whether a district in which one group is more likely to have a monopoly of violence exhibit a larger conflict-reducing effect. This is complicated by the absence of reliable time-varying data about Taliban-dominated districts. Nevertheless, using a variable estimating contemporaneous group control would be endogenous, and thus problematic to use as part of an interaction term. It is preferable to employ time-invariant and pre-determined variation prior to the start of our sample period.

In order to proxy for Taliban control, we gather information on whether Pashtuns, one of Afghanistan's major ethnic groups, are present in a district (using data from Weidmann *et al.*, 2010), and whether the district has been controlled by the Taliban in 1996 (Dorronsoro, 2005). Trebbi & Weese (2016, p. 5) argue that support for the Taliban as the main insurgent group is best explained by ethnic boundaries. The Taliban are an initially Pashtun group, even though they also feature non-Pashtun members. For areas under Taliban control before 1996, we expect that due to the common past, the Taliban will, all else equal, find it easier to expand their power again in those areas. We use a variety of different sources for these variables, ranging from maps provided by experts at the UN, data from the American military, satellite data and newspaper reports. Figure 7 visualizes the data. Appendix H documents the steps involved in the construction and all sources in detail.

In uncontested districts, the Taliban also have higher incentives to maintain peace to avoid distorting the production process. These incentives rise with the profitability of production. A local farmer describes that in a prominent opium growing area "the Taliban have a court there to resolve people's problems," and despite their presence, "the security situation is good for the people living there."[26] Existing ethnic institutions, in particular in Pashtun areas, might help in maintaining plausibly existing conflicts at the small-scale level between individual farmers and sharecroppers from escalating. Other

[26] See http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204, accessed June 14, 2018.

sources verify the link between the Taliban and the drug production process, sometimes even providing seeds, tools, and fertilizer. A local Taliban leader is described as "just one of dozens of senior Taliban leaders who are so enmeshed in the drug trade."[27] In contrast to other countries, there is no strong competing producer or trafficker group. It is rather the case that "the drug cartel is the Taliban."[28] Trebbi & Weese (2016, p. 5) support that "insurgent activity in Afghanistan is best represented by a single organized group." This suggests that the Taliban have an active interest in an undisturbed drug production process, which should be the more relevant the higher the likelihood that they control a district.

Table 6: Degree of group competition - Taliban vs. government-affiliated groups and between ethnic groups, 2002-2014 period

	(1)	(2)	(3)	(4)	(5)	(6)
	Taliban dominance			**Ethnic Groups**		**All groups**
	Pashtun presence	**Former Territory All**	**Former Territory w/o North**	**Mixed (binary)**	**Number of groups**	**Pre-2002**
			Panel A: All districts			
Opium Profitability (t-1)	0.312	-0.207	-0.221	-0.763**	-0.977*	0.182
	(0.365)	(0.372)	(0.365)	(0.370)	(0.568)	(0.645)
Opium Profitability (t-1)*X	-1.723***	-1.013**	-1.063**	0.130	0.114	
	(0.412)	(0.477)	(0.491)	(0.421)	(0.280)	
			Panel B: Excluding districts within 50 km of Kabul			
Opium Profitability (t-1)	0.362	-0.199	-0.200	-0.761*	-1.004*	-0.079
	(0.372)	(0.378)	(0.371)	(0.392)	(0.592)	(0.640)
Opium Profitability (t-1)*X	-1.937***	-1.202**	-1.293**	0.009	0.087	
	(0.424)	(0.490)	(0.505)	(0.454)	(0.290)	

Notes: Linear probability model with province-times-year- and district-fixed effects. The dependent variable is the log of battle-related deaths in (t). Opium Profitability is defined as the interaction between the normalized international heroin price (in logarithms) and the suitability to grow opium. Regressions include interactions of the opium profitability with a variable X as indicated in in the column heading. For definitions of the variables X please see Appendix A. Number of observations: 5174 in columns 1-5, adjusted R-squared varies between 0.649 and 0.653 (column 6: 0.437). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 6, panel A shows that the conflict-reducing effect is indeed stronger in districts that are more likely to be under Taliban control (columns 1-3). Columns 4 and 5 show that the relationship between opium and conflict is not influenced by whether a district is ethnically mixed or by the number of ethnic groups. Column 6 highlights another interesting feature of the Afghan conflict. Although limited in terms of years, evidence from the five years before 2001 points to no significant conflict-reducing effect of higher prices. The years before 2001 were different in many respects. At that time different groups and warlords were still competing about territorial control of lucrative production grounds. Besides, this was the time when the Taliban ruled Afghanistan, and in July 2000 even imposed a ban on opium

[27] See https://www.nytimes.com/2017/10/29/world/asia/opium-heroin-afghanistan-taliban.html and https://thediplomat.com/2016/10/how-opium-fuels-the-talibans-war-machine-in-afghanistan/, accessed June 14, 2018.

[28] See, https://qz.com/859268/americas-failed-war-on-drugs-in-afghanistan-is-threatening-to-doom-its-war-on-terror-as-well/, accessed June 14, 2018.

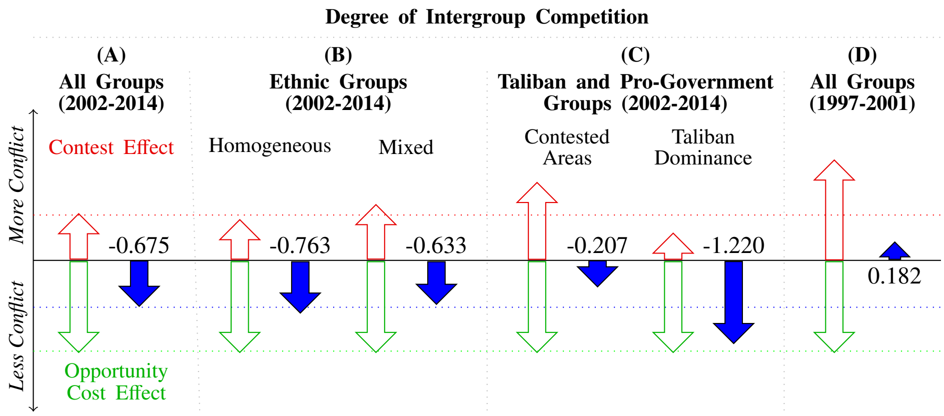

Figure 10: Degree of intergroup competition

production.[29] Panel B regressions correspond to panel A, but omits the districts within a radius of 50 km around Kabul where government influence is stronger.

The regressions show that (i.) the degree of group competition over an area matters in addition to legal status and (ii.), as we would expect, the differences between more likely Taliban dominated districts and the rest is even more pronounced when excluding districts close to Kabul. Figure 10 summarizes our insights from Table 6 graphically. Ethnic group competition matters little after 2001, but whether a district was more likely dominated by the Taliban determines whether the net effect is negative.

7. Further results and sensitivity analysis

This section explores further results and the sensitivity of our main findings. The most important tests are explained here with tables and figures reported in Appendix E. All other sensitivity tests along with corresponding tables and figures are presented in Appendix F.

Aggregate effects: Our results do not rule out that local Taliban forces use part of the revenue extracted from the opium business 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 enable countrywide operations. Figure 11 does not indicate such a mechanism at the large scale. On average, an increase in opium revenue correlates with a decrease in casualties. Table 13 shows a regression aggregating all our data at the provincial level and again find a negative coefficient for opium profitability. We would expect the opposite pattern if higher revenues in one district were causing more conflict in neighboring districts in other provinces.

[29] In Appendix F we reconstruct measures on ethnic groups and in particular on the presence of Pashtuns by relying on the NRVA 2003 household survey. While the 2003 wave is likely not to be nationally representative, it serves as a suitable proxy to using the GREG dataset. Results are robust to relying on household level information of native languages (see, Table 37).

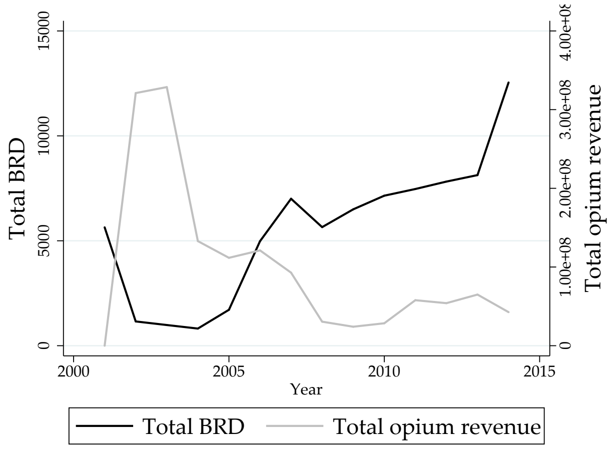

Figure 11: Variation in total opium revenue and total battle-related deaths

Timing of shocks: We consider different lag structures by including opium profitability in periods $t+1$, t, and $t-1$ at the same time in Table 14, with $t+1$ testing for pre-trends. Table 14 shows that opium profitability in t and $t-1$ is related to a conflict-reducing effect, while the lead effect of international opium prices in *t+1* interacted with the suitability to grow opium has no significant effect on conflict. This is reassuring and supports the causal order and mechanism that we hypothesize. Table 15 shows that including the contemporaneous and lagged variables individually yields very similar coefficients, with slightly larger coefficients for our preferred timing ($t-1$).

Types of fighting: Table 8 shows that almost all events reported by UCDP are conflicts between the Taliban and the Afghan government, i.e., two-sided violence involving the state. Table 16 compares our baseline results to a more distinct analysis distinguishing actors and deaths per conflict side. Column 2 shows that casualties caused by Taliban violence against civilians – about 4% of all casualties – exert a smaller and statistically insignificant negative coefficient. For the majority of violent events, which are conflicts involving Taliban and pro-government groups, there is a clear negative and significant effect on total casualties (column 3) and casualties individually for each side (column 4 and 5). Very importantly, we compare our results to using conflict data based on military reports. Table 17 reports the reduced form results when using conflict indicators from the SIGACTS dataset. For the three different types of events, direct fire, indirect fire, and IED (both normal and in logs), we find the same pattern as for the different UCDP GED conflict measures that we apply in our baseline regressions.

Outcome variable (conflict onset and ending): We consider heterogeneous effects of opium profitability on onset and ending of conflict events. Bluhm *et al.* (2016) point to the importance of differentiating between the probability of switching from one conflict state to another as, for instance, from peace to conflict versus from conflict to peace.[30] Thus, we also measure the effects for conflict incidence

[30] Berman & Couttenier (2015), for instance, argue that conflict persistence is very low at their level of analysis (a cell equivalent to 55 times 55 km 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 10.

(panel A), onset (panel B), and ending (panel C) in separate models. Results are presented in Table 18. Panel A verifies our main finding with a linear probability model by showing similar results when using conditional logit. In panel B, we find that opium profitability consistently reduces the likelihood of a conflict onset for conflict measured up to a threshold of 25 battle-related deaths. For conflict ending, we only find a significantly positive effect for smaller conflicts. These result indicate that a positive income shock and more opium cultivation raise the likelihood that an ongoing small conflict ends, and reduces the likelihood that conflicts break out.

Alternative instrument (legal opioid prescriptions): Legal opioids are useful as they are mostly driven by US-specific factors clearly unrelated to Afghanistan (Dart *et al.*, 2015). They can shift heroin demand upwards by causing addictions, or downwards by substituting for the illegal drug. The negative coefficient in the first stage reported in Table 20 shows that overall more legal prescriptions are linked to a lower opium price. The results using opium profitability along or in tandem with time-varying legal opioid prescriptions (interacted with opium suitability) in Table 19 also show a negative effect of opium revenues on conflict that is comparable in size to our main specification.

Sensitivity analysis: Appendix F discusses all other tests in detail. We show that our results are robust to (i.) modifications of the treatment variable, like using the unweighted suitabilities and de-trended price data, (ii.) modifications of the empirical model, as including different sets of fixed effects, (iii.) replacing revenues with cultivation, (iv.) adjusting the timing in the IV analyses and instrumenting opium profitability rather than revenues, (v.) different choices on how to cluster standard errors, (vi.) leaving out wheat suitability, adding a baseline set of pre-determined covariates such as luminosity and population as well as an exogenous measure of droughts, the VHI, and allowing for time-varying effects of time-invariant district-specific control variables, (vii.) and to dropping potential outliers like border districts, the two southern provinces Kandahar and Helmand, and to leave out each year and province one at a time. Finally, to rule out problems caused by non-linear trends in the time series (see Christian & Barrett, 2017), we randomize the time-varying variable (international heroin price) across years, as well as the district-specific suitability across districts, and find no evidence for problematic trends in these placebo tests.

8. Conclusion

This paper provides new evidence on the mechanisms linking resource-related income shocks to conflict, augmenting an important literature (e.g., Berman & Couttenier, 2015; Brückner & Ciccone, 2010; Morelli & Rohner, 2015; Berman *et al.*, 2017). For this purpose, we focus on Afghanistan, which is an exemplary case of a country with a weak labor market, limited state capacity, difficulties to form stable governing coalitions between existing groups, and ongoing conflict. Through the data we collected and the strategies we employ, we hope to provide new insights that allow for a better understanding of the conflict in Afghanistan as well as of other cases.

Overall our reduced form results show that, on average, a 10% rise in international heroin prices decreases the number of battle-related deaths by about 7% in districts with the highest possible suitability to grow opium. These results are robust to a battery of sensitivity tests, including IV estimations that exploit legal opioid prescriptions in the United States. All analyses indicate that our baseline specification using heroin prices is – if one is worried about potential biases – most likely an upper bound of the true negative effect.

Our results add to the literature in several ways. First, we verify the insight from Dube & Vargas (2013) and Dal Bó & Dal Bó (2011) on the role of the commodity's relative labor intensity and show that opium, which is a highly labor intensive crop, indeed matters for household living standards. Second, our results augment the scarce literature on the effect of illegal resource-shocks (e.g., Angrist & Kugler, 2008; Chimeli & Soares, 2017; Mejia & Restrepo, 2015), and document that the degree to which the *de jure* illegality of a crop influences conflict decisively depends on *de facto* government control and enforcement. Third, we add to the studies on countries with ongoing conflicts like Iraq (Berman *et al.*, 2011a; Condra & Shapiro, 2012) or Colombia (Wright, 2018). Finally, we highlight that the extent to which contest effects link higher prices to more conflict depends not only on the number of groups, but also on the degree to which they are competing over resources.

While we do not claim that our findings can explain the conflict in Afghanistan in all its complexity, they augment existing insights (e.g., Bove & Elia, 2013; Child, 2018; Lyall *et al.*, 2013; Lind *et al.*, 2014; Condra *et al.*, 2018). Although we make no strong claims beyond our observation period, the findings are in line with the spread of conflict in Afghanistan in the last years, which featured falling prices and lower opium profitability. We use results at the province level and country level to verify that higher opium revenues do not, on average, seem to spill-over and create conflict in other parts of Afghanistan.

At the same time, it is, of course, also too simplistic and naive to conclude that opium production should not be considered a potential problem. Instead, we aim to highlight the importance of understanding the underlying trade-offs in order to derive sound policy measures. In a context with weak labor markets and few outside opportunities, depriving farmers of their main source of income by enforcing rules through eradication measures has to be weighted against the impact on households and the risk of fueling conflict. Our results show that households are, on average, indeed negatively affected by lower opium prices. Most available evidence suggests that strict enforcement in production countries has little to no effect on cultivation (Clemens, 2008; Ibanez & Carlsson, 2010; Mejía *et al.*, 2015), as long as drug demand from consumer countries remains high.

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Appendix

A. Definition and sources of the variables

Any Lab: We count all types of heroin laboratories. This variable takes on the value 1 if there is at least one lab in a district *i*, and 0 otherwise. As described in Appendix H, we georeference maps from UNODC reports regarding drug markets, labs, and trafficking routes, assign coordinates to the labs, and later compute district averages. Source: UNODC (2006/07, 2014, 2016).

Any Military Base: This variable takes on the value 1 if there is at least one open military base in a district *i* in year *t*, and 0 otherwise. The approach is described in detail in Appendix H. Note that we are most likely not capturing all existing locations, as we did not receive the exact information about opening and closing for all military bases. Opening and closing dates were coded with the available information; if there was no information about shutting down a base we assume it is still active. Source: For the more well-known bases, we use Wikipedia's GeoHack program; for the less well-documented bases, we use Wikimapia and Google Maps satellite data.

Battle-Related Deaths (BRD): This variable measures the best (most likely) estimate of total fatalities resulting from an event, with an event being defined as "[an] incident where armed force was [used] 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 the Uppsala Conflict Data Program Georeferenced Event Dataset (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 one 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). To capture the lowest level of conflict in a binary measure, we classify a district-year observation with at least five BRD *small conflict*. 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*. Since UCDP GED provides information on the parties and the type of violence we also construct specific outcome measures according to those categories. Besides different measures of incidence, we also construct measures on onset and ending. 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 in the current year ($Conflict_{i,t} = 0 | Conflict_{i,t-1} = 1$). 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. Source: UCDP GED (Sundberg & Melander, 2013; Croicu & Sundberg, 2015).

Calorie Intake: We use a questionnaire in which women self report amounts, frequencies, and sources of a large set of food items, to construct measures on calorie intake and food insecurity. We multiply amounts consumed with kcal values for that food item to get total household calorie intake. Total household daily calorie intake is divided by the number of members that were resident and ate at least dinner regularly in the household during the last seven days to get per capita measures. Source: For kcal values, we use the CSO & The World Bank (2011). The questionnaire responses are from the NRVA women's questionnaire (CSO, 2005, 2007/08, 2011/12).

Consumer Price Index (CPI): Source: For the Euro area (19 countries), we draw data from the OECD (2016); for the remaining countries (2010 = 100), we use the World Bank (2016).

