University of Heidelberg

Department of Economics

Discussion Paper Series | No. 652

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Resource-related income shocks and conflict

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July 2018

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July 19, 2018

Abstract

We provide new evidence about the mechanisms linking resource-related income shocks to conflict. To do so, we combine temporal variation in international drug prices with new data on spatial variation in opium suitability to examine the effect of opium profitability on conflict in Afghanistan. District level results indicate a conflict-reducing effect over the 2002-2014 period, both in a reduced-form setting and with three different instrumental variables. We provide evidence for two main mechanisms. First, the importance of contest effects depends on the degree of violent group competition over valuable resources. By using data on the drug production process, ethnic homelands, and Taliban versus pro-government influence, we show that on average group competition for suitable districts is relatively low in Afghanistan. Second, we highlight the role of opportunity costs by showing that opium profitability positively affects household living standards, and becomes more important after a sudden rise in unemployment due to the dissolution of large armed militias after an exogenous policy change.

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

JEL Classification: D74, K4, O53, Q1

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Acknowledgments:
We thank Coen Bussink (from UNODC), Sascha Becker, Lars-Erik Cedermann, Travers Child, Axel Dreher, Martin Gassebner, Anita Ghodes, Douglas Gollin, Valentin Lang, Guilherme Lichand, Jason Lyall, Elias Papaioannou, Marta Reynal-Querol, Dominic Rohner, Luis Royuela (from EMCDDA), David Schindler, Lorenzo Vita (from UNODC), Philip Verwimp, Austin Wright, David Yanagizawa-Drott, Josef Zweimüller, and participants at the Spring Meeting of Young Economists (Palma 2018), 2017 Barcelona Workshop on Regional and Urban Economics, 13th Annual Workshop of the Households in Conflict Network (Brussels 2017), 26th Silvaplana Workshop on Political Economy (2017), Beyond Basic Questions Workshop (Gargnano 2017), DIAL Development Conference (Paris 2017), 17th Jan Tinbergen European Peace Science Conference (Antwerp 2017), Development Economics and Policy Conference (Göttingen 2017), European Public Choice Society Meeting (Budapest 2017), 1st FHM Development Workshop (Mannheim 2016), and seminars at Hamburg University, University of Barcelona (UB), Université Libre de Bruxelles, University of Leicester, Heidelberg University, and at the policial science and economics faculties of the University of Zurich and ETH Zurich for their helpful comments. Austin Wright and Andrew Shaver generously shared data. Marco Altorfer, Patrick Betz, Jacob Hall, Dominik Jockers, Michele McArdle, Suraj Renagathan, Franziska Volk, and Lukas Willi provided excellent research assistance. We thank Michele McArdle for proofreading. All remaining mistakes are ours.

1. Introduction

An important strand of the resource-curse literature examines how resource-related income shocks are linked to conflict (e.g., Brückner and Ciccone, 2010; Morelli and Rohner, 2015; Berman et al., 2017). Yet, we've only begun to understand the micro-foundations 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 and Vargas, 2013).

Our paper makes three main contributions, which relate to the the contest or rapacity hypothesis – where fights about valuable resources increase conflict – and the opportunity cost effect – where higher resource prices improve living conditions and lower conflict. First, we augment the contest hypothesis by highlighting that one has to consider the degree of competition between groups that fight for valuable resources. Afghanistan is an ideal setting to analyze the role of group competition, as it comprises many ethnic groups, but at the same time the conflict is mainly between two opposing sides since 2001. Our results show that higher opium prices reduce conflict incidence and intensity in Afghanistan. We provide evidence that, in line with our hypothesis, there is on average little between-group competition about opium production sites, and further show that the conflict-reducing effect of opium is stronger in districts that are more plausibly dominated by the Taliban. On the contrary, existing evidence for Colombia suggests a rapacity effect as rising cocaine prices lead to more conflict (Angrist and Kugler, 2008; Mejia and Restrepo, 2015). Both findings are in line with our hypothesis as in the setting of Colombia, rival groups compete for cocaine production grounds.