Dietary Diversity: This variable varies between 0 and 8, with eight indicating a high food diversity. According to Wiesmann *et al.* (2009, p. 5) "Dietary diversity is defined as the number of different foods or food groups eaten over a reference time period, which in my case is one week, not regarding the frequency of consumption." We classify the different food items from the survey into eight food groups as explained in Wiesmann *et al.* (2009). These groups are staples, pulses, vegetables, fruit, meat/fish, milk/dairy, sugar, and oil/fat. Source: NRVA (CSO, 2005,2007/08,2011/12).

Distance/Proximity/Travel Time to Kabul (capital) and Kandahar, Kunduz, Jalalabad, Hirat, and Mazari Sharif (next five largest cities): For the proximity to Kabul and other main cities we define binary indicators for the distance being smaller than 75 km (1 if < 75) or smaller than 100 km (1 if < 100). In analogy to these categories, we construct indicators for the travel time to Kabul or one of the other main cities falling below 2 or 3 h. We use the shapefiles provided by the Afghan statistical authority on the 398 Afghan districts. Note that the shapefiles available at www.gadm.org do not reflect the current status of administrative division in Afghanistan, and instead we use the one from Empirical Studies of Conflict (ESOC) Princeton (https://esoc.princeton.edu/files/administrative-boundaries-398-districts). To compute the distances, we first create the centroid of each district polygon. To compute road distances we combined road shapefiles from the official Afghan authorities with street maps from open street map, which were improved by voluntary contributors to close gaps in the official maps. 3D-distances were computed using elevation data from the US Geological Survey (https://lta.cr.usgs.gov/GMTED2010, accessed July 9, 2018). We add the elevation information to the shapefile containing the roads, and then compute and save three-dimensional distances. We then use the network analyst in ArcGIS to set up a network between all district centroids, clipping centroids that do not overlap with a street in that district that is closest with regard to the as-the-bird-flies distance. Then, we compute the most efficient routes using road distances in two- and three-dimensions. The distances are saved in a matrix and exported in a table that is further processed in Stata. For the variable "distance to other main cities" we use the minimum distance to any of the five cities. For travel time we use the distinction of roads in three classes (motorways, rural, urban), and assign commonly used values for average traveling speed for that road type based on three sources. Sources: The first source is UNESCAP (http://www.unescap.org/sites/default/files/2.4.Afghanistan.pdf, p. 14) which assumes that the speed on motorways is 90 km/h and on urban roads 50 km/h. The second source is IRU (https://www.iru.org/apps/infocentre-item-action?id=560&lang=en) which states no limits except for urban areas with 50 km/h. The 3rd source is WHO (http://apps.who.int/gho/data/view.main.51421) reporting 90 km/h for rural. We choose the following average traveling speeds, assuming that no strictly enforced limits and little traffic on motorways (120 km/h), and accounting for some (90km/h-10km/h) and moderate traffic in cities (50-20 km/h). Thus our main choice is the following. Motorways: 120 km/h, rural: 80 km/h, urban: 30 km/h. These choices are not perfect, but we verify that our results hold with other variations as well.

Drug Prices (International): Variables are normalized so that prices vary between 0 and 1. We use data on average prices per gram across all available countries in Europe for the following drugs: amphetamines, cocaine, ecstasy, heroin (brown). To construct the average price of alternative drugs we use a mean of the three stimulant drugs amphetamines, cocaine, and ecstasy. For the analysis we convert all drug prices into constant 2010 euros per gram. We then normalize the prices by using a linear min-max function such that all prices vary between 0 and 1. Source: European Monitoring Center for Drugs and Drug Addiction (EMCDDA).

Economically Improved: This variable refers to the question "How do you compare the overall economic situation of the household with 1 year ago?" A value of 1 indicates much worse, 2 slightly worse, 3 same, 4 slightly better, and 5 much better. This is a self-reported measure. Source: NRVA (CSO, 2005, 2007/08, 2011/12).

Ethnic Groups: We record the majority and minority ethnic groups on a district-level. We have used the GIS-coordinates of all ethnic groups. Source: 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 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.

Ethnically Mixed: We construct two measures of whether a district is ethnically mixed. The first variable is the number of ethnic groups; the second is a binary indicator, which takes a value of 1 if the number of ethnic groups is larger than 1, and 0 otherwise. For more extensive methodology, see Ethnic Groups.

Ethnic Trafficking Route: The variable takes on the value of 1 if there is a potential trafficking route leading from a district to at least one unofficial border crossing point without crossing the ethnic homeland of another group. The underlying intuition is that trafficking is cheaper and significantly easier to conduct, and the accruing additional profits are higher, if there is no need to cross the area of other ethnic groups to transport over the border. Source: For data on unofficial border crossings, we used the UNODC; for information about the homelands of ethnic groups, we used the (GREG) dataset (Weidmann *et al.*, 2010).

Food Expenditures (Paasche/Laspeyres): Precise food amounts were merged with local prices to estimate household food expenditure. We show three food expenditure measures, which are all measured in constant 2011 prices, i.e., prices of the 2011/12 survey wave. Only food items that appear in all three waves are included to build the measure. The first measure “Food Exp. 2011 Prices” does not account for spatial price differences. “Food Exp. 2011 Prices, Paasche” and “Food Exp. 2011 Prices, Laspeyres” adjust for spatial price differences, since households in different districts face different prices. Missing values of district prices are replaced by the province median, which in case of missing values has been replaced by the national median price. For close to all reported food items, prices have been given in the district questionnaire. Prices vary at the district level.Following the literature, we include food items from all possible sources, i.e., purchased food or food in form of gifts etc. Information on food and drinks consumed outside the house (from the male survey section) are also included in the total food expenditure measures (adjusted for inflation and regional price differences depending on the measure). Expenditures are measured in per capita terms by dividing the total household food expenditure with the number of households (resident and ate at least dinner regularly in the household during the last seven days). We use the section on food consumption from the NRVA women’s questionnaire as this section offers precise amounts per food item. Source: NRVA women’s and male’s questionnaire and district questionnaire (CSO, 2005, 2007/08, 2011/12).

Inflation, GDP Deflator: We use a GDP deflator for the United States with 2010 as the base year. Source: World Bank (2016).

Insecurity/Violence Shock: The share of sampled households per district that have experienced a shock due to insecurity/violence. At the household level, the variable takes on the value of 1 if the household has experienced an insecurity/violence shock. Source: NRVA survey (CSO, 2005, 2007/08, 2011/12).

Legal Opioids: Since most single publications do not cover our whole sample period, we want to cross-verify the numbers using a variety of sources. Source: A main source is the US CDC Public Health surveillance report 2017 (https://stacks.cdc.gov/view/cdc/47832). Other important sources were Manchikanti *et al.* (2012); Kenan & Mack (2012); Dart *et al.* (2015).

Local Opium Price: We utilize reports of (monthly) province level dry opium prices by farmers and by traders as well as country-wide yearly data on fresh opium farm-gate prices 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 use the country-wide yearly data on fresh opium farm-gate prices in Afghanistan interacted with the suitability as one proxy for opium profitability in our regressions in Table 2, panel A. Source: Annual Afghanistan Opium Price Monitoring reports (UNODC).

Luminosity: We use this variable as a proxy for GDP and development (Henderson *et al.*, 2012). The yearly satellite data are cloud-free composites made using all the available 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 and glare are excluded based on the solar elevation angle, Moonlit data 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. Source: Version 4 DMSP-OLS nighttime lights time series, National Oceanic and Atmospheric Administration-National Geophysical Data Center (NOAA/NGDC, https://www.ngdc.noaa.gov, 2013). We take the logarithm.

Markets (Major/Sub) and Sum of all Markets: The first variable takes on the value 1 if there is at least one major or sub-market in district i, and 0 otherwise. The second variables counts the sum of all opium markets in a district (both sub and major). Source: UNODC reports on drug markets, labs, and trafficking routes (e.g., UNODC 2006/07, 2014, 2016).

Market Access: Market access for a district i is computed as $MA_i = \sum_{j=1}^{N} dist_{i,j}^{-\theta} W_j$. W_j is the importance of district j proxied using either the number of opium markets or mean luminosity (or population). $dist_{i,j}$ are the distances between the district and the other districts and θ is the factor discounting other districts that are further way. We use a factor of 1, as in Donaldson & Hornbeck (2016). To take account of the topography and mountainous terrain in Afghanistan, we compute distances using the two-dimensional road network (Market Access 2D) as well as a three-dimensional road network when adjusting for elevation (Market Access 3D).

Mixed/Taliban Territory 1996: The binary indicator on Taliban Territory that we create takes on the value 1 if a district belongs to the territory that was occupied or under the control of the Taliban in 1996, and 0 otherwise. A second indicator (Taliban Territory 1996 - No North) takes on a value of 1 if the district is exclusively occupied by the Taliban and is characterized by no presence of the Northern Alliance. We use an existing map which indicates the territory of the Taliban in 1996 as well as the territory of other major groups of the Northern Alliance (Dschunbisch-o Islami, Dschamiat-i Islami, Hizb-i Wahdat). 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. We classify a district as a Mixed Territory if it is part of the Taliban 1996 territory and part of the territory of any of the three groups belonging to the Nothern Alliance. Source: The map is from Dorronsoro (2005), and more details can be found in Giustozzi (2009).

Opium Cultivation and Revenues: This variable measures 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 and for revenues. 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 constant 2010 EU/kg. Source: Annual Opium Poppy Survey (UNDCP, 2000) and Afghanistan Opium Survey (UNODC, 2001-2014).

Opium Suitability: This is an index with possible values ranging between 0 and 1 which acts as a proxy for potential of opium production based on exogenous underlying information about land cover, water availability, climatic suitability, and soil suitability. 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 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 and described in the World Drug Report (2011) for Myanmar. The data and the index itself was modeled on a $1km^2$ 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.

We weight the opium and wheat suitabilities with the (lagged) population distribution within the districts. This is helpful as, for instance, the south features large desert areas and at the same time concentrated areas with dense population, and accounting for the suitability in uninhabited desert areas might be misleading (although our results are not significantly affected by this choice).

Source: The index 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.*, 2017).

Pashtun: Our binary indicator takes on the value 1 if Pashtuns are present to any degree in a district i, regardless of whether they were the majority group, and 0 otherwise. The GREG polygons can contain more than one ethnic group. For more extensive methodology, see Ethnic Groups.

Population: This is a minimally-modeled gridded population data 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 then take the logarithm. Source: The Center for International Earth Science Information Network - CIESIN - Columbia University. 2016. Gridded Population of the World, Version 4 (GPWv4): Administrative Unit Center Points with Population Estimates. Palisades, NY: NASA Socioeconomic Data and Applications Center (SEDAC) http://dx.doi.org/10.7927/H4F47M2C, accessed October 5, 2017.

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

Sigacts Conflict Data: These variables measure SIGACTS (Significant Activities) in a given district based on military reports; SIGACTS are defined as direct fire (DF), indirect fire (IDF), and improvised explosive device (IED) events. DF attacks can be defined as close combat events that are characterized by the use of weapons like small arms or rocket-propelled grenades. IDF attacks, including mortars and rockets, can be heard within a large area, but are less precise when being launched from great distances. While DF and IDF involve fighters, IEDs involve less risk for the perpetrators. IEDs can be placed around roads and directed against moving targets, for instance pro-government convoys. Source: We use data from Shaver & Wright (2016).

Southern Provinces: Dummy variable which we assign a value of 1 for districts located in one of the two provinces Kandahar and Hilmand, and 0 otherwise.

Sum of Assets (weighted): The number of assets the households possess over a set of assets that is constant over 3 survey waves. This set consists of Radio/Tape, Refrigerator, TV, VCR/DVD, Sewing Machine, Thuraya (any phone), Bicycle, Motorcycle, Tractor/Thresher, and Car. Sum of Assets weighted is the sum of asset weighted by the proportion of households not possessing the specific item. Source: NRVA (CSO, 2005, 2007/08, 2011/12).

Vegetation Health Index (VHI): We compute an index that captures inter-annual variations in drought conditions, 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 of the National Oceanic and Atmospheric Administration (NOAA) and Meteorological Operational Satellite (METOP) satellites. It is superior to simply using precipitation data, which do not directly measure drought conditions, require assumptions about the linearity of the effect and, in particular in Afghanistan, have severe limitations in terms of quality and resolution. The index is based on earth observation data and is available on a monthly basis with a resolution of 1 km^2. As cultivation and harvest times differ within Afghanistan, we use the yearly average. The remote sensing based index is operationally used to monitor drought conditions in the Global Early Warning System (GEWS), low VHI values indicate drought conditions. For a similar approach to a VHI, see Harari & La Ferrara (2018).

Wheat Price (International): Prices are period averages in nominal US dollars with 2005 as baseline. We use benchmark prices, representative of the global market. They are determined by the largest exporter of a given commodity. Source: International Monetary Fund (IMF) Primary Commodity Prices database (IMF, 2005-2017).

Wheat Suitability: Seven different soil quality ratings (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/Land Utilization Type (LUT) with respect to the soil characteristics present in a soil map unit of the HWSD and is depending on input/management level. The FAO-GAEZ (2012) model provides for each crop/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. Source: Global Agro-ecological Zones (GAEZ v3.0) by the Food and Agriculture Organization of the United Nations (FAO-GAEZ 2012). Details are provided on http://www.fao.org/nr/gaez/about-data-portal/agricultural-suitability-and-potential-yields/en/, accessed October 12, 2016. Go to the section "Agro-ecological suitability and productivity" to find the suitability we use and access the data portal for downloads.

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	5174	0.31	0.46	0.00	1.00
Low Conflict	5174	0.23	0.42	0.00	1.00
Conflict	5174	0.14	0.34	0.00	1.00
War	5174	0.03	0.18	0.00	1.00
(log) Taliban-Civilians BRD	5174	0.08	0.37	0.00	4.14
(log) Taliban-Government BRD	5174	1.05	1.52	0.00	8.20
(log) Government BRD caused by Taliban	5174	0.53	0.94	0.00	8.03
(log) Taliban BRD caused by Government	5174	0.77	1.33	0.00	6.39
(log) Wheat Profitability	5174	-0.48	0.46	-2.11	0.01
(log) Opium Profitability - Int. Heroin	5174	-1.52	0.66	-4.61	-0.00
(log) Opium Profitability - Local Opium	5174	-1.04	0.70	-4.61	0.01
(log) Opium Profitability - Int. Complement	5174	-1.30	0.56	-3.17	-0.00
(log) Opium Profitability - Int. Cocaine	5174	-1.15	0.67	-4.61	-0.00
Opium Suitability	5174	0.53	0.18	0.00	1.00
Wheat Suitability	5174	0.55	0.23	0.00	1.00
(log) Cultivation	5174	1.38	2.15	0.00	6.91
(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)	5173	124.08	23.20	51.28	191.99
(log) Population	5174	3.96	1.24	0.44	9.58
Ruggedness in 1000	5148	299.18	216.54	4.48	877.01
Any Military Base	5174	0.04	0.20	0.00	1.00
Market Access - Opium Market 2D	5174	4.47	1.10	2.24	11.23
Market Access - Opium Market 3D	5174	2.63	0.69	1.33	6.93
Market Access - Luminosity 2D	5174	6.51	4.86	1.85	41.26
Market Access - Luminosity 3D	5174	6.47	4.84	1.85	41.24
Major/Sub Market	5174	0.27	0.44	0.00	1.00
Sum of all Markets	5174	0.40	0.85	0.00	8.00
Any Lab	5174	0.13	0.34	0.00	1.00
Ethnic Trafficking Route	5174	0.52	0.50	0.00	1.00
Distance to Kabul: Linear	5148	277.05	181.54	0.00	817.64
Distance to Kabul - Road 2D	5174	345.03	212.05	0.00	959.78
Distance to Kabul - Road 3D	5174	347.47	213.08	0.00	964.48
Travel Time to Kabul - 2D	5174	7.53	5.91	0.00	28.40
Travel Time to Kabul - 3D	5174	7.57	5.94	0.00	28.45
Pashtuns	5174	0.74	0.44	0.00	1.00
Ethnic Groups - 1 if Mixed	5174	0.59	0.49	0.00	1.00
Ethnic Groups - Number	5174	1.93	0.97	1.00	5.00
Mixed Territory 1996	5174	0.04	0.20	0.00	1.00
Taliban Territory 1996	5174	0.58	0.49	0.00	1.00

Notes: The sample is based on the specification in Table 2, 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.

Table 9: Balancing tests - high and low opium suitable districts

	Mean Values per Group		**P-Value**
	High Suitability	Low Suitability	
Ruggedness in 1000	286.052	342.550	0.000
Distance to Kabul - Linear	248.425	371.647	0.000
Distance to Kabul - Road 2D	311.787	454.068	0.000
Distance to Kabul - Road 3D	314.037	457.126	0.000
Travel Time to Kabul - Road 2D	6.560	10.693	0.000
Travel Time to Kabul - Road 3D	6.597	10.755	0.000
Pashtuns	0.780	0.602	0.000
Mixed Ethnic Groups	0.538	0.742	0.000
Number Ethnic Groups	1.830	2.247	0.000
Mixed Territory 1996	0.030	0.075	0.000
Taliban Territory 1996	0.593	0.527	0.000
Ethnic Trafficking Route	0.557	0.409	0.000
BRD 2000	14.308	11.075	0.172
Luminosity 2000	0.160	0.213	0.322
(log) Population 2000	3.974	2.654	0.000
Wheat Suitability	0.609	0.371	0.000

Notes: Sample based on Table 1, column 1. To assign a districts to low or high suitability, we use a cut-off of 0.4. In Table 34 we control for an interaction of all the variables (above the separating line) with a time trend or with time-fixed effects.

Table 10: 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 2, column 1.

C. Geographical overview

Afghanistan and its neighboring states

Notes: Opium is reported to be mostly trafficked through Iran, Pakistan as well as through Turkmenistan according to UNODC.