Second, we further examine and verify the main hypothesis in Dube and 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, which is characterized by a weak labor market and by 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 all across the country; opium, which is very labor-intensive, and wheat, which requires less labor (Mansfield and Fishstein, 2016).[1] Accordingly, a relative decline in opium prices causes marginal producers to shift towards wheat production and decreases labor demand.[2] In absence of good alternatives, joining a rebel group like the

[1] 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.

[2] 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.

Taliban is one of the few options (e.g., Bove and Elia, 2013). We use survey data to verify that opium profitability indeed matters for well-being at the household level, and show that the apparent reliance on opium increases after an exogenous policy shock that deprived people of an important alternative source of income.

Exploring those mechanisms helps to understand the role of opium in the Afghan conflict, which caused more than 100.000 battle-related deaths since 2002. In addition to learning more about this individual case, lessons from this conflict might turn out to be useful for other cases. Afghanistan resembles other countries, in that it has a weak government that cannot effectively enforce its monopoly of violence as well as a high level of ethnic fractionalization and weak labour market with few opportunities of formal employment.

Third, we establish causality through the combination of novel data with different identification strategies. In particular, by combining temporal variation in international drug prices with a new dataset on spatial variation in opium suitability (Kienberger et al., 2017), we can observe changes in opium profitability across time and districts. We exploit patterns in consumer preferences in the drug market and use the international price of heroin (which is made of opium) and of complements to heroin, along with local opium prices in a reduced-form setting to verify the causal interpretation of our findings. In addition, we propose two alternative identification strategies in an instrumental variable setting, based on climatic differences and changes in legal opioid prescriptions in the United States. All these strategies lead to the same result. We find that a higher opium profitability consistently reduces both conflict incidence and intensity.

Our dataset allows us to identify if this effect is indeed driven by changes in opportunity costs. First, 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 consistently higher food consumption and living standards using various indicators, suggesting that a more profitable opium economy increases the opportunity costs of fighting. Second, we georeference data provided by 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 do not only cultivate opium in its raw form, but also process and trade it can capture a larger share of the 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 and Hornbeck, 2016). If there was strong between-group competition in the Afghan drug market, we would expect more fighting in those districts. The conflict-reducing effect is, however, even stronger in those districts that feature further processing steps and have high drug-market access. This is in line with an explanation based on the opportunity costs of fighting, and implausible if there was strong between-group competition in the drug market (as it is apparently the case in Colombia, see, Angrist and Kugler, 2008; Mejia and Restrepo, 2015).

We complement the evidence on little competition between rival groups for suitable districts in Afghanistan by relying on the geographical distribution of ethnic homelands (Weidmann et al., 2010). We compute whether a district is ethnically mixed and how many ethnic groups it features. Building on the literature about the role of ethnic groups for conflict (e.g., Esteban et al., 2012), we would expect no or a smaller conflict-reducing effect in ethnically heterogeneous districts if there was strong violent competition between those groups. We find no significant differences, supporting our hypothesis of limited group competition.

Furthermore, our hypothesis on the role of group competition for suitable districts would predict that the conflict-reducing effects should be the strongest in districts that are plausibly dominated by one group. We exploit the fact that after 2001 almost all fighting occurs between pro-government groups including Western military forces and the Taliban. We use maps on the historical Taliban presence and the homelands of the Pashtun ethnic group, as well as data about the location of foreign military bases and main cities to measure whether a district is (i) more plausibly controlled by the Taliban or (iii) controlled by the government or foreign military.[3] With regard to the first point, we find that the conflict-reducing effect after 2001 is stronger in areas that are more likely controlled by the Taliban. This supports qualitative evidence about the ideological turn of the group towards protecting opium farmers and their apparently strong relations with the opium economy. The finding is also in line with anecdotal evidence that the group is acting as a stationary bandit, which maximizes revenues in the districts it controls.