Elevation and mountainous terrain in Afghanistan

Notes: The central and north-eastern part of Afghanistan feature the most mountainous terrain. Mountains are correlated with opium suitability, for instance very high altitude areas with a lot of snow are obviously unsuitable, but generally opium can be produced in many places as our map for the suitability indicator shows. We will run regressions with and without the border districts, as well as regressions controlling for elevation or ruggedness (in a flexible way interacted with year dummies) to account for potentially time-varying effects of these factors. Source for elevation data: (U.S. Geological Survey (USGS) Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010), available at https://lta.cr.usgs.gov/GMTED2010, accessed 06.04.2018). Source for ADM1 administrative data is www.gadm.org, accessed 06.04.2018.

Figure 12: ADM1-level (provinces) of Afghanistan

Notes: The figure plots the 34 provinces (ADM1-level). Source: Central Statistical Office Afghanistan (http://afghanag.ucdavis.edu/country-info/about-afghan.html).

D. Identification using complement prices

Assume that we estimate a regression

$$conflict_{d,t} = b \times drug\ price_{t-1} \times suit_d + \tau_t + \delta_d + \varepsilon_{d,t}, \tag{4}$$

but the true regression is

$$conflict_{d,t} = \beta \times drug\ price_{t-1} \times suit_d + \tau_t + \delta_d + \gamma \times suit_d * OV_{t-1} + \vartheta_{d,t}. \tag{5}$$

The drug prices (of opium and complements) depend on the following factors: i) changes in demand, to which we refer to as common demand shifters (DS'), ii) changes in opium supply (q^O), and iii) changes in the supply of the complement (q^C).

Accordingly, we have

$$p^O_{t-1} = f(\overset{(+)}{DS'_{t-1}}, \overset{(-)}{q^O_{t-1}}, \overset{(+)}{q^C_{t-1}}) \tag{6}$$

and

$$p^C_{t-1} = f(\overset{(+)}{DS'_{t-1}}, \overset{(+)}{q^O_{t-1}}, \overset{(-)}{q^C_{t-1}}). \tag{7}$$

The omitted variable OV_t varies at the time level, in our case by year. To be relevant for our estimation, we assume that OV has a nonzero effect on the outcome, i.e., $\gamma \neq 0$, and the effect varies conditionally on suitability ($suit_d$). $suit_d \sim [0, 1]$, with higher values indicating a higher suitability for production. At the same time, OV must also affect opium supply and in turn opium prices, again differentially conditional on *suit*. More formally, in case $E[q^O_{t-1}, \text{suit}_d \times OV_{t-1}] \neq 0$, a potentially problematic bias could arise. Given the negative point estimates in our regression analysis when we use the opium price, we would be worried about a downward bias in the coefficient b, which could lead to the false rejection of the null hypothesis. However, what we show in the following is relevant for both an upward and a downward bias. Note that $\frac{\partial q^O_{t-1}}{\partial(\text{suit}_d \times OV_{t-1})} < 0$, so that $\frac{\partial p^O_{t-1}}{\partial(\text{suit}_d \times OV_{t-1})} > 0$. We exploit the fact that the bias resulting from the omitted variable (conditional on suitability) through its effect on opium supply works in different directions for the complement than it does for opium: $\frac{\partial p^C_{t-1}}{\partial OV_{t-1}} = (-1)\frac{\partial p^O_{t-1}}{\partial OV_{t-1}}$.

How does this help us in the causal interpretation of our estimations? We describe the opium price and the price of complements, how the two relate to each other, and under which assumptions we can use the relationship between the two to better understand causality. We then verify and illustrate this relationship and its implications with a Monte Carlo simulation. We are particularly interested in the relationship between the two prices, and a potential suitability-specific effect of an omitted variable on opium supply.

Opium price:

Consider the price of opium as a linear function:

$$p^O_{t-1} = DS_t - q^O_{t-1} + \varpi \times q^C_{t-1} + \epsilon^O_{t-1},$$

where the factors directly influencing supply can be distinguished as

$$q^O_{t-1} = X_{t-1} + \eta \times \sum_{d=1}^{D} \text{suit}_d \times \text{OV}_{t-1} + \epsilon^{q^O}_{t-1}.$$

ϖ indicates to which degree opium and the complement are related ($\varpi \sim \mathcal{U}[0,1]$), i.e., how strong the cross-price elasticity is. The second equation means that the opium supply in year t is influenced by factors X_{t-1} like temperature and precipitation that are unrelated to the suitability-specific effect of the omitted variable, and by the suitability-specific shock caused by the omitted variable.[31] η indicates the degree to which the omitted variable influences opium supply and the opium price ($\eta \sim |\mathcal{N}(0, \sigma^2)|$). We sum up over all districts d, and assume that the omitted variable has a stronger effect on high suitability districts. Furthermore, we make one important assumption: We assume that supply shocks of the complement q^C_{t-1} can be related to overall opium supply, but are exogenous to district level differences in supply in Afghanistan, $\rho(q^C_{t-1}, suit_d \times OV_{t-1}) = 0$. We further validate this assumption by considering both an index of complements, as well as cocaine for which supply and trafficking routes (and related shocks) clearly differ from opium (heroin). Accordingly, both the term X_{t-1} and q^C_{t-1} are captured by year-fixed effects τ_t in Equation 4, and can be omitted without affecting the estimation of b. $\epsilon^O_{t-1} \sim \mathcal{N}(0, \sigma^2)$ is an iid error term. Assuming for simplicity that demand shifters and potentially endogenous opium supply influence the price in an additive manner yields

$$p^O_{t-1} = DS_t - \eta \times \sum_{d=1}^{D} \text{suit}_d \times OV_{t-1} + \epsilon^O_{t-1}, \tag{8}$$

with $\eta \sim |\mathcal{N}(0, \sigma^2)|$ being the degree to which the omitted variable influences p^O_{t-1} and ϵ^O_{t-1} being an iid error term.

Complement price:

The price of the complement is

$$p^C_{t-1} = DS_t - q^C_{t-1} + \varpi \times q^O_{t-1} + \epsilon^C_{t-1},$$

and inserting q^C_{t-1} leads to

$$p^C_{t-1} = DS_t + \varpi \times (X_{t-1} + \eta \times \sum_{d=1}^{D} \text{suit}_d \times OV_{t-1} + \epsilon^O_{t-1}) - q^C_{t-1} + \epsilon^C_{t-1}.$$

For a negative cross-price elasticity, ϖ is positive: as q^O increases, the price of opium decreases, polydrug consumers have more money available, the demand for the complement increases, which leads to a price

[31] We simplify and just use X instead of summing up over all potential factors weighted by their importance.

increase in the complement. To be problematic, a supply-side shock must be caused by an omitted variable and must be suitability-specific. The main feature that we exploit is that the effect of those shocks, which might also be correlated with conflict, affect the opium and the complement price in different directions.[32] As above, the assumption that supply shocks of the complement are exogenous to district level differences in supply in Afghanistan means that the terms X_{t-1} and q^C_{t-1} are captured by year-fixed effects τ_t and can be dropped. This results in the following equation:

$$p^C_{t-1} = DS_t + \varpi \times \eta \sum_{d=1}^{D} \text{suit}_d \times OV_{t-1} + \epsilon^O_{t-1} + \epsilon^C_{t-1}, \tag{9}$$

with $\varpi \sim \mathcal{U}[0, 1]$ being the degree to which supply side shocks to opium affect the price of the complement(s). With a negative cross-price-elasticity, as for complement goods, it holds that $\varpi > 0$, i.e., a positive supply shock to the good decreases the price of the good, and increases demand and the price of the complement. The error term is $\epsilon^C_{t-1} \sim \mathcal{N}(0, \sigma^2)$. If the additional random noise ϵ^C_t becomes too large, the complement price becomes less informative and less useful as this would dominate the former part of the equation.

Opium and complement price:

Accordingly (focusing on those parts relevant for the coefficient estimate that are not captured by FE), we have:

$$p^O_{t-1} = DS_t - \eta \times \sum_{d=1}^{D} \text{suit}_d \times OV_{t-1} + \epsilon^O_{t-1}, \tag{10}$$

$$p^C_{t-1} = DS_t + \varpi \times \eta \sum_{d=1}^{D} \text{suit}_d \times OV_{t-1} + \epsilon^O_{t-1} + \epsilon^C_{t-1}. \tag{11}$$

Subtracting Equation 10 from Equation 11 gives

$$p^C_{t-1} = p^O_{t-1} + (\varpi \times \eta + \eta) \times \sum_{d=1}^{D} \text{suit}_d \times OV_{t-1} + \epsilon^C_{t-1}. \tag{12}$$

Equation 12 shows that p^C can be considered as the opium price plus a difference in the bias and an iid error term ϵ^C_{t-1}, which we can treat as additional random measurement error in a regression on conflict.

[32] One simplifying assumption we make is that adjustment effects take time, for instance until the next year. Over time, the quantity of the complement that is produced will of course adjust to the higher price and increase as well, which will limit the price increase until a new equilibrium is reached. It also matters whether a supply shock is temporary or persistent.

We can then write the prices at the district-year level using Equation 10 and Equation 11 as

$$p^O_{d,t} = DS_t - \eta \times suit_d * OV_{t-1} + \epsilon^O_{d,t-1}, \tag{13}$$
$$p^C_{d,t} = DS_t + \varpi \times \eta \times suit_d \times OV_{t-1} + \epsilon^C_{d,t-1}. \tag{14}$$

We can then compare the three estimating equations

$$conflict_{d,t} = b^{True(1)} \times p^O_{t-1} \times suit_d + \gamma \times suit_d \times OV_{t-1} + \tau_t + \delta_d + \vartheta_{d,t}, \tag{15}$$
$$conflict_{d,t} = b^{Opium(2)} \times p^O_{t-1} \times suit_d + \tau_t + \delta_d + \vartheta^O_{d,t}, \tag{16}$$
$$conflict_{d,t} = b^{Complement(3)} \times p^C_{t-1} \times suit_d + \tau_t + \delta_d + \vartheta^C_{d,t}. \tag{17}$$

Equation 15 is the "true" regression and Equations 16 and 17 "short" equations in the sense Angrist & Pischke (2008) use true and short. Short equations do not capture the effect of the omitted variable, and thus yield biased coefficients b. Inserting the terms from above yields

$$conflict_{d,t} = b^{True(1)} \times p^O_{t-1} \times suit_d + \gamma \times suit_d \times OV_{t-1} + \tau_t + \delta_d + \vartheta_{d,t}, \tag{18}$$
$$conflict_{d,t} = b^{Opium(2)} \times (DS_t - \eta \times suit_d \times OV_{t-1} + \epsilon^C_{t-1}) \times suit_d + \tau_t + \delta_d + \vartheta^O_{d,t}, \tag{19}$$
$$conflict_{d,t} = b^{Complement(3)} \times (DS_t + \varpi \times \eta \times suit_d \times OV_{t-1} + \epsilon^C_{t-1}) \times suit_d + \tau_t + \delta_d + \vartheta^C_{d,t}. \tag{20}$$

This means the coefficients in the short regressions are

$$b^{Opium} = \beta - \eta \times suit_d \times OV_{t-1} + \vartheta^O_{d,t},$$
$$b^{Complement} = \beta + (\varpi \times \eta \times suit_d \times OV_{t-1}) - \beta \times \frac{\sigma^{\epsilon^C}}{\sigma^C + \sigma^{\epsilon^C}} + \vartheta^C_{d,t}.$$

The expectation for the coefficients when regressing both prices in the short regressions on conflict are

$$E[b^{Opium}] = \beta + \gamma \times \frac{\rho(opiumprice_{t-1} \times suit_d, OV_{t-1} \times suit_d)}{\mathrm{Var}(opium\ price_{t-1} \times suit_d)} \tag{21}$$

$$E[b^{Complement}] = \beta - \beta \times \frac{\sigma^{\epsilon^C}}{\sigma^C + \sigma^{\epsilon^C}} + (-\varpi) \times \gamma \times \frac{\rho(opium\ price_{t-1} \times suit_d, OV_{t-1} \times suit_d)}{\text{Var}(opium\ price_{t-1} \times suit_d)}$$

$$\implies$$

$$E[b^{Complement}] = \beta \times \frac{\sigma^C}{\sigma^C + \sigma^{\epsilon^C}} - \varpi \times \gamma \times \frac{\rho(opium\ price_{t-1} \times suit_d, OV_{t-1} \times suit_d)}{\text{Var}(opium\ price_{t-1} \times suit_d)}. \tag{22}$$

The first term in Equation 22 indicates the attenuation bias, moving the coefficient towards zero, as the complement price is only a noisy proxy for the opium price. The second term shows that a potential omitted variable bias points in the opposite direction for the two prices, as $-\varpi \leq 0$ and $\varpi \sim \mathcal{U}[0, 1]$. We can see that if $\varpi = 0$, the estimate would not be affected by omitted variable bias at all; it would however also not be informative about the opium price. For the case $\varpi = 1$, i.e., perfect complements in the sense that the good's price reacts to changes in the supply of the complement as strong as to changes in its own supply, the omitted variable bias would point in the opposite direction and be of exactly equal size for both prices.

Equations 21 and 22 make it very obvious which properties we would want from a "useful" complement.

- Common demand shifters must affect both prices simultaneously, so that $\frac{\sigma^C}{\sigma^C + \sigma^{\epsilon^C}}$ remains close to 1, i.e., the complement price is informative about the opium price.
- Supply side shocks to the complement must be exogenous to suitability-specific shocks in Afghanistan such that we can ignore their influence for the estimation.

We can conclude the following:

- Estimates using the complement price will be attenuated towards zero, making it less likely to find a significant effect.
- Omitted variable bias shifts both coefficients in opposite directions. Accordingly, if the true effect is zero, one of the estimates should be larger, and one smaller than zero. It is unlikely that both are negative (or positive), if the true effect is not negative or positive (Scenario A and B in the simulation below).
- If both coefficients are negative (positive) and the opium coefficient is more negative (positive), this indicates a downward (upward) bias in the opium coefficient. The complement coefficient is an upper (lower) bound of the true negative (positive) effect (Scenario C in the simulation below).
- If both coefficients are negative (positive) and the complement coefficient is more negative (positive), this indicates an upward (downward) bias in the opium coefficient. The opium coefficient is an upper (lower) bound of the true negative (positive) effect (Scenario D in the simulation below).

Taken together, our exercise serves two purposes. First, we can test whether both coefficients are significantly larger or smaller than zero. If this is the case, we can be confident about the sign of the true effect. In addition we can test which coefficient is further away from zero to assess the direction of OVB and estimate an upper or lower bound of the true effect.

We can also illustrate and show this using a simulation. In a Monte Carlo simulation, we can draw parameters from general distributions to account for the fact that we do not know the true cross-price elasticity, the size of random errors, and the degree to which omitted variables influence the endogenous parameter.

Simulation:

The Monte Carlo approach simulates four different scenarios, which vary by featuring an upward or downward bias and by having a true estimate that is either 0 or -1. As we cannot observe the true data generating process, we simulate a very general data generating process to assess the validity of our approach. We assume for the common demand shifters $DS_t \sim |\mathcal{N}(0, \sigma^2)|$. Moreover, we use $\eta \sim U[0,1]$ for different degrees of endogeneity and $\varpi \sim |\mathcal{N}(0, \sigma^2)|$ for different cross-price elasticities.

The outcome, conflict in district d at time t is then

$$\begin{aligned} conflict_{d,t} = \alpha + \beta^{True} \times drug\ price_{t-1} \times suit_d + \tau_t + \delta_d + \\ \gamma \times suit_d \times OV_{t-1} + \vartheta_{d,t}, \end{aligned} \tag{23}$$

with $\vartheta_{d,t} \sim \mathcal{N}(0, \sigma^2)$. We add a positive constant α to always ensure a positive outcome, but this is not necessary and not biasing the results. In each round, we draw 1000 observations, clustered in 100 districts with 10 time periods, and compute all variables. We then in each row estimate the following.

$$conflict_{d,t} = b^{True(1)} \times p^O_{t-1} \times suit_d + \gamma \times suit_d \times OV_{t-1} + \tau_t + \delta_d + \vartheta_{d,t}, \tag{24}$$

$$conflict_{d,t} = b^{Opium(2)} \times p^O_{t-1} \times suit_d + \tau_t + \delta_d + \vartheta^O_{d,t}, \tag{25}$$

$$conflict_{d,t} = b^{Complement(3)} \times p^C_{t-1} \times suit_d + \tau_t + \delta_d + \vartheta^C_{d,t}. \tag{26}$$

We want to understand how the likelihood that $b^{complement} < b^{opium}$ depends on the direction of omitted variable bias and how likely it is that both point estimates significantly differ from the true parameter value.

The simulation is repeated 5,000 times and we store b^1, b^2 and b^3 in each round, as well as SE^1, SE^2 and SE^3, and $pval^1$, $pval^2$ and $pval^3$. We then compute the likelihood that across all these different data generating processes i) the estimates using complement prices are more negative than the estimates using opium prices, ii) both prices yield a negative point estimate, and iii) both prices yield a negative point estimate and are significantly different from the true parameter value at the 5% level. These estimations are run for four different cases:

A. $\beta = 0$ and $\gamma = 1$.

B. $\beta = 0$ and $\gamma = -1$.

C. $\beta = -1$ and $\gamma = 1$.

D. $\beta = -1$ and $\gamma = -1$.

The implications would be the same for positive values of β. The simulation results verify the two main insights from above. First, if the true parameter value is 0, the likelihood that both the estimate using opium and using the complement are significantly smaller than zero is comparable to the false rejection rate. In simple terms, under rather general conditions it is extremely unlikely that both estimates would be significantly negative if the true effect is 0. Second, if the true parameter value is -1, we can compare the point estimates using the complement and the opium price to assess the direction of potential omitted variable bias. If the estimate using the opium price is downward biased, it is extremely unlikely that the point estimate using the complement price is more negative. If the point estimate using the complement price is in such a scenario more negative, the likelihood that both estimates are more negative than the true parameter value is extremely small. Our estimations reveal that both point estimates are negative and significantly different from zero with small p-values, and that the point estimate using the complement price is more negative. Thus, it is extremely unlikely that the true parameter value is equal or larger than zero, and it is likely that the estimates using the opium price is an upper bound of the true negative effect. Table 11 shows these results in detail for the scenarios A to D. Based on the table and Figures 13 and 14, scenario D seems to fit our data best. In that case, the estimate using the opium price is an upper bound of the true negative effect.

More specifically, the table and figures illustrate several important aspects. The figures clearly illustrate the differences between using the opium price or a complement price. First, we can see that in the majority of cases one of the estimates is higher, and one lower than the true value. Consequently, testing whether both are more positive or negative than 0 (or any value Z) is a good indication about the direction of the causal effect (or it being higher or lower than Z). It is apparent that the estimates using the complement are more dispersed and on average closer to zero. The dispersion comes from draws with a weaker cross-price elasticity, in which case the relationship with the treatment and outcome are also weaker. The estimates are closer to zero compared to the opium estimates due to attenuation (see Equation 22).

The first rows of Table 11 verify that the simulation works as intended. The parameter estimates using the true regression is close to the true relationship, the hypothesis of it being different is only rejected at the 5% level in 5% of the cases, about equal to the false rejection rate (row 4). Due to the omitted variable bias that we created, the estimates of the "short" regressions using opium or the complement alone differ quite often significantly from the true β. So how to make use of this strategy? First, one can check whether the estimate using the complement price is more negative or more positive than the estimate using the opium price. In our case it is more negative, clearly suggesting that scenario B or D (upward bias) is the relevant one for us. In B and D this can happen in 0.965 and 0.751% of all draws, whereas in A or C only in 0.033 and 0.075% of all cases.

Scenario B is based on a true effect of 0, scenario D on a negative true effect of -1. The second aspect we can consider is the likelihood of both estimates being more negative than the true effect. Rows 6 and 7 show that the likelihood that both are more negative is around 10% only, the likelihood that they are both significantly more negative even smaller.[33] As in our case, the estimate using the complement is more negative than using opium, we are also interested in the likelihood that this happens **and** both are significantly more negative than the true value. The last row shows that this likelihood is about equal to the false rejection rate.[34]

This is what we exploit in our case. First, estimates using opium (international heroin) prices, as well as prices using cocaine and an index of three complements are all negative. Consequently, it is unlikely that the true effect is not negative. Second, because both complement estimates are more negative, the (less negative) estimate using opium serves as an upper bound for the true negative effect. This is best visible in the right hand side of Figure 14.

[33] This likelihood is slightly higher with an upward bias in scenario A or C as we focus here on the likelihood of estimates being more negative. Considering simply whether both are significantly different (positive or negative), yields similar values for all scenarios.

[34] 0.073 and 0.008, close to 5% if the true value is 0, and 0.032 and 0.028 if the true value is -1. This is due to the fact that in the former case (B) both "short" estimates are more often negative than in the latter case (D). The reasons is the attenuation of the complement estimate towards zero, making it less likely to be more negative than -1 in scenario D.

Table 11: Simulation

	A ß=0 & Downward bias (1)	**B** ß=0 & Upward bias (2)	**C** ß=-1 & Downward bias (3)	**D** ß=-1 & Upward bias (4)
$\bar{b}$(true)	-0.000	0.001	-0.999	-1.000
$\bar{b}$(opium)	-0.369	0.374	-1.369	-0.633
$\bar{b}$(complement)	0.248	-0.247	-0.296	-0.802
p [$b(true) \neq< \beta$]	0.051	0.052	0.048	0.051
b(opium)) $< \beta \wedge$ b(complement) $< \beta$	0.232	0.110	0.221	0.102
p [b(complement) $< \beta \wedge$ b(opium) $<\beta$]	0.087	0.036	0.091	0.035
b(opium) < b(complement)	0.967	0.035	0.925	0.249
b(opium) < b(complement) $< \beta$	0.018	0.099	0.069	0.057
p [b(opium)< b(complement) $< \beta$]	0.015	0.028	0.065	0.010
b(complement) < b(opium)	0.033	0.965	0.075	0.751
b(complement)< b(opium) $< \beta$	0.214	0.011	0.151	0.045
p [b(complement)< b(opium) $< \beta$]	0.073	0.008	0.032	0.028

Notes: Simulations with 5000 repetitions. b(true) is the estimate from the true regression, i.e. one taking account of omitted variable bias (upward or downward). b(opium) is the estimate using the opium price, and b(complement) using the complement price. Row five gives an idea in which scenario we are in, looking at whether the estimate using opium or its complement is more negative. Combining row 5 and rows 8 and 9 indicates the likelihood of both estimates being negative given an upward or downward bias scenario. p( ) indicates that coefficient estimates are significantly different/more negative than the true value at the 5%-level.

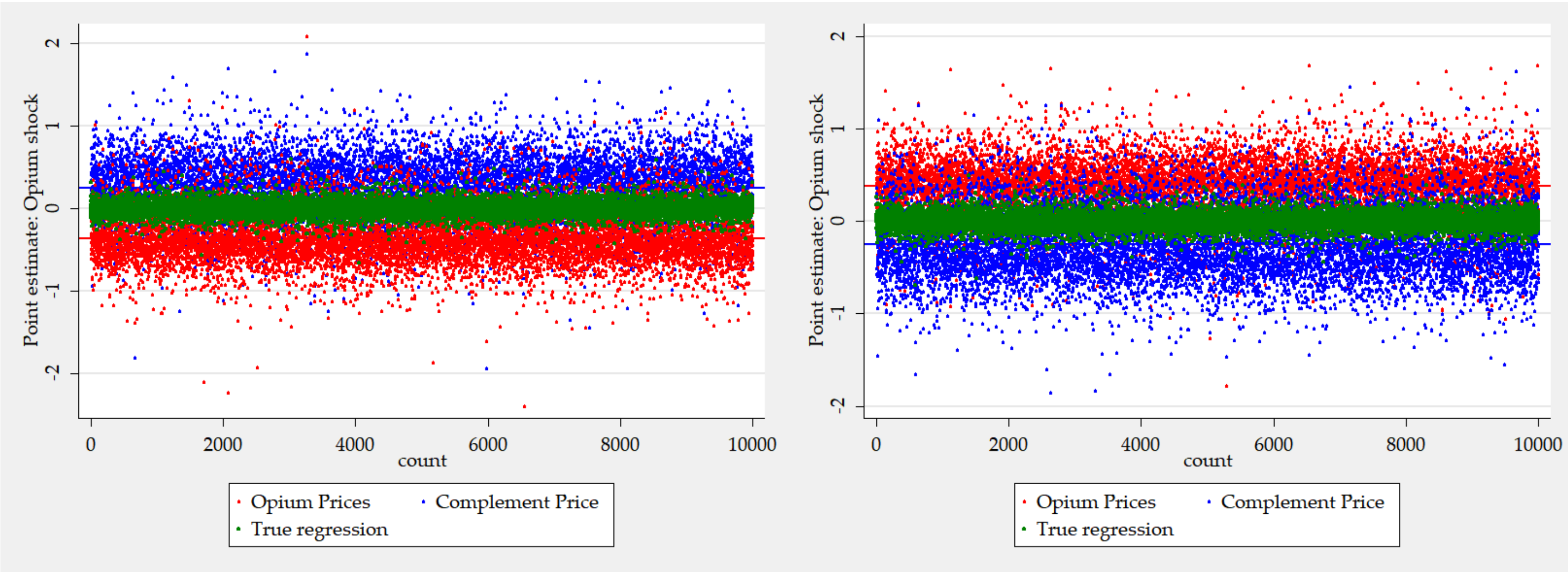


Figure 13: Simulations with true parameter estimate ß=0. A (left side): Downward bias, B (right side): Upward bias

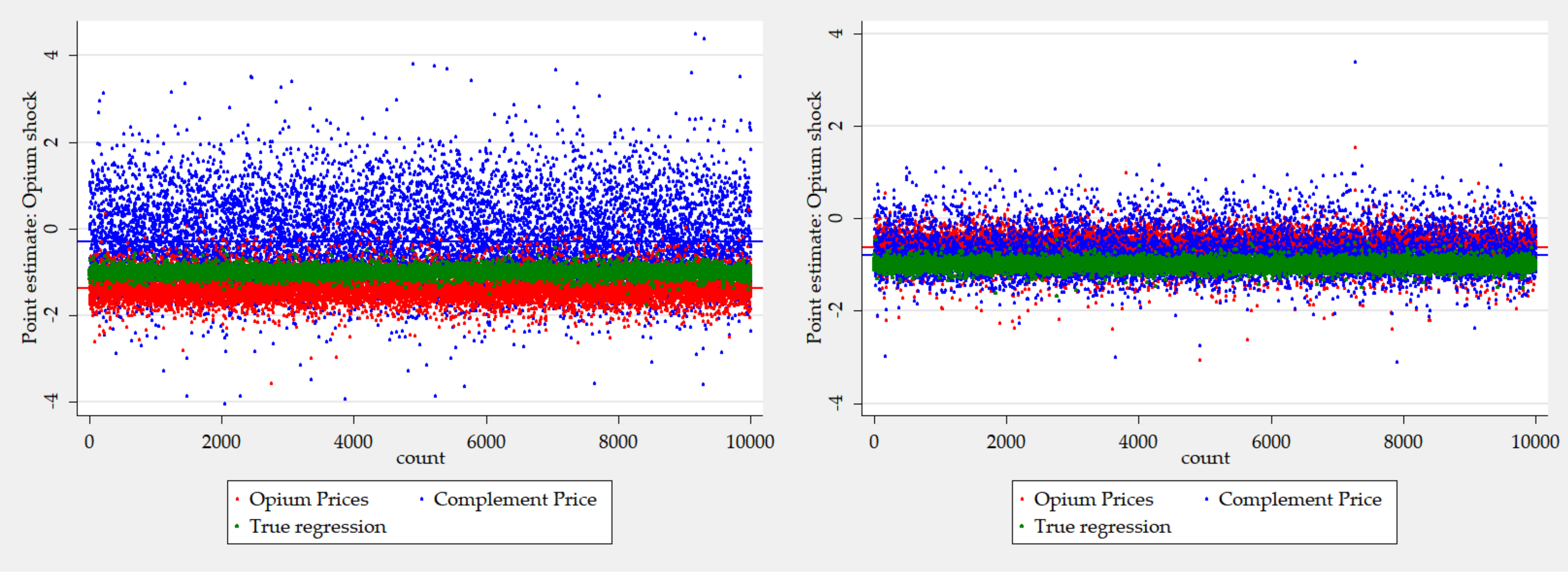


Figure 14: Simulations with true parameter estimate ß=-1. C (left side): Downward bias, D (right side): Upward bias

E. Further results

Regressions at the province level

Table 12: Effect of income shocks on opium revenues, at the province level 2002-2014

	Outcome: (t) (1)	**Outcome: (t) and (t-1)** (2)
Opium Profitability (t-1)	5.885*	5.461*
	(3.199)	(3.074)
Number of observations	442	442
Adjusted R-Squared	0.609	0.679

Notes: Linear probability models with with province- and year-fixed effects. The dependent variable opium revenues in (t) is in logarithms. Standard errors clustered at the province-level are displayed in parentheses. Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 13: Main results using normalized drug prices, at the province level 2002-2014

	Local Opium Price (1)	**International Heroin Price** (2)	**Complement Price** (3)	**International Cocaine Price** (4)
Opium Profitability (t-1)	-0.290	-0.717	-1.101*	-0.661*
	(0.299)	(0.566)	(0.647)	(0.368)
Number of observations	442	442	442	442
Adjusted R-Squared	0.723	0.724	0.726	0.726

Notes: Linear probability models with with province- and year-fixed effects. The dependent variable is the log of BRD in (t). Opium Profitability is defined as the interaction between the normalized drug prices (in logarithms) as indicated in the column heading and the suitability to grow opium. Standard errors are in parentheses (clustered at the province-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Different timing of the shocks

Table 14: Leads and lags, 2002-2014

	Wheat Profitability: Not included (1)	**Wheat Profitability: (t-1)** (2)
Opium Profitability (t+1)	-0.066	0.011
	(0.251)	(0.254)
Opium Profitability (t)	-0.660**	-0.670**
	(0.320)	(0.319)
Opium Profitability (t-1)	-0.773***	-0.585*
	(0.289)	(0.314)
Number of observations	4776	4776
Adjusted R-squared	0.648	0.649

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is the logarithm of BRD in (t). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 15: Timing of shocks, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: Contemporaneous effect		
Opium Profitability (t)	-0.608**	-0.168**	-0.161**	-0.130*	-0.021
	(0.246)	(0.075)	(0.074)	(0.066)	(0.033)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.483	0.454	0.310
			Panel B: Lagged effect		
Opium Profitability (t-1)	-0.675**	-0.167*	-0.191**	-0.147*	-0.040
	(0.296)	(0.090)	(0.085)	(0.075)	(0.037)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.484	0.454	0.310

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) 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.

Types of fighting

Table 16: Types of fighting, 2002-2014

Conflict Actor:	**All**	**Talib. vs. Civil.**	**Taliban versus Government**		
BRD:	**Any**	**Talib.&Civil.**	**Talib.&Gov.**	**Taliban**	**Government**
	(1)	(2)	(3)	(4)	(5)
Opium Profitability (t-1)	-0.675**	-0.098	-0.677**	-0.539***	-0.521*
	(0.296)	(0.069)	(0.302)	(0.187)	(0.274)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.200	0.658	0.555	0.596

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is the log of BRD in (t) 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 17: Main results using SIGACTs conflict data, 2002-2014 period

	DF	**IDF**	**IED**	**(log) DF**	**(log) IDF**	**(log) IED**
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Local Opium Price			
Opium Profitability (t-1)	-45.696	-5.094***	-12.263**	-0.464***	-0.312***	-0.441***
	(33.593)	(1.721)	(5.266)	(0.107)	(0.090)	(0.087)
Adjusted R-Squared	0.444	0.545	0.576	0.809	0.737	0.774
			Panel B: International Heroin Price (Baseline)			
Opium Profitability (t-1)	-58.929*	-3.009	-16.402**	-0.747***	-0.371**	-0.654***
	(32.575)	(1.953)	(7.175)	(0.223)	(0.152)	(0.197)
Adjusted R-Squared	0.442	0.544	0.574	0.808	0.736	0.773
			Panel C: International Complement Price			
Opium Profitability (t-1)	-96.148*	-7.921***	-26.719***	-1.099***	-0.618***	-1.006***
	(54.138)	(2.821)	(10.143)	(0.269)	(0.193)	(0.231)
Adjusted R-Squared	0.444	0.544	0.578	0.810	0.737	0.776
			Panel D: International Cocaine Price			
Opium Profitability (t-1)	-35.442*	-2.114*	-10.289**	-0.497***	-0.236**	-0.434***
	(19.908)	(1.177)	(4.164)	(0.149)	(0.097)	(0.129)
Adjusted R-Squared	0.442	0.544	0.574	0.808	0.736	0.773

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading (DF - Direct Fire, IDF - Indirect Fire, IED - Improvised Explosive Devices). Opium Profitability is defined as the interaction between the normalized drug prices (in logarithms) and the suitability to grow opium. The number of observations is equal across all panels (5174). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Outcome variable (onset and ending)

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

	1 if ≥ 5 (1)	**1 if** ≥ 10 (2)	**1 if** ≥ 25 (3)	**1 if** ≥ 100 (4)
		Panel A: Incidence		
Opium shock (t-1)	-6.376***	-6.823***	-6.849**	-3.148
	(1.764)	(2.519)	(3.249)	(6.672)
Number of observations	4407	3510	2431	806
Pseudo R-Squared	0.350	0.272	0.272	0.213
		Panel B: Onset		
Opium shock (t-1)	-4.505***	-6.076**	-5.729*	-1.719
	(1.686)	(2.375)	(3.092)	(5.601)
Number of observations	2953	2739	1995	714
Pseudo R-Squared	0.170	0.136	0.149	0.149
		Panel C: Ending		
Opium shock (t-1)	4.053**	0.445	-0.446	-9.784
	(1.698)	(2.430)	(2.939)	(8.124)
Number of observations	1931	1195	730	207
Pseudo R-Squared	0.105	0.077	0.102	0.161

Notes: Conditional logit model with year- and district-fixed effects. The dependent variable is conflict onset/ending in (t) 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.

Alternative instrument (legal opioid prescription)

Table 19: Alternative IVs for revenue (t-1), 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
	Panel A: Legal Opioids (t-1) as IV				
(log) Revenue (t-1)	-0.193**	-0.058**	-0.046*	-0.025	-0.009
	(0.086)	(0.025)	(0.024)	(0.017)	(0.007)
Number of observations	5104	5104	5104	5104	5104
Kleibergen-Paap F stat.	13.050	13.050	13.050	13.050	13.050
	Panel B: Opium Profitability (t-1) and Legal Opioids (t-1) as IVs				
(log) Revenue (t-1)	-0.192**	-0.057**	-0.046*	-0.025	-0.008
	(0.086)	(0.025)	(0.024)	(0.017)	(0.007)
Number of observations	5104	5104	5104	5104	5104
Kleibergen-Paap F stat.	8.143	8.143	8.143	8.143	8.143
Hansen J p-val.	0.220	0.211	0.541	0.420	0.210

Notes: Linear probability models with year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium revenues are in (t-1). The corresponding IVs are indicated in the panel heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 20: Corresponding 1st stage results for revenues (see Table above), 2002-2014

	Legal Opiods (1)	**Legal Opioids & Opium Prof.** (2)
Legal Opioids (t-1)	-15.384***	-14.915***
	(4.259)	(5.581)
Opium Profitability (t-1)		0.149
		(0.726)

Notes: Linear probability models with year- and district-fixed effects. The dependent variable is opium revenue in (t-1). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

F. Sensitivity analysis

Modifications of the treatment variable: We use multiple modifications of our treatment variable, both by replacing drug prices and crop suitabilities with alternative measures. Tables 21 and 22 are equivalent to our main results presented in Table 2 apart from the fact that drug prices are not normalized in Table 21 and in Table 22 the prices are not in logarithms. In Table 23, we use the deviation of the international prices from their long-term mean.[35] This is a first attempt to rule out that our results are driven by the long-term negative trend in international drug prices as visible in Figure 4. We find our results to be unaffected by all these choices. With regard to the suitability, we replace the population-weighted suitability for opium and wheat with an unweighted version (see Table 24). Weighting is important as population density differs strongly across Afghanistan, but causes potential bad control problems due to endogenous migration. While the wheat profitability turns insignificant, the results for opium profitability remain unaffected for all specifications.