Regarding the second point, we analyze the role of the Afghan government and foreign military more specifically. The degree to which the illegality of opium influences conflict decisively depends on actual government strategies, i.e, control and enforcement. In Mexico, for instance, the culmination of violence in recent years coincides with the government taking stricter actions and enforcement, potentially breaking up existing and more peaceful equilibria among drug cartels and the government (for studies on Mexico see, for instance, Dell, 2015; Mejía et al., 2015). Illegality increases profits and the risk of production, as well as fostering the creation of organized criminal groups, that fight for suitable areas and rents. Another dimension of government influence is that if rules are enforced, this creates an incentive for opium farmers to cooperate and finance the Taliban who offer protection against those measures. Consequently, this can lead to more fights between Taliban and government (Peters, 2009), and a smaller or no conflict-reducing effect.

The foreign coalition officially takes a strong stance on drugs in general and opium in

[3] The Taliban are initially a Pashtun group (although not exclusively anymore), so that Pashtun presence makes it easier to establish a presence of the Taliban in a district.

particular. Several United Nations Security Council (UNSC) bulletins claim resolute actions against drug producers and traffickers. According to our data, we find no evidence of a heterogeneous effect according to the presence of the foreign military forces. This is in line with statements by the US military leadership who do not regard "anti-drug enforcement" as part of their agenda.[4] To measure government influence, we follow Michalopoulos and Papaioannou (2014) and use the distance to the capital as a measure of the Afghan government's influence. To account for the specific topography of Afghanistan, we do not only measure the distance in a straight-line, but also compute two- and three-dimensional road distances and estimated travel times to Kabul and other big cities. We generally find no moderating effect of any of those approximations. The influence of the government, leading to potential conflict with producers of *de jure* illegal crops, seems to be confined to a radius of about 75 km or 2 hours travel time to Kabul.

Finally, we use a policy change in the Western military strategy to further shed light on the difficulties associated with nation-building during and after a military intervention, and suggest some important trade-offs. In a nutshell, between 2001 and approximately 2005 the Western forces financially supported warlords and local strongholds to build a strong anti-Taliban coalition. Estimates report that several hundred thousands of men were armed and became part of those militias, and that more than 60% of the provincial governors "were leaders of armed groups and most of the remaining ones had links to the latter" during that time (Giustozzi, 2009, p. 91). Around 2005, the Western coalition switched their strategy towards a nation-building approach that attempted to pacify and "clean" Afghan politics by putting pressure on the Afghan government to force political leaders and governors to give up and abandon their connection to the militias (Giustozzi, 2009, p. 94ff.). In the following, many trained and armed men who were part of those groups lost a substantial source of income and the reliance on other income sources like opium production assumedly increased. By exploiting the approximate timing of this change, we can show that the connection between drug profitability and conflict indeed becomes much stronger after 2005. This suggests a trade-off between reducing the influence of non-state armed groups and fighting the production of an illegal resource at the same time. Both policy goals apparently cannot be achieved simultaneously.

We proceed as follows. Section 2 discusses the relevant theoretical considerations and the related literature, Section 3 introduces the data, and Section 4 the empirical

[4] 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.

strategy. The main results are presented in Section 5. We investigate heterogeneity of the results and the underlying channels in Section 6. We discuss sensitivity tests in Section 7. Section 8 summarizes and provides policy implications.

2. Theoretical considerations and contributions to the literature

A. Theoretical considerations

From a theoretical perspective, it is *ex ante* unclear in which direction income in general, and opium-related income in particular, affects conflict. The 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). The first theory hypothesizes that with a rise in income the opportunity costs of fighting increase, leading to, on average, less violence. For an individual, joining or supporting anti-government troops like the Taliban, becomes less attractive after an increase in the profitability of opium. In contrast, the contest model, or rapacity effect, would predict that with higher opium profitability, highly suitable territories become relatively more attractive, because the potential gains from fighting are greater. This would predict relatively more fighting in attractive districts when opium prices are high.

In Afghanistan, the main alternative to growing poppies is considered to be growing wheat (UNODC, 2013; Lind et al., 2014) or, if neither is sufficiently attractive, joining a rebel group.[5] Many studies suggest that growing poppies is generally far more profitable and the gross wheat-to-opium income-ratio ranges between 1:4 to 1:27 (UNODC, 2005, 2013). Nevertheless, Mansfield and Fishstein (2016) criticize this over-simplified approach for focusing on gross instead of net returns, and ignoring differences in the production process. We consider this a valid criticism, in particular against the background of the evidence provided by Dube and Vargas (2013) that labor intensity is crucial to understand the effect of resource shocks on conflict. The differences in Afghanistan are indeed large. Mansfield and 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." This leads to two important implications.