Finally, we dichotomize the levels of the interaction. This reduces the complexity of the DiD-like interpretation. In panel A of Table 25 we dichotomize the suitability based on the sample median. This allows us to interpret a price increase for two groups of districts, i.e., suitable (above the median) and less suitable (below the median). In panel B both variables are dichotomized based on the respective sample median. The coefficient in panel A indicates that a 10% increase in prices leads to about a 2.3% decrease in battle-related deaths in districts with a high suitability. Panel B finds that changing from a low- to a high-price-period reduces deaths by about 50% in districts with high suitability. Across all columns, the results are robust to this adaption.

Empirical model: First, we show our main results with a less restrictive set of fixed effects in Table 26 for the different prices in panels A to D. The results using only district- and year-fixed effects all point in the same direction, with somewhat smaller coefficients. Again, all four prices consistently indicate a negative effect, both when looking at conflict intensity and incidence. The fact that the effects in our baseline specification become larger in absolute terms, when using province-times-year-fixed effects, suggests that the FE succeed in eliminating biasing variation.

Outcome (cultivation and revenue): In Sections 4 and 5, we show that there is a strong effect of prices on opium revenues. Table 27 also supports the positive effect of a higher opium profitability on opium cultivation (in hectares), with positive coefficients that are marginally insignificant in column 1 and significant at the 5% level in column 2 when considering both periods that are most likely affected by the price change. This is not surprising as opium revenues are affected through changes in price and

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

quantity produced, and cultivation only by the latter.

We then turn to the baseline IV results. To account for the different timing as shown in Figure 3, we show the second and first stage results when we replace revenue in $t-1$ with the moving average of revenue in $t-1$ and t in Table 28 and Table 29. The two IVs, opium profitability and legal opioid prescription, are again strong as indicated by the F-statistic. Having alternative sources of exogenous variation also enables us to compare the LATE of the different IVs. We find that the local effects do not differ much either in terms of magnitude or with regard to statistical significance.

Instrumenting opium profitability: Table 30 uses the number of legally prescribed opioids interacted with the opium suitability as an instrument for opium profitability. The F-statistics are very high because one part of the interaction, the suitability, is identical. The assumption is that legal opioid prescriptions, conditional on year-fixed effects, are not affected differentially by district-year specific events in Afghanistan that differ between high and low suitability areas. Note that, in contrast to complements, the price (and hence the supply) of legal opioids could theoretically be biased in the same direction as the main estimate using international heroine prices directly. Still, we present this as an additional robustness test and the results are in line with the main results, and further indicate that the baseline specification presents an upper bound of the true negative effect.

Standard errors: In a next step, we use different choices on how to cluster standard errors. In the baseline models we used the district level, allowing for serial correlation over time within a district. In Table 31 we use two-way clustering, i.e., district and year clusters in panel A and province and year clusters in panel B (Cameron *et al.*, 2011). Clustering at the province level is problematic as the number of clusters might be too small, which can lead to the over- or under-rejection of the null hypothesis (Cameron & Miller, 2015). Instead, we 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 15 plots the distribution of the bootstrap estimates. The null hypothesis of no effect is rejected both when using the international heroin price or the complement price index at least at the 5% level.

Covariates and trends: Our specifications so far only include wheat profitability and different fixed effects as covariates. It is natural to first compare these results to results without those main covariates. In Table 32, we find our results to remain robust when we exclude wheat profitability, with slightly more negative coefficients. Table 32 also shows the tables including the coefficient of wheat profitability for comparison. To account for the persistence of conflict, we include the lagged dependent variable in a next step. Opium profitability remains negative in all columns and statistically significant in columns 1 to 3 (see Table 33). In Table 34 (panel A) we add a baseline set of pre-determined covariates such 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 district-specific control variables.[36] One concern with our specification is that the time trends in prices interact not only with opium suitability, but also with other district characteristics. One way to model this is by adding interactions between these characteristics and a time trend. Another more flexible way is to interact the time invariant control variables with year dummies (panel C). This last specification allows for fully flexible trends interacting with a wide range of district features. The coefficients of our treatment variable are remarkably stable, ranging from -0.675 in the baseline (column 1, panel B, Table 2) to -0.694 in the most flexible specification for conflict intensity. They also remain significant with p-values below at least 0.1 for all conflict proxies (with the sole exception of the category "war").

Sensitivity to outliers: In Table 35 we drop potential outliers. In panel A we exclude all border districts from the specification as they could be either very different to other districts or shocks in neighboring countries could affect border districts in a different fashion. For instance, we expect a large share of trafficking to occur close to the border. This could drive the results if international price increases would not reach the average farmer but only the traders, which are closer to the final customer along the supply chain. We find that our results are not driven by this particular group of districts. In panel B we drop the two southern provinces Kandahar and Helmand 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 are thus likely to still have a strong support base here. Second, these provinces are known to be the largest producers of opium. Third, because of their direct connection to Pakistan, which is not only important in relation to trafficking routes but is also a major base of military support for the Taliban.

Apart from these rather obvious heterogeneous groups we systematically investigate whether results are driven by a particular province or year. Figure 16 reports the coefficients and the 90% confidence intervals when we drop each year or province one at a time. All coefficients remain stable and within a narrow band.

Randomization: One of the important points raised by Christian & Barrett (2017) is that non-linear trends in the time series of Bartik/shift-share like instruments can be problematic. We address this by looking at prices of different drugs and different versions of these prices (de-trended, log vs. non-log). To further rule out that the results are driven by non-linear trends, we implement further randomization

[36] The set of time-invariant covariates includes Ruggedness, Ethnic Trafficking Route, Pashtuns, Mixed Ethnic Groups, Taliban Territory 1996, Mixed Territory 1996, Distance Linear, Distance 2D and 3D, Travel Time 2D and 3D (all distances to Kabul).

placebo tests. We first randomize the time-varying variable (international heroin price) across years, and in a second specification randomize the district-specific suitability across districts. We would be worried if any of these specifications would create a negative effect similar in magnitude to our treatment effect. Figure 17 plots the distribution of the coefficients generated by 5'000 randomizations per test along with the actual coefficient. We can also use this to conduct a randomization inference (RI) exercise, in which we compare how many of the random draws generate coefficients that are more negative than ours in order to compute an RI p-value. Reassuringly, we find that if the treatment was randomized according to the two different strategies, the simulated coefficients are always centered around zero. The p-values computed using two-sided symmetric randomization inference are 0.021.

Modifications of the treatment variable: Drug prices

Table 21: Non-normalized drug prices, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: Local Opium Price		
Opium Profitability (t-1)	-0.644***	-0.166***	-0.165***	-0.143***	-0.079***
	(0.200)	(0.059)	(0.056)	(0.052)	(0.030)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.650	0.502	0.484	0.454	0.311
			Panel B: International Heroin Price (Baseline)		
Opium Profitability (t-1)	-2.103**	-0.503*	-0.550**	-0.465**	-0.183*
	(0.835)	(0.256)	(0.233)	(0.206)	(0.108)
Adjusted R-Squared	0.649	0.501	0.483	0.454	0.310
			Panel C: Complement Price		
Opium Profitability (t-1)	-4.023***	-1.016**	-0.982***	-0.870***	-0.371**
	(1.337)	(0.399)	(0.364)	(0.329)	(0.176)
Adjusted R-Squared	0.651	0.502	0.484	0.455	0.311
			Panel D: International Cocaine Price		
Opium Profitability (t-1)	-3.594***	-0.888**	-0.871***	-0.780**	-0.318**
	(1.229)	(0.363)	(0.334)	(0.302)	(0.159)
Adjusted R-Squared	0.651	0.502	0.484	0.455	0.311

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the drug prices (in logarithms) 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 Heroin Price, price not in logarithms, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
Opium Profitability (t-1)	-6.970***	-1.665**	-1.781***	-1.438***	-0.553**
	(2.232)	(0.696)	(0.618)	(0.537)	(0.277)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-squared	0.649	0.501	0.483	0.454	0.310

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the normalized international price (prices are not in logarithms) 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: International Heroin Price in deviations, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
Opium Profitability (t-1)	-6.197*	-1.434	-1.567*	-1.387*	-0.620*
	(3.136)	(0.875)	(0.887)	(0.747)	(0.350)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.483	0.453	0.310

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability 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.

Modifications of the treatment variable: Suitability

Table 24: Unweighted suitabilities, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
Opium Profitability (t-1)	-0.988***	-0.249***	-0.244***	-0.188**	-0.031
	(0.290)	(0.093)	(0.088)	(0.077)	(0.041)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-squared	0.650	0.501	0.483	0.454	0.310

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the normalized international prices (in logarithms) and the unweighted suitability to grow opium (in analogy for wheat). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Modifications of the treatment variable: Dyadic Diff-in-Diff

Table 25: Diff-in-Diff - Dyadic treatment, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
	Panel A: Suitability dichotomized				
Opium Profitability (t-1)	-0.229***	-0.052*	-0.041	-0.042*	-0.017
	(0.087)	(0.027)	(0.026)	(0.022)	(0.013)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.648	0.500	0.482	0.453	0.311
	Panel B: Suitability and Heroin Price dichotomized				
Opium Profitability (t-1)	-0.397***	-0.107***	-0.090**	-0.071**	-0.029
	(0.117)	(0.038)	(0.035)	(0.030)	(0.018)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.483	0.453	0.311

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Suitability (for opium and wheat) dichotomized according to the sample median in Panel A. Suitability (for opium and wheat) and international prices (for heroin and wheat) dichotomized according to the sample median in Panel B. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Empirical model

Table 26: Main results using normalized drug prices, district- and year-fixed effects, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: Local Opium Price		
Opium Profitability (t-1)	-0.280***	-0.097***	-0.078***	-0.026	0.000
	(0.091)	(0.028)	(0.026)	(0.021)	(0.012)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.562	0.423	0.410	0.389	0.264
			Panel B: International Heroin Price (Baseline)		
Opium Profitability (t-1)	-0.451**	-0.132**	-0.122*	-0.050	-0.010
	(0.209)	(0.064)	(0.063)	(0.051)	(0.023)
Adjusted R-Squared	0.561	0.421	0.409	0.389	0.264
			Panel C: Complement Price		
Opium Profitability (t-1)	-0.707***	-0.217***	-0.172***	-0.091*	-0.028
	(0.222)	(0.068)	(0.064)	(0.050)	(0.023)
Adjusted R-Squared	0.563	0.423	0.410	0.390	0.264
			Panel D: International Cocaine Price		
Opium Profitability (t-1)	-0.363***	-0.102**	-0.088**	-0.046	-0.012
	(0.138)	(0.042)	(0.041)	(0.034)	(0.015)
Adjusted R-Squared	0.562	0.422	0.410	0.390	0.264

Notes: Linear probability models with year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the normalized drug prices (in logarithms) and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Outcome and timing (cultivation and revenue)

Table 27: Effect of income shocks on opium cultivation, 2002-2014

	Outcome: (t)	**Outcome: (t)+(t-1)**
	(1)	(2)
Opium Profitability (t-1)	0.483	0.705**
	(0.307)	(0.308)
Number of observations	5174	5174
Adjusted R-Squared	0.399	0.488

Notes: The dependent variables opium cultivation is in logarithms. Column (1) presents lagged effects. Column (2) reports lagged and contemporaneous effects by defining the outcome as the moving average, i.e. (revenues(t)+revenues(t-1))/2. Opium Profitability is defined as the interaction between the normalized heroin price (in logarithms) and the suitability to grow opium. Standard errors clustered at the district-level are displayed in parentheses. Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 28: IVs for revenue in (t)+(t-1), 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: Opium Price Shock (t-1) as IV		
(log) Revenue:(t)+(t-1)	-0.173*	-0.049*	-0.045	-0.020	-0.004
	(0.099)	(0.030)	(0.030)	(0.022)	(0.010)
Number of observations	5085	5085	5085	5085	5085
Kleibergen-Paap F stat.	11.047	11.047	11.047	11.047	11.047
			Panel B: Legal Opioids (t-1) as IV		
(log) Revenue:(t)+(t-1)	-0.252*	-0.075*	-0.060*	-0.032	-0.011
	(0.133)	(0.039)	(0.036)	(0.025)	(0.011)
Kleibergen-Paap F stat.	6.672	6.672	6.672	6.672	6.672

Notes: Linear probability models with year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium revenues is operationalized as the moving average between (t) and (t-1). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 29: Corresponding 1st stage results for revenues (t)+(t-1), 2002-2014

	Opium Profitability (1)	**Legal Opiods** (2)
Opium Pro 1)	2.489***	
	(0.749)	
Legal Opi 1)		-11.489**
		(4.448)

Notes: Linear probability models with year- and district-fixed effects. The dependent variable is opium revenue or cultivation as indicated in the panel heading. The corresponding IVs are indicated in the column heading. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Instrument opium profitability

Table 30: Instrument opium profitability with legal opioid prescriptions times suitability, 2002-2014

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(5)
Opium Profitability (t-1)	-1.310***	-0.335**	-0.303**	-0.276**	-0.113*
	(0.437)	(0.134)	(0.124)	(0.108)	(0.058)
Kleibergen-Paap F stat.	53755.409	53755.409	53755.409	53755.409	53755.409

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the normalized heroin price (in logarithms) and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Standard errors

Table 31: Standard errors clustered at different levels, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: Clustered at district- and year-level		
Opium Profitability (t-1)	-0.675*	-0.167*	-0.191**	-0.147*	-0.040
	(0.325)	(0.092)	(0.080)	(0.074)	(0.051)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.484	0.453	0.310
			Panel B: Clustered at province- and year-level		
Opium Profitability (t-1)	-0.675*	-0.167	-0.191*	-0.147*	-0.040
	(0.365)	(0.103)	(0.103)	(0.082)	(0.044)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.484	0.453	0.310

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) 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.

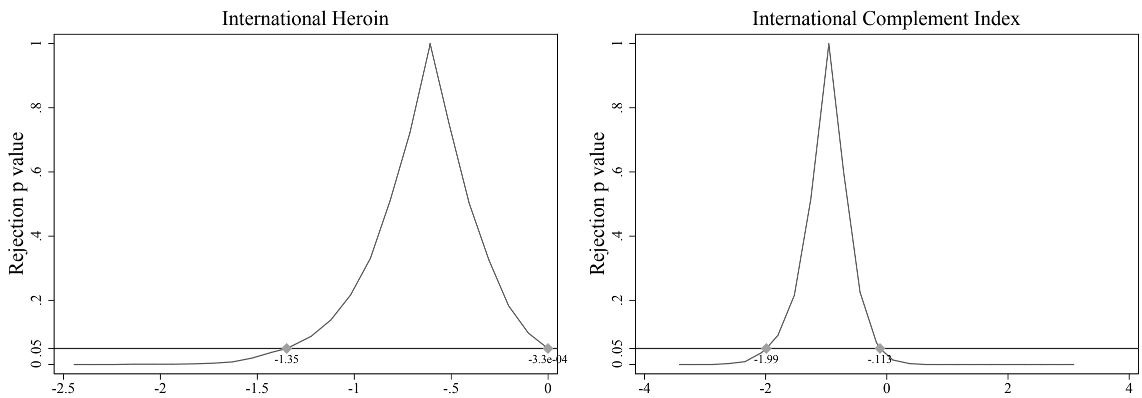


Figure 15: Wild Bootstrap (province-level clustered se, 95% confidence intervals)

Notes: Figures show the distribution of bootstrap estimates. The dependent variable is the (log) of BRD. Regressions correspond to Table 2 column 1 (Panel B and C). The number indicate the left and right 95%-confidence interval. The test of the the null hypothesis at the 5%-level is whether this intervall contains 0.

Covariates and trends

Table 32: Wheat Profitability, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			Panel A: Wheat Profitability included		
Opium Profitability (t-1)	-0.675**	-0.167*	-0.191**	-0.147*	-0.040
	(0.296)	(0.090)	(0.085)	(0.075)	(0.037)
Wheat Profitability (t-1)	0.307**	0.088**	0.077**	0.034	-0.010
	(0.123)	(0.039)	(0.036)	(0.031)	(0.019)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.484	0.454	0.310
			Panel B: Wheat Profitability excluded		
Opium Profitability (t-1)	-0.923***	-0.238***	-0.253***	-0.175**	-0.031
	(0.279)	(0.084)	(0.079)	(0.069)	(0.030)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.501	0.483	0.453	0.310

Notes: Linear probability modelswith province-times-year- and district-fixed effects. The dependent variable is conflict in (t) 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 33: Dynamics - lagged dependent, 2002-2014

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
Opium Profitability (t-1)	-0.455*	-0.140*	-0.160**	-0.102	-0.021
	(0.252)	(0.084)	(0.076)	(0.065)	(0.032)
Dependent (t-1)	0.236***	0.114***	0.153***	0.228***	0.207***
	(0.023)	(0.019)	(0.023)	(0.027)	(0.040)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.670	0.508	0.496	0.482	0.340

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) 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 34: Including covariates, 2002-2014

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(5)
			Panel A: Baseline covariates		
Opium Profitability (t-1)	-0.595**	-0.177**	-0.188**	-0.132*	-0.014
	(0.275)	(0.086)	(0.082)	(0.070)	(0.038)
Wheat Profitability (t-1)	0.282**	0.093**	0.077**	0.028	-0.019
	(0.129)	(0.041)	(0.037)	(0.032)	(0.019)
VHI (t)	0.000	-0.000	-0.000	0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Luminosity (t-2)	0.018	0.005	0.002	-0.003	-0.000
	(0.020)	(0.006)	(0.006)	(0.005)	(0.003)
(log) Population (t-2)	1.417	-0.478	0.037	0.611	0.789**
	(3.472)	(0.911)	(0.900)	(0.958)	(0.308)
Number of observations	5173	5173	5173	5173	5173
Adjusted R-Squared	0.650	0.501	0.483	0.453	0.311
			Panel B: Baseline covariates, time-invariant covariates×trend		
Opium Profitability (t-1)	-0.676**	-0.180**	-0.197**	-0.175**	-0.030
	(0.269)	(0.084)	(0.081)	(0.068)	(0.039)
Wheat Profitability (t-1)	0.268**	0.091**	0.082**	0.025	-0.016
	(0.130)	(0.041)	(0.037)	(0.032)	(0.020)
VHI (t)	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)
Luminosity (t-2)	0.014	0.004	0.001	-0.004	-0.000
	(0.020)	(0.006)	(0.006)	(0.005)	(0.003)
(log) Population (t-2)	-0.656	-0.905	-0.724	-0.244	0.910**
	(3.484)	(0.952)	(0.961)	(0.936)	(0.381)
Number of observations	5147	5147	5147	5147	5147
Adjusted R-Squared	0.654	0.504	0.487	0.461	0.317
			Panel C: Baseline covariates, time-invariant covariates×time dummies		
Opium Profitability (t-1)	-0.754***	-0.209**	-0.222**	-0.186**	-0.040
	(0.289)	(0.089)	(0.087)	(0.073)	(0.042)
Wheat Profitability (t-1)	0.276*	0.090**	0.081**	0.034	-0.020
	(0.141)	(0.043)	(0.041)	(0.036)	(0.022)
VHI (t)	-0.000	-0.001	-0.000	0.000	-0.000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Luminosity (t-2)	0.011	0.003	0.001	-0.005	-0.000
	(0.020)	(0.006)	(0.006)	(0.005)	(0.003)
(log) Population (t-2)	-0.881	-0.868	-0.775	-0.352	0.860**
	(3.540)	(0.988)	(0.978)	(0.941)	(0.380)
Number of observations	5147	5147	5147	5147	5147
Adjusted R-Squared	0.654	0.503	0.486	0.462	0.314

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. The set of time-invariant covariates includes Ruggedness, Ethnic Trafficking Route, Pashtuns, Mixed Ethnic Groups, Taliban Territory 1996, Mixed Territory 1996, Distance Linear, Distance 2D and 3D, Travel Time 2D and 3D (all distances to Kabul). Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Outlier analysis

Table 35: Drop potential outliers, 2002-2014

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(5)
			Panel A: No border districts		
Opium Profitability (t-1)	-0.601**	-0.160	-0.161*	-0.146*	-0.014
	(0.304)	(0.098)	(0.096)	(0.086)	(0.055)
Number of observations	3718	3718	3718	3718	3718
Adjusted R-Squared	0.678	0.523	0.513	0.483	0.342
			Panel B: No Southern provinces (Kandahar and Hilmand)		
Opium Profitability (t-1)	-0.674**	-0.174*	-0.215**	-0.118	-0.007
	(0.311)	(0.096)	(0.091)	(0.078)	(0.033)
Number of observations	4732	4732	4732	4732	4732
Adjusted R-Squared	0.620	0.480	0.458	0.407	0.255

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. In Panel A all border districts are exlcuded and in Panel B all districts in the two provinces Kandahar and Hilmand are excluded. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

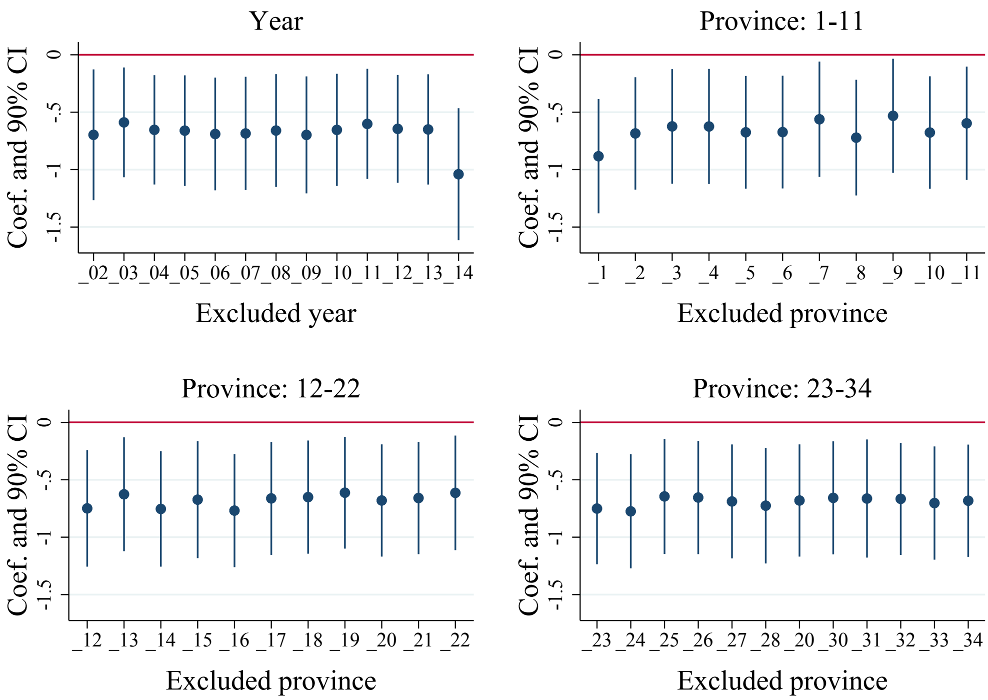


Figure 16: Leave one out - year and province

Notes: This figure shows results for 47 separate regressions in analogy to Panel B's column (1) of Table 2, where we leave out one year or one province at the time. This also alleviates concerns whether particular outliers in the cross-sectional variation drive our result.

Randomization

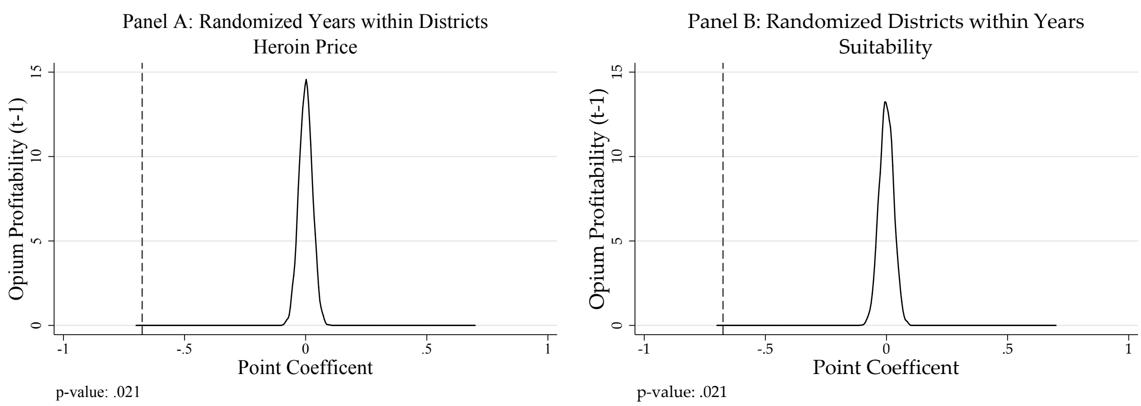


Figure 17: Randomization: Heroin Price and Opium Suitability

Notes: This figure plots the distribution of the coefficients generated by 5'000 randomizations, with Panel A randomly reordering prices across years within districts and multiplying with the actual suitability and Panel B reordering the suitability across districts and multiplying with the actual price in the respective yes. Based on the regression model in Panel B's column (1) of Table 2. For this placebo test, we want to see whether the randomized coefficients are centered around zero, and what share of the draws turn out to be more negative than the actual treatment coefficient. This share is used to compute the randomization inference p-value shown in the bottom of the graph.

Tables and robustness for regressions at the household level

Table 36: Living standards at the household level, 2005-2012

	(1)	(2)	(3)
	Panel A: Food consumption		
	Dietary Diversity	**Calorie Intake**	**Food Insecurity**
Opium Profitability (t-1)	0.571**	143.915	698.905**
	(0.289)	(256.750)	(303.057)
Number of observations	72224	71634	72643
Adjusted R-Squared	0.371	0.139	0.225
	Panel B: Food expenditures		
	Food Exp.	**Food Exp. Paasche adj.**	**Food Exp. Laspeyres adj.**
Opium Profitability (t-1)	698.905**	788.172**	750.822**
	(303.057)	(312.228)	(314.647)
Number of observations	72643	72643	72635
Adjusted R-Squared	0.225	0.196	0.217
	Panel C: Assets		
	Sum of Assets	**Sum of Assets weighted**	**Economically improved**
Opium Profitability (t-1)	0.925***	0.614***	0.431*
	(0.327)	(0.217)	(0.225)
Number of observations	72447	66620	70670
Adjusted R-Squared	0.323	0.336	0.249

Notes: Linear probability models with with province-times-year- and district-fixed effects. The dependent variable in (t) is operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the normalized drug prices (in logarithms) and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-year-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

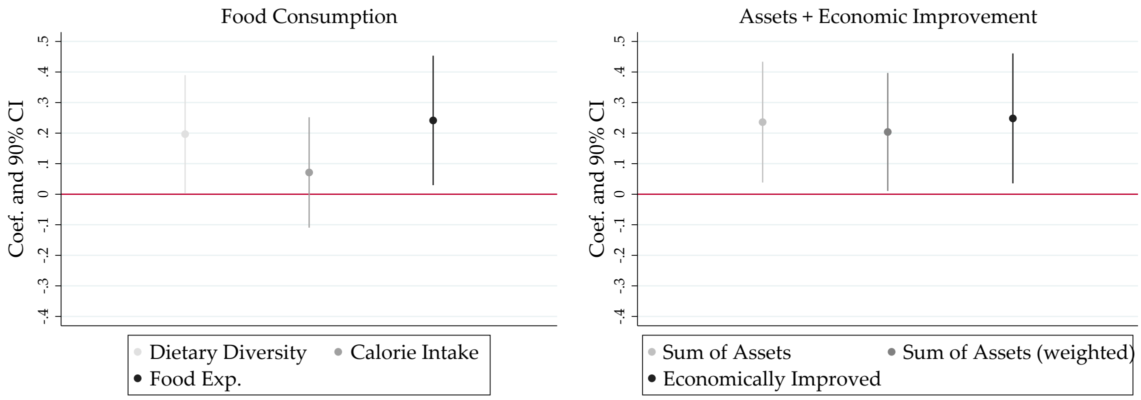


Figure 18: Effect of Opium Profitability (t-1) on living standard indicators in (t) based on food consumption, expenditures an assets, accounting for household survey weights

Notes: The figure shows results of 6 separate regressions in analogy to Table 36. The difference is that we include household survey weights in the regressions. Results are also robust to using robust standard errors rather than clustering at the district-year-level.

Robustness for Table 6

Table 37: Ethnic groups measured by NRVA, 2002-2014

	Any Pasthuns	**Share Pasthuns**	**Ethnic Groups 1 if Mixed**	**Ethnic Groups Number**
	(1)	(2)	(3)	(4)
Opium Profitability (t-1)	-0.062	-0.283	-0.403	-0.380
	(0.402)	(0.359)	(0.380)	(0.529)
Opium Profitability (t-1)*X	-1.157***	-1.005*	-0.524	-0.179
	(0.433)	(0.577)	(0.423)	(0.223)

Notes: Linear probability models with province-times-year- and district-fixed effects. The dependent variable is the log of battle-related deaths in (t). Opium Profitability is defined as the interaction between the normalized drug prices (in logarithms) and the suitability to grow opium. Regressions include interactions of the opium profitability with a variable X as indicated in in the column heading. For definitions of the variables X please see Appendix A. For this table the different measures on ethnic groups are derived from the NRVA 2003, which is not nationally representative, but serves as suitable a proxy for ethnic group distribution. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Differences conditional on degree of group competition - omitting districts around Kabul. Figure 19 shows that within that area within 50 kms around Kabul, the effect of a higher opium profitability on household food consumption and assets are also much more heterogeneous and on average more negative. This is in line with more government effort with respect to eradication, which can affect a significant share, but not all producers, and thus increase the variance and decrease the average positive impact of higher prices.

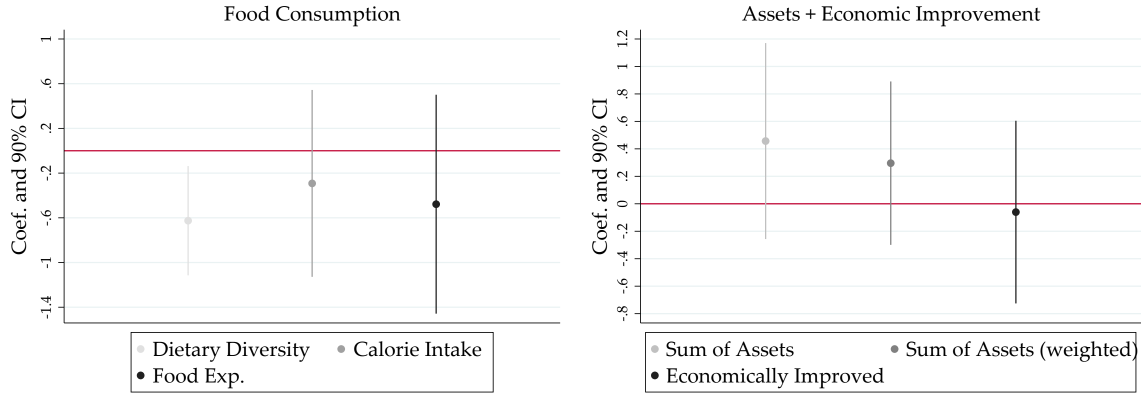


Figure 19: Effect of Opium Profitability (t-1) on standard of living indicators in (t)

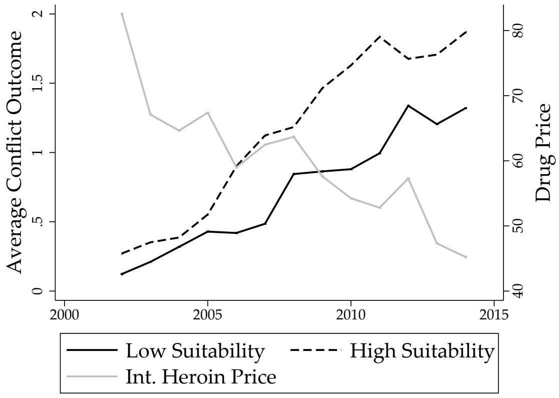


Figure 20: Variation of conflict across high and low suitable districts over time

Notes: To assign a district to low or high suitability, this figure use an alternative cut-off of 0.3.

Robustness for Figure 9.

Robustness for Table 6 - Before and after 2001

Table 38: Before and after 2001, 1997-2001/2014 period

	(log) BRD (1)	**1 if** ≥ 5 (2)	**1 if** ≥ 10 (3)	**1 if** ≥ 25 (4)	**1 if** ≥ 100 (5)
			1997-2001		
			Panel A: International heroin price		
Opium Profitability (t-1)	0.182	0.099	0.117	0.071	-0.033
	(0.645)	(0.152)	(0.145)	(0.129)	(0.095)
Number of observations	1990	1990	1990	1990	1990
Adjusted R-Squared	0.437	0.393	0.374	0.300	0.186
			Panel B: International complement price		
Opium Profitability (t-1)	0.200	0.123	0.138	0.079	-0.042
	(0.887)	(0.210)	(0.199)	(0.179)	(0.129)
Number of observations	1990	1990	1990	1990	1990
Adjusted R-Squared	0.437	0.393	0.374	0.300	0.186
			1997-2014		
			Panel C: International heroin price		
Opium Profitability (t-1)	-0.590***	-0.138***	-0.140***	-0.104**	-0.036*
	(0.165)	(0.044)	(0.043)	(0.043)	(0.022)
Number of observations	7164	7164	7164	7164	7164
Adjusted R-Squared	0.557	0.463	0.426	0.373	0.221
			Panel D: International complement price		
Opium Profitability (t-1)	-0.716***	-0.174***	-0.166***	-0.131***	-0.052**
	(0.184)	(0.050)	(0.048)	(0.048)	(0.025)
Number of observations	7164	7164	7164	7164	7164
Adjusted R-Squared	0.558	0.464	0.427	0.374	0.221

Notes: Linear probability models with with province-times-year- and district-fixed effects. The dependent variable is conflict in (t) operationalized as indicated in the column heading. Opium Profitability is defined as the interaction between the normalized heroin drug price (in logarithms) and the suitability to grow opium. Standard errors are in parentheses (clustered at the district-level). Significance levels: * 0.10 ** 0.05 *** 0.01.