First, whether opium is profitable (and more profitable than an alternative, e.g., wheat) depends on the price in the respective year and differs between districts, also because it is costlier than wheat in terms of inputs like fertilizer. Mansfield and Fishstein (2016) report that there were years where opium was profitable across nearly all locations they examined, and other years where this depends on the specific location. This supports

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

our empirical strategy exploiting that price changes have heterogeneous effects depending on the suitability of soil. Second, other crops are plausible alternatives when considering the net returns. We take this into account by controlling for shocks on wheat profitability in a similar manner as we do for opium. Due to the differences in labor intensity and legal status, we expect different effects of both shocks. The effect of a positive wheat shock on opportunity costs is ambiguous. While the income of some producers and farmers increases, most farmers grow wheat as a staple crop and many households are net buyers of wheat (Mansfield and Fishstein, 2016). The net effect on opportunity costs is hence a combination of both a positive and a negative effect and thus remains an open empirical question.

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

In Afghanistan, a further channel linking illegal crop production and conflict, is producers turning to rebel groups which offer protection, against eradication or expropriation, in exchange for some form of a taxation. According to a survey conducted in southern Afghanistan, more than 65% of the farmers and traffickers stated that protection of opium cultivation and of trafficking is the main opium-related activity of the Taliban (Peters, 2009). UNODC (2013, p. 66) states that "[i]n some provinces, notably those with a strong insurgent presence, some or all farmers reported paying an opium tax" in the form of land or road taxes. If the Taliban were to use these revenues to expand their battle activities, this could amplify conflict.[7] Depending on whether the group acts as stationary or roving bandits (De La Sierra, 2015), they could also establish monopolies of violence to sustain taxation contracts and try to avoid conflict when the profitability of the taxable resources is higher. Wright (2018) argues that the tactics of rebel groups depend on their and the state's capacity as well as on outside options available to civilians, which can all be affected by income shocks. While rebel tactics are not the focus of our study, we distinguish between different types of violence in a robustness test. Taken together, a positive price shock on opium production could lead to less conflict through

[6] 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).

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

an opportunity cost channel or to more conflict via higher expected gains from fighting and financing rebel activity.

B. Contributions to the 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 and Laitin, 2003; Collier and Hoeffler, 2004; Blattman and 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., Miguel et al., 2004; Brückner and Ciccone, 2010; Bazzi and Blattman, 2014) and subnational level (e.g., Caselli and Michaels, 2013; Dube and Vargas, 2013; Berman and 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 the different features of resources and income sources and the role of violent group competition.[8]

Second, our analysis adds to the scarce causal evidence on the effect of illegal commodities. Despite the importance of the illicit economy, in particular in many developing and conflict-ridden societies, the literature provides very limited evidence on the effects of illegal commodity shocks on conflict. One notable exception is Dell (2015), who uses a regression discontinuity design to identify a causal relationship between drug trafficking, the political approaches to cope with it, and drug-related violence at the municipal level in Mexico. Our paper is similar to the extent that we also foster the understanding of the causal effect of drug cultivation and related activities on the behavior of people in affected regions. Closely related to our paper is the work by Angrist and Kugler (2008) and Mejia and Restrepo (2015), who exploit demand and supply shocks to cocaine and find a positive relationship with conflict in the Colombian context. Mejia and Restrepo (2015) show that when cocaine production was estimated to be more profitable the number of homicides increases. This effect is stronger in municipalities with a high suitability to grow cocaine, while a higher profitability of alternative crops such as cocoa, sugar cane, and palm oil tends to reduce violence. We augment these findings by showing that it is not only labor intensity and illegality per se, but that the nature of violent group competition over valuable resources moderates the resource-

[8] Ross (2004) and Lujala (2009) differentiate between various types of resources, but do not address endogeneity. Ross (2004) analyses 13 cases and provides evidence on a relationship between oil, non-fuel minerals, and drugs with conflict. Lujala (2009) finds a negative correlation of conflict with drug cultivation, but suggests a conflict-increasing effect of gemstone mining and oil and gas. La Ferrara and Guidolin (2007) analyze the effect of conflict on diamond production, i.e., the opposite direction of causality. Gehring and Schneider (2016) show that oil shocks do not lead to violent conflict, but their distribution can foster separatist party success in democracies.

conflict-relationship. Additionally, we argue that illegality can matter if it is actually enforced by the government, which can lead to conflict with the producers and create support for cartels or rebel groups. With that said, we also contribute to the literature on the provision of state-like institutions by non-state actors (e.g., De La Sierra, 2015). This relates to problems of imposing rules upon occupied territory in general (Acemoglu et al., 2011) and establishing a credible government in a poor and economically constrained environment (Berman et al., 2011). Our results highlight the importance of distinguishing between de jure illegality and de facto enforcement. In Afghanistan, our results support anecdotal evidence that the government apparently takes a very loose stance on drug enforcement outside areas directly surrounding Kabul. Our results also hint towards the role of local Taliban groups as stationary bandits. Qualitative evidence emphasizes that the Taliban collect taxes from opium farmers and traffickers and even implement conflict-solving mechanisms within the districts under their control to minimize violence that would potentially disturb the profitable production process. Our contribution thus stresses the need to consider differences between the types of resources as well as local circumstances like market structures before drawing general conclusions about the effect of resources on conflict.

An important strand of literature emphasizes existing cleavages between ethnic groups as an important driver of conflict (e.g., Esteban and Ray, 2008; Besley and Reynal-Querol, 2014; Morelli and Rohner, 2015; Michalopoulos and Papaioannou, 2016). We argue that since 2001 there is on average little competition between ethnic groups about suitable districts in Afghanistan, because the conflict is between two major sides, and ethnic groups and tribes have to choose to support one side or the other. This is supported by the fact that our results do not differ between mixed and more or less ethnically fractionalized districts.

We also add to the emerging literature on conflict and violence in Afghanistan. For instance, Sexton (2016) uses plausibly random variation in the allocation of US counterinsurgency aid to show that more aid leads to more conflict in contested districts. In an experimental set up, Lyall et al. (2013) study the determinants of International Security Assistance Force (ISAF) support and show that harm caused by Western forces increases support for the Taliban. Trebbi and Weese (2016) propose a new method to study the internal organization of rebel groups in Afghanistan, supporting that the Taliban are by far the most important group. Condra et al. (2018) show that the Taliban try to undermine electoral institutions with attacks, but minimize direct harm to civilians. In contrast, most of the conflicts we capture within our sample period are between rebels and pro-government groups rather than against civilians.

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 and 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 the findings in Bove and Elia (2013) with a larger sample, longer time period and 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.[9] Our results seem to be at odds with Berman et al. (2011), 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 their reliance on a fixed effects strategy without exogenous variation. Our findings based on household level data from the NRVA over the 2005-2012 period show that opium profitability coincides with households being better off.

3. Data

Conflict data: We use the UCDP Georeferenced Event Dataset (GED) as our primary source for different conflict indicators.[10] This dataset includes geocoded information (based on media reports) on the "best estimate of total fatalities resulting from an event" (Sundberg and Melander, 2013; Croicu and Sundberg, 2015), with specific information about the types of fighting (one-sided, state-based, non-state) and the actors involved as illustrated in Table 9.[11] 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

[9] 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 United Nations Security Council 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).

[10] We prefer this over data from the Armed Conflict Location & Event Data Project (ACLED), because 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).

[11] 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 and Melander, 2013; Croicu and Sundberg, 2015). These battle-related deaths include dead civilians and deaths of persons of unknown status. For more details see Appendix A.

and civilians as the victims. We differentiate between these different types in Section 7.

Our analysis is at the district level (ADM2). There are 398 districts, which belong to 34 provinces (ADM1) as presented in Figure 11 in Appendix C. There is no perfect threshold in the casualty number that identifies a conflict as relevant.[12] 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] Weidmann (2015) documents some under-reporting of media-based conflict data in areas with low population density compared to the SIGACTS data (Significant Activities), 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. Using different thresholds, each somehow arbitrary, along with a continuous measure of BRD alleviates these concerns, ensures transparency and allows us to capture conflict at the local level in a comprehensive way. We also use population-weighted and unweighted suitabilities to test potential differences with regard to population density, a jackknife approach (i.e., drop one province at a time) to account for the influence of high-conflict areas, and consider different conflict types in robustness tests. None of this suggests that the choice of conflict indicator introduces a systematic bias in our results.[14] To further verify the reliability of the UCDP GED data, Figure 23 in Appendix G shows a high correlation with a subjective conflict indicator derived from the NRVA household survey.

Opium suitability index: We exploit a novel data set measuring the suitability to grow opium based on exogenous underlying information about land cover, water availability, climatic suitability, and soil suitability. Conceptually, the index is comparable to suitability indices by the Food and Agricultural Organization (FAO). It was developed in collaboration with UNODC, and is described in detail in a publication in a geographical science journal (Kienberger et al., 2017). The left hand side of Figure 1 plots the distribution of the opium suitability index across Afghan districts. While an index of one would indicate perfect suitability in terms of land cover, water availability, climatic suitability, and suitability of soils, an index of zero means that the district is least suitable for growing opium. Given that it is generally possible to grow opium in many parts of Afghanistan and that it is "renewable," this suitability can also be understood as the actual "resource" that varies across districts. We weigh the suitability with the population

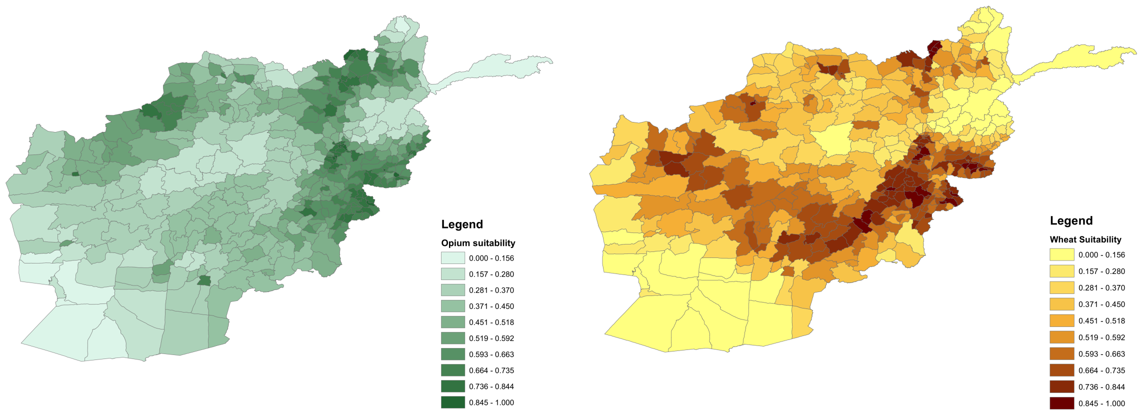
[12] Although it is standard at the macro level to only use the two thresholds of 25 and 1000, the latter threshold is evidently not appropriate for an analysis at the district level.

[13] Berman and Couttenier (2015) 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.

[14] We also use the SIGACTS data on the events direct fire, indirect fire, and improvised explosive device (IED), for which we received access by Shaver and Wright (2016) to verify the reliability of UCDP GED data. The results for all three types of events point in the same negative direction and are available on request.

density, but this does not affect our results.

Figure 1
Distribution of crop suitability across districts (weighted by population)



(A) Opium suitability (Kienberger et al., 2017) (B) Wheat suitability (*FAO GAEZ*)

Drug prices: For the measure of the external price shock we rely on international drug price data from the European Monitoring Center for Drugs and Drug Addiction (EMCDDA), which provides data for a large number of drugs in European countries (also including Turkey that is crossed by many drug trafficking routes). We take the mean prices for each country-year and calculate the average across all countries for which data are available, in order to eliminate the effects of country-specific shocks. The average variation should be a clearer estimate of global demand shocks.[15] Local price data on opium are derived from the annual Afghanistan Opium Price Monitoring reports by UNODC. The international price is the price for heroin, which is an opiate derived from morphines that are extracted from the opium poppy.[16]

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 kg multiplied with the yearly

[15] In the robustness section (Section 7), we try alternative definitions by taking price deviations from the long-term mean. Our results are not affected by this choice.

[16] 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.

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.

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. These 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.

Other data: As covariates we take the average luminosity computed using nighttime satellite data as a proxy for development (Henderson et al., 2012) and population (Henderson et al., 2018), which is computed using estimates from the Gridded Population of the World, Version 4 (GPWv4), dataset. Development and population are potentially affected by our outcome variable conflict and thus potentially bad controls. Accordingly, we take the (pre-determined) lagged values, and use them only for robustness. Using district-fixed effects and only within-district variation ensures that our main estimations are not affected by cross-sectional differences in population size. Similar to Harari and La Ferrara (2018) we use an index that captures inter-annual variations in drought conditions, the vegetation health index (VHI) provided by the FAO (Van Hoolst et al., 2016). In contrast to precipitation data (which are of low quality in Afghanistan) this requires no assumptions about the linearity of the effect and directly measures drought conditions. Additional time-invariant data on geographic conditions and further potentially relevant factors are used to identify mechanisms and for robustness tests. To analyze heterogeneous effects, we georeferenced district level information about opium production in labs, opium markets, and trafficking, as well as on military and government presence that are explained in the respective sections (Sections 6 and 7). All variables and their sources are described in detail in Appendix A and descriptive statistics are reported in Appendix B.

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.[17] 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-like instruments that combine cross-sectional variation with variation in a times series (e.g., Nunn and Qian, 2014). Our baseline equation at the district-year level over the 2002 to 2014 period is:

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

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, Table 32). 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 $wheat\,shock_{d,t-1}$, are defined as:

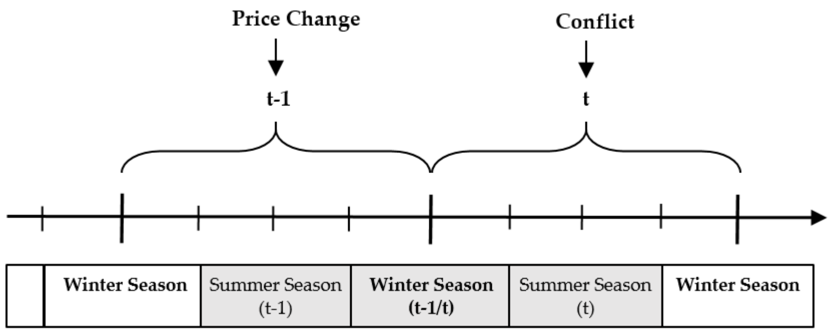
$$opium\,profitability_{d,t-1} = drug\,price_{t-1} \times opium\,suitability_d,$$
$$wheat\,shock_{d,t-1} = wheat\,price_{t-1} \times wheat\,suitability_d.$$

We include wheat-related income shocks ($wheat\,shock_{d,t-1}$), since wheat is the main (legal) alternative crop that farmers grow throughout Afghanistan. This allows us to identify differential effects for two types of income shocks, one affecting the main legal and the other the main illegal crop. $Wheat\,shock_{d,t-1}$ uses variation in the international wheat price interacted with the suitability to produce wheat ($wheat\,suitability_d$). 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

[17] 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.

exogenous (e.g., Berman and Couttenier, 2015). Note, that our main results regarding $opium\,profitability$ all hold without including this variable.

FIGURE 2
Time structure of price effects



Market price changes can plausibly influence opium cultivation and revenues in the same and the following year, as Figure 2 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 and 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, and often receive their remuneration in advance (Mansfield and Fishstein, 2016).[18] 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.

It might be problematic to use the international opium (heroin) price p^O_{t-1} because Afghanistan contributes a large share of the global opium production (UNODC, 2013b). More specifically, we would be worried about omitted variables OV_{t-1} that affect both opium production and p^O_{t-1}, as well as $conflict_{d,t}$, differentially, conditional on the time-invariant $opium\,suitability_d$. Problematic omitted variables would be any time-varying factors that affect high and low suitability districts differentially and follow a similar pattern as the heroin price.

One example of such an omitted variable could be changes in district-specific government institutions. Assuming that well-working government institutions are bad for

[18] 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."

opium production and trafficking, the effect of better institutions on production would be more negative in highly suitable regions. If good institutions also lead to less conflict, omitting this variable would bias our estimated effect upwards. Note that as we find a negative relationship we are more concerned about a potential downward bias. This could, for instance, occur if endogenously decided eradication campaigns correlate positively with the heroin price, and are less likely to take place in highly suitable areas that could be more risky to enter for government forces. If eradication campaigns also cause conflict, this would lead to a spurious correlation biasing the coefficient for $opium\,profitability_{d,t-1}$ downwards. Based on the notorious ineffectiveness of eradication policies (see, Rubin and Sherman, 2008; Felbab-Brown, 2013; Mejía et al., 2015), this possibility seems rather unlikely, yet there could be other biasing factors.

Note that we are less worried about overall opium supply shocks in Afghanistan. While these shocks would of course affect world market prices, this variation is captured by year-fixed effects. The year-fixed effects τ_t capture, for instance, yearly changes in crop diseases or shifts in anti-drug policies to the degree that they affect all districts in Afghanistan in the same way. District-fixed effects δ_d account for time-invariant unobservable characteristics at the district level. Province-times-year-fixed effects $\tau_t\delta_p$ account in addition for time-varying unobservables at the province level. These can include institutions provided by ethnic group or tribal leaders or warlords, which are in many provinces more important than the central government. As a large share of the drug trade is organized at the ethnic or provincial level (Giustozzi, 2009), changes in those institutions plausibly affect both conflict and opium production. Identification in this setting then relies only on within-province variation in a particular year due to differences in opium suitability.

Moreover, although our main specification does not rely on control variables, Appendix F shows that the results also hold with using $X_{d,t}$ and $X_{d,t-2}$, vectors of district level time-varying covariates including climate conditions and some baseline covariates frequently used in other conflict regressions such as luminosity (as a proxy for GDP) and population. Climate conditions are exogenous to conflict and can plausibly be used as contemporaneous values. We lag the luminosity and population twice with the aim to use a pre-determined value and to mitigate the bad control problem.

Table 10 in Appendix B shows that low and high suitability differ in some covariates X_d, as for instance in the distance to Kabul or ethnic group distribution. We would be worried if time-varying omitted variables would affect opium prices and conflict differentially depending on those covariates. A problematic case would be if high suitability districts, for reasons unrelated to opium, experience an increase in conflict over the sample period, and low suitability districts exhibit no change. The decrease in prices would then on average be associated with increasing conflict in highly suitable districts, even though it was caused by other characteristics that distinguish high from low suitability districts. 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 those observable differences (see, Appendix F).

Next, we would be concerned if 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. We thus take the issues raised in, e.g., Goldsmith-Pinkham et al. (2018) and Barrett and Christian (2017) about the role of cross-sectional differences and spurious non-linear trends very seriously. However, section D verifies that, even though prices decline in early years as well, the trends only start to differ after an exogenous change in Western policy around 2005, which increased the reliance of the local population on opium revenues. Moreover, we alleviate this concern in 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 the prices across years and find that random assignment yields to no significant relationship with coefficients being distributed around zero. Third, section C examines price trends and suggests that long term trends are mostly driven by demand rather than supply factors. Nonetheless, the next section introduces an additional identification strategy exploiting the relationship of opium with complement drugs to alleviate remaining concerns.

B. Identification using price changes

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.

We show that for this comparison to be helpful, 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 does only attenuate the coefficient towards zero.

3. The degree to which drug prices are affected by common demand shifters (a change in overall income of consumers, a shift in consumers' preferences about drugs, or the number of buyers in the drug market) must be sufficiently high relative to ϵ^C.

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, 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.

Regarding the identification of complements, we exploit the fact that drugs are classified as stimulants (uppers) or depressants