G. Additional maps

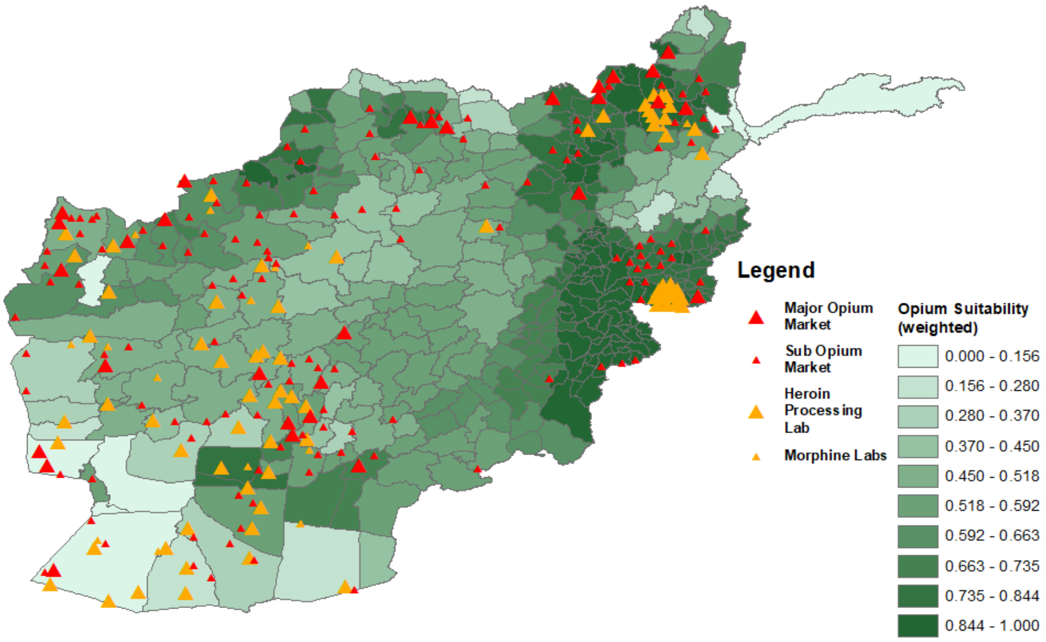


Figure 21: Opium suitability and the location of opium markets and processing labs

Notes: Opium suitability is from Kienberger *et al.* (2017) and is weighted by population. Opium market and lab information based on UNODC.

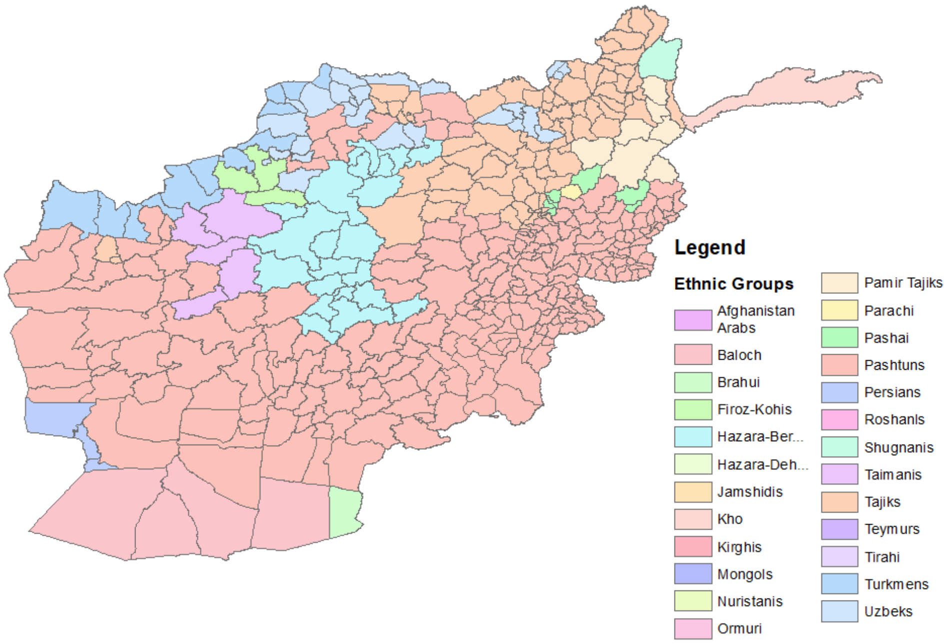


Figure 22: Distribution of ethnic groups (homelands)

Notes: Distribution of ethnic groups (homelands) in Afghanistan. Note that these are partly overlapping polygons, i.e. some districts feature more than one group even though this is not visible in the map, but we account for this in later estimations. Source: GREG (Weidmann *et al.*, 2010).

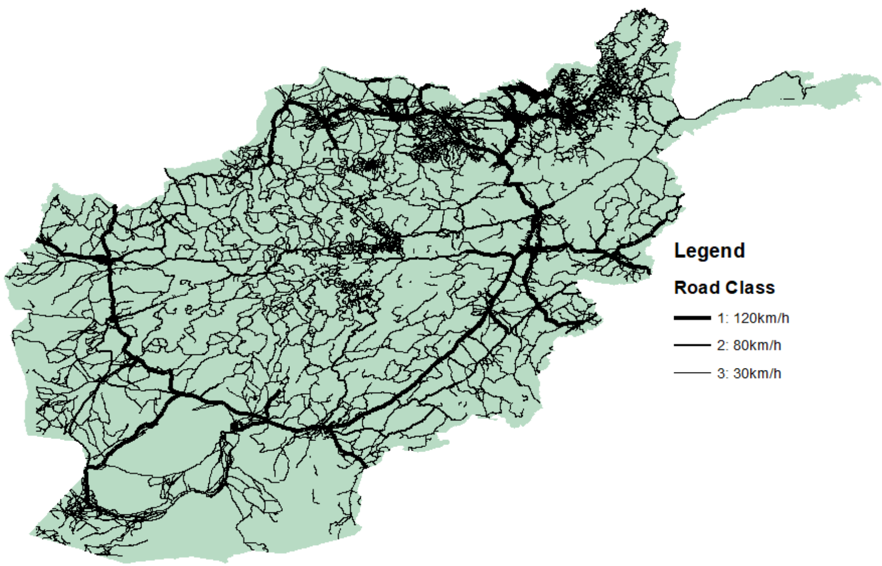


Figure 23: The road network

Notes: The road network in Afghanistan distinguishing in highways (assumed speed 120 km/h), rural roads (ass. speed 90 km/h), and urban roads (ass. speed 50 km/h). The distinction in road types and the choice of average speed is not decisive for our results.

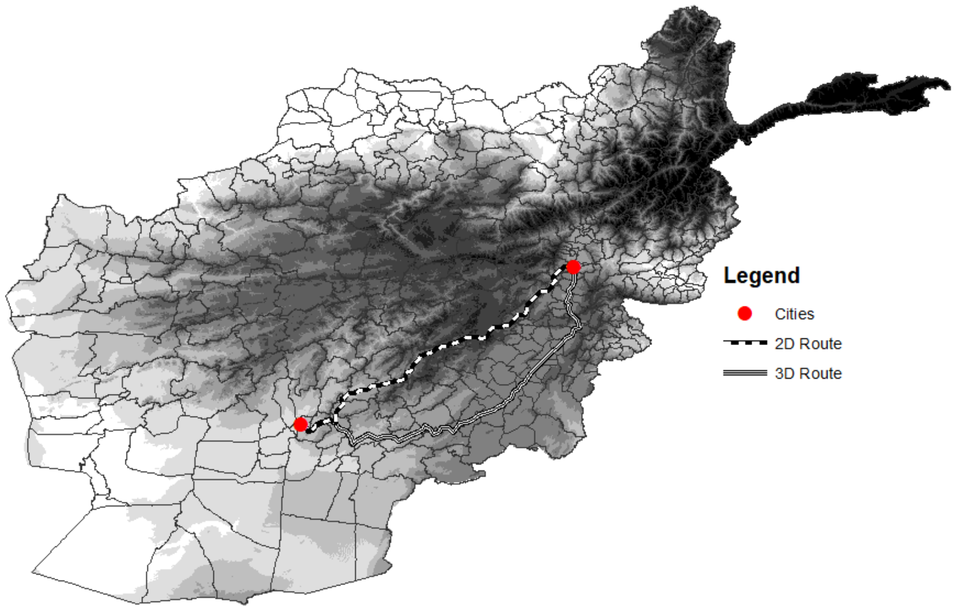
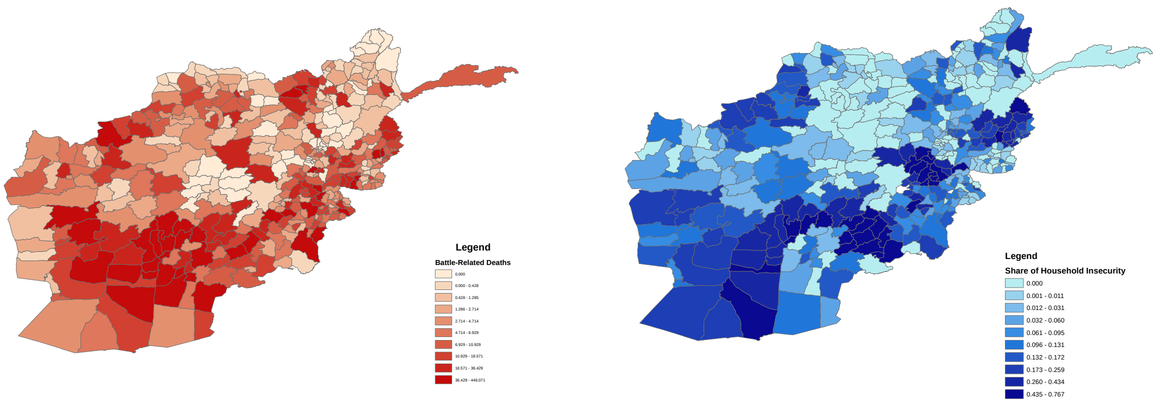


Figure 24: Elevation and distance

Notes: The intensity of black indicates the elevation in Afghanistan. The white-black dashed line shows the shortest road distance between to district centroids. The second white/black line indicates the shortest distance when accounting for elevation differences along the roads. In particular the central part of Afghanistan is very mountainous, which can have a large effect on transportation costs and travel time.



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

Figure 25: Distribution of objective (BRD) and subjective (NRVA) conflict indicators (2002-2014)

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

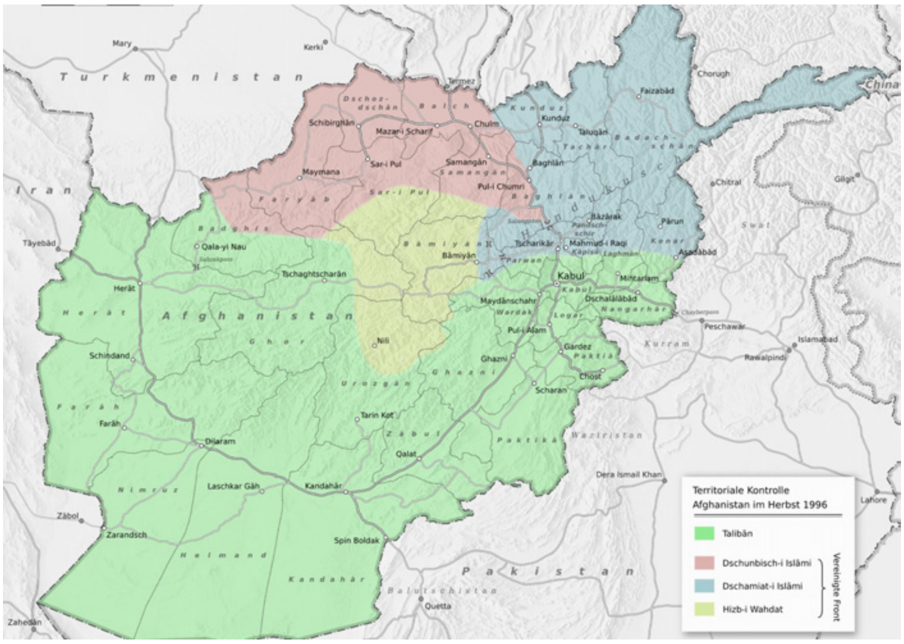
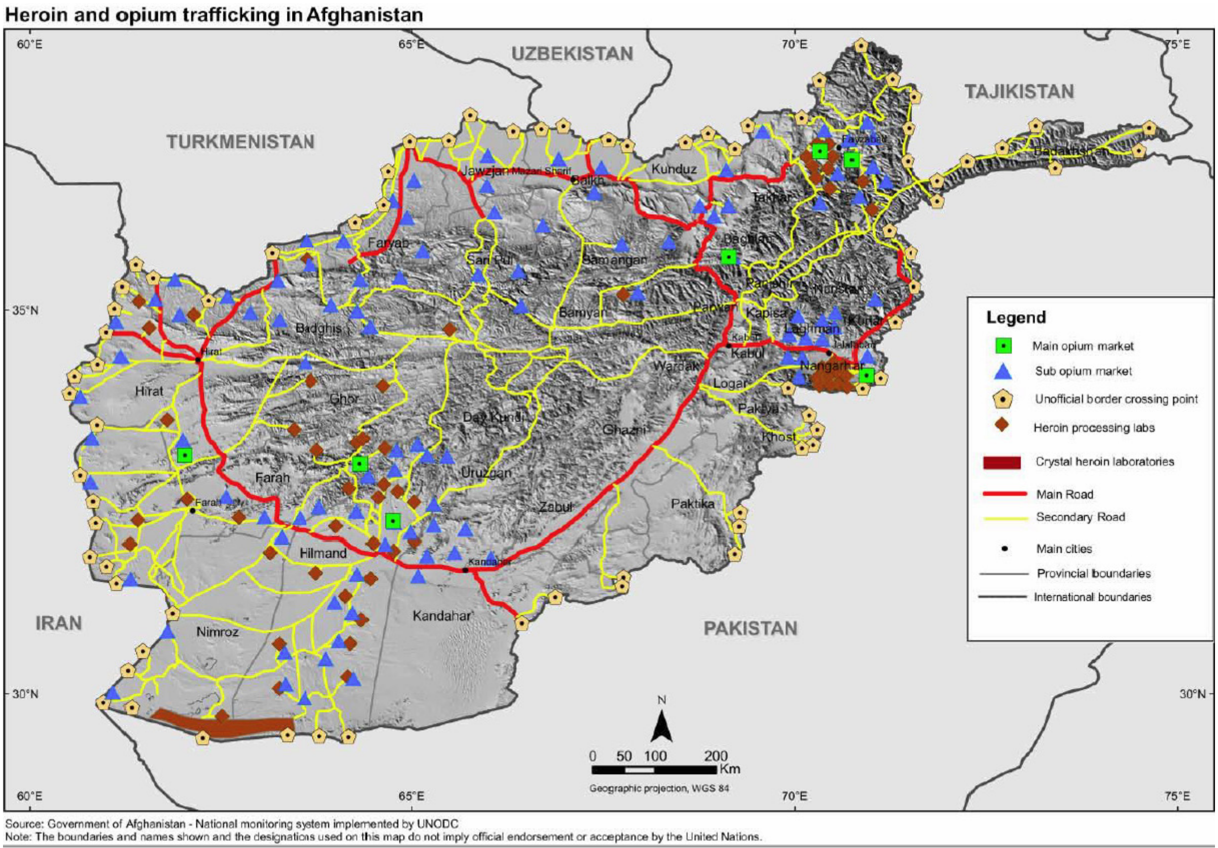


Figure 26: Political control in Afghanistan in the fall of 1996

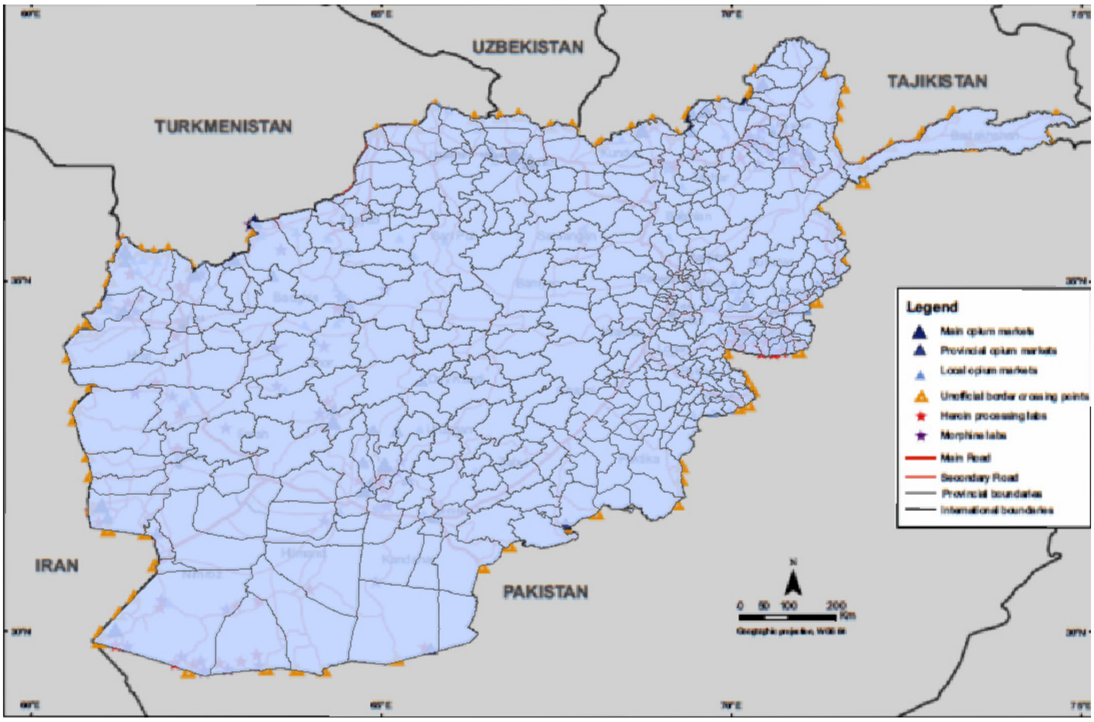
H. Data coding and map generation

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 the other variables such as main opium markets and heroin processing labs.



Original UNODC map (2007)

Map making process: The source of the original map is 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 the indicators that we create are time-invarying, also due to the availability of data. 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 (Coordinate system GCS WGS 1984) shapefile for Afghan authorities (ESOC Princeton, https://esoc.princeton.edu/files/administrative-boundaries-398-districts). This way, we are accurately overlaying the data points and not simply making an educated guess as to where to place the points. Below are the two final digitized maps based on the UNODC data, overlaid with the district data. The binary indicators that we use in Section 5 on heterogeneous effects are coded as one if the respective feature is present within the boundaries of the district polygon at least once. Alternatively, we use the number of feature per district, e.g. for opium markets.

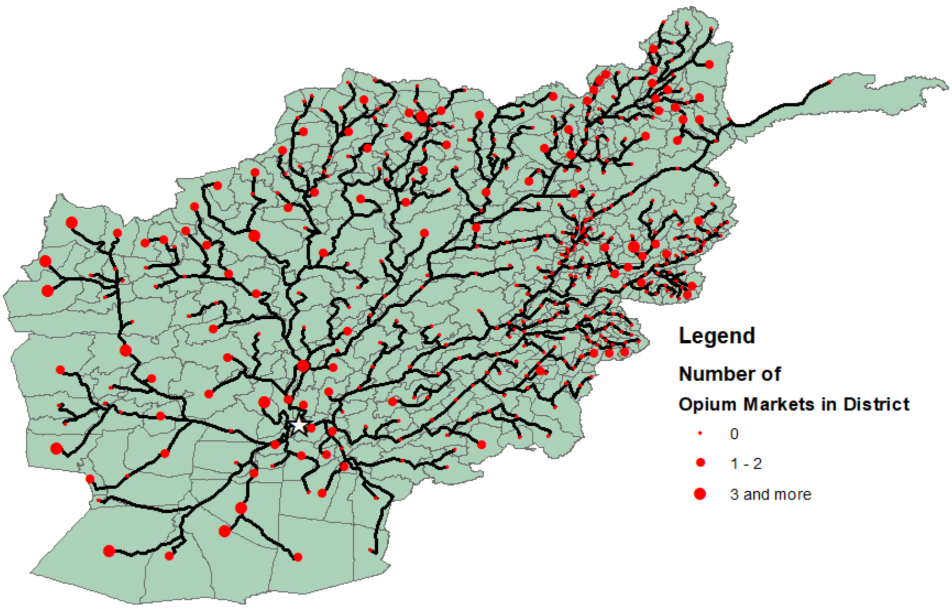


Figure 27: Final Map 1

Notes: The dots indicate district-specific centroids, and the black lines are the shortest roads connections to the other centroids in the network. To compute market access, the same computation is done for every centroid in the district, leading to different optimal road connections. The distances are then used as weights and multiplied with the importance of the respective network members, in this case the number of drug markets. Sources: UNODC (2016), Open Street Map and Afghanistan Information Management Service (AIMS).

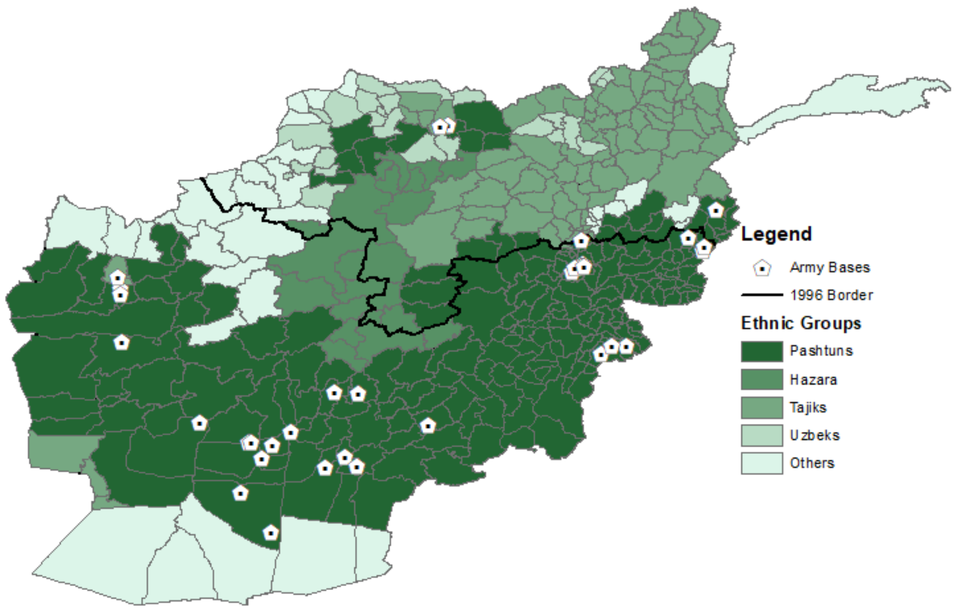


Figure 28: Final map 2

Notes: The map shows the four major ethnic groups in Afghanistan in different shades of green (Source: GREG). The white symbols with the black dots indicate the location of a foreign military base, for which we could track location, opening and closing date (sources in detail in Appendix H). The area south of the thick black line was controlled by the Taliban prior to 2001. (Dorronsoro, 2005).

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 most bases release no official information as to their geographic location for security reasons. In order to find this information, we compile data from different sources about the most relevant bases to include. We then pinpoint, with latitude and longitude coordinates, the exact location of these bases. Since some are now closed, some data points record past base locations. We rely on information from Wikipedia's GeoHack program for the more well-known bases and on news articles, 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 the bases (if available) with available satellite data to verify their location. Below, we show the table with the locations of the about 50 bases that we could identify. The exact locations are blackened out for confidentiality reasons, even though we are convinced none of this information is confidential and could be misused or endanger soldiers. Without access to confidential NATO and US military information this is the best data we could assemble. It is certainly not a complete list of bases, which introduces considerable measurement error to the indicator variable we create based on it. At the same time, we have no reason to expect this measurement error to be non-normal.

OBJECTID *	Base Name	Installation Type	Militaries Present	Lat	Lon	District
1	Delaram	FOB	USMC	[redacted]		Delaram
2	Leatherneck	Camp	USMC			Nahri Saraj
3	Kabul International Airport	Camp	ISAF, Turkish Army, US Army, USMC, USAF, Mongolian Armed Forces			Kabul
4	Kandahar Airfield	Airfield	RAF, USAF, US Army			Kandahar
5	Shindand Airbase	Airbase	USAF, AAF			Shindand
6	Bagram Airfield	Airfield	US Army, USAF			Bagram
7	Bastion	Camp	British Army, RAF, Royal Navy (RN), Royal Marines (RM), USMC, Estonian Land Forces, Danish Defence, Tonga Defence Services			Nahri Saraj
8	Price	MOB	RM, British Army, Danish Defence, US Army, USMC			Nahri Saraj
9	Lashkar Gah	MOB	British Army, RM			Lashkargah
10	Eggers	Camp	NATO, US Army, USMC, US Air Force, Australian Army, New Zealand Army, French Army, Turkish Army, Mongolian Armed Forces			Kabul
11	Salerno	FOB	US Army, USAF, US Navy			Khost (Matun)
12	Chapman	FOB	US Special Operation Command, US Army, CIA			Khost (Matun)
13	Marmal	Camp	German Army, German Navy, German Air Force, Royal Netherlands AF, Swedish Air Force, US Army, Mongolian Armed Forces			Mazar-e Sharif
14	Dwyer	Camp	USMC, British Army, RM			Garmsir
15	Rhino	Camp	USMC, US Navy, US Army, USAF, SASR			Garmsir
16	Holland	Camp	Australian Army, New Zealand Army, US Army, Royal Netherlands Army, ANA			Tarin Kot
17	Black Horse	Camp	US Army, Canadian Army			Kabul
18	Dogan	Camp	<Null>			Kabul
19	Invicta	Camp	Italian Army			Kabul
20	Julien	Camp	Canadian Army			Kabul
21	Julien	Camp	Canadian Army			Kabul
22	Phoenix (Qargha)	Camp	US Army			Kabul
23	Souter	Camp	British Army			Kabul
24	Warehouse	Camp	Canadian Army			Kabul
25	Pucino	Camp	USSOCOM			Khost (Matun)
26	Clark	Camp	US Army			Mandozayi
27	Blessing	Camp	US Army, USMC			Waygal
28	Bostick	FOB	US Army			Nari
29	Joyce	FOB	US Army			Sarkani
30	Wright	Camp	US Army			Asadabad
31	Albert	Camp	US Army			Bagram
32	Blackjack	Camp	US			Bagram
33	Bulldog	Camp	US			Bagram
34	Civilian	Camp	US			Bagram
35	Cunningham	Camp	US			Bagram
36	Gibraltar	Camp	US			Bagram
37	Warrior	Camp	US			Bagram
38	Pratt	Camp	US Army			Mazar-e-Sharif
39	Spann	Camp	US Army			Mazar-e-Sharif
40	Baker	Camp	Australian Army			Daman
41	Nathan Smith	Camp	Canadian Army, US Army			Kandahar
42	Hadrian	Camp	Royal Netherlands Army			Deh Rawod
43	Russell	Camp	Australian Army			Tarin Kot
44	Hamidullah	FOB	USMC, British Army, RM			Sangin
45	Arena	Camp	Italian Army, Italian Air Force, US Army			Hirat
46	Stone	Camp	Carabinieri, US Army			Hirat
47	Vianini	Camp	Italian Army			Hirat
48	Losano	Camp	RNLAF, US Army, USAF			Kandahar
49	Lagman	FOB	US Army, US Navy, Romanian Army, ANA			Qalat
50	Shorabak	Camp	ISAF, US, Britain, Denmark, Estonia, Tonga			Lashkargah
51	Pasab (Wilson)	FOB	US Army			Panjwayi

Main bases and relevant information (1/2)

Opened	Closed	Field9	Notes	Shape *
2009	2014	<Null>	<Null>	Point
2008	2014	<Null>	Regional Command Southwest Headquarters	Point
2001	.	Open	ISAF Headquarters, ISAF Joint Command Headquarters, Headquarters for RC-Capital	Point
2001	.	Open	RC-S headquarters	Point
2004	2014	<Null>	<Null>	Point
2001	.	Open	Largest US base in Afghanistan, RC-East Headquarters	Point
2006	2014	<Null>	Main British base and formerly home to Task Force Helmand	Point
2006	2014	<Null>	<Null>	Point
2006	2014	<Null>	<Null>	Point
2006	2014	<Null>	NATO Training Mission – Afghanistan Headquarters	Point
2003	2013	<Null>	<Null>	Point
2001	.	Open	Major CIA and Special Operations counter-insurgency outpost	Point
2005	.	Open	<Null>	Point
2007	2009	<Null>	<Null>	Point
2001	2002	<Null>	First Marine land base in Afghanistan	Point
2006	2013	<Null>	<Null>	Point
2008	2013	<Null>	<Null>	Point
2002	2015	<Null>	<Null>	Point
2006	2012	Close unk, camp was open in 2012	<Null>	Point
2003	2005	<Null>	Reopened as a Counterinsurgency Academy in April 2007	Point
2007	.	Open	Reopened as a Counterinsurgency Academy in April 2008	Point
.	.	Open	Opening unknown	Point
2007	2014	Slated to close in 2014	<Null>	Point
2002	2014	Slated to close in 2014, Canada withdrew all troops at this time	<Null>	Point
2002	2013	<Null>	<Null>	Point
.	.	Open unk, close unk	<Null>	Point
2002	2011	<Null>	<Null>	Point
2006	2012	<Null>	<Null>	Point
2002	2013	Close unk, camp was open in 2013	<Null>	Point
2001	.	Close unk	<Null>	Point
2004	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
.	2012	Open unk, close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
.	2012	Open unk, close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
2003	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
2004	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
2002	2012	Close unk, camp still open 2012	Located in/related to Bagram Airfield	Point
.	.	Open	Located in/related to Bagram Airfield, opening date unknown	Point
.	2014	Open unk	<Null>	Point
.	2014	Open unk, between 2001 and 2004	<Null>	Point
2006	2015	<Null>	Located in/related to Kandahar Airfield	Point
2003	2013	<Null>	<Null>	Point
.	2013	Open unk, task force Uruzgan started 2006	<Null>	Point
2005	2013	<Null>	<Null>	Point
2007	2014	<Null>	<Null>	Point
2012	.	Open	<Null>	Point
Before/in 2008	2014	<Null>	<Null>	Point
Before/in 2006	2012	<Null>	<Null>	Point
.	.	Open unk, close unk	Located in/related to Kandahar Airfield	Point
2004	2014	<Null>	<Null>	Point
2005	.	Open	ISAF logistics hub	Point
.	2014	Open unk, slated to close in 2014	<Null>	Point

Main bases and relevant information (2/2)

This table shows the available data for about 50 bases that we deemed to be the most important foreign bases in Afghanistan over the last 15 years. We list the name, type, location (coordinate system CGS WGS 1984), militaries present (countries of origin), 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 closure time or that the base is still open. See Field 9 for explanatory notes in these cases), and general notes of interest.

Confirming the location of these districts using satellite imagery

Example: "Base Blackhorse"

This is an example of the Wikimapia satellite imagery, which we used to locate bases. This is an image of Base Blackhorse, now closed. We were able to locate this as Base Blackhorse by first searching for the camp on wikimapia which offered two possible locations (approximately 9 miles away from each other) where the base could be. After we discovered in a news report that the base 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 determine 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 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 not included (for example, we included no firebases on account of their temporary nature and generally small size). Below this, we provide more 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 satellite data and through available news reports, photos and satellite imagery. All definitions below are adapted or directly taken fromWikipedia to provide a rough idea about the types of military bases that exist in Afghanistan. We do not rely on the distinctions and simply code whether there is an open base or not.

Additional information about bases (from wikipedia):

- 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 - A 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.

- 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; the station is occupied by troops, it is usually a small military base or settlement in an outlying frontier, limit, political boundary or in a foreign country.

- 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.

- 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 locations are taken from Wikimedia's GeoHack program if available. We do not consider Firebases and COPs, which are smaller and often temporary outposts. In addition, we found or updated the information for the following cases:

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 satellite imagery.

3. Camp Russell location determined using Wikimapia satellite 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 satellite imagery.

7. Camp Warehouse determined using Wikimapia satellite imagery.

8. Camp Phoenix location determined using google maps and Wikimapia satellite data.

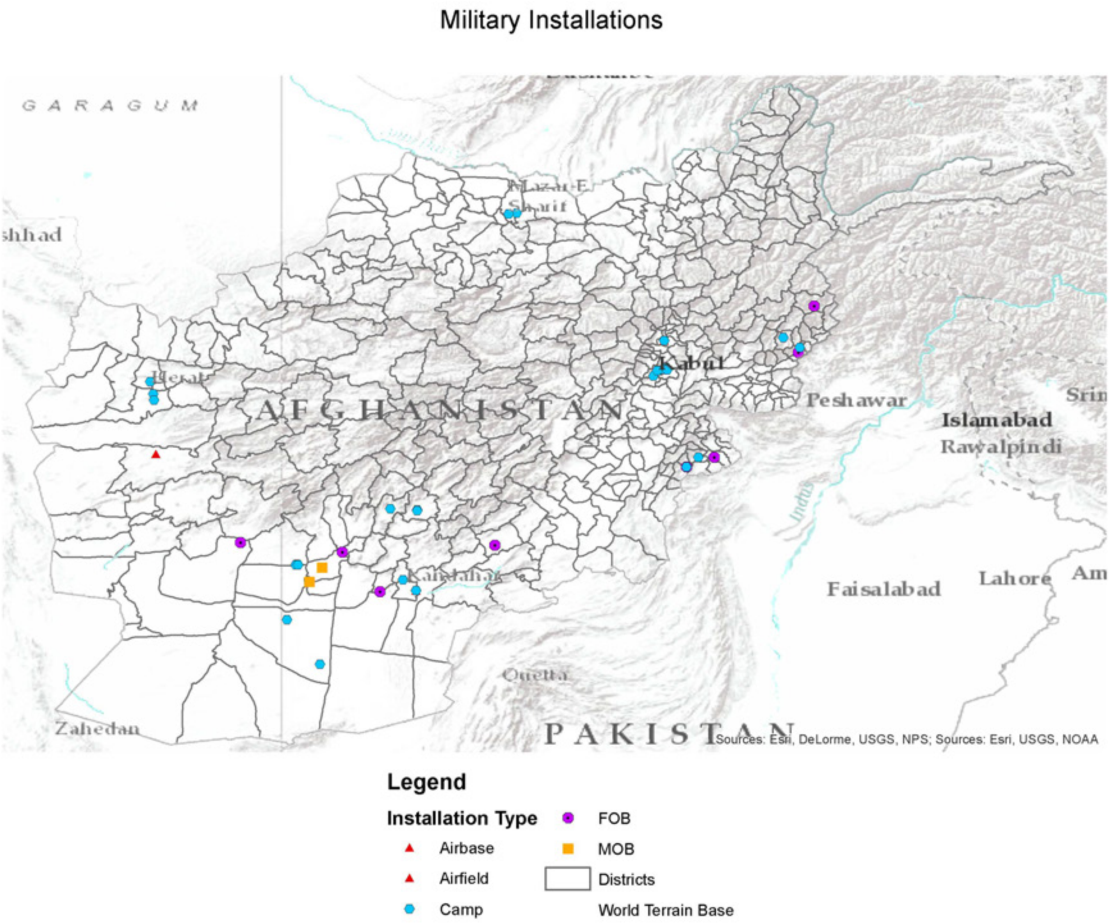
9. Camp Invicta located using Wikimapia satellite data.

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

11. Camp Blessing located using Wikimapia satellite data.

12. FOB Joyce located using satellite 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 satellite data; it is listed as 'USA Army Base" on the Wikimapia site.



Final Map of Located Military Installations

This map shows the geographic location of the bases that we identified. Some bases are not visible in this view as a result of closely overlapping with other bases, in which case the map displays only one symbol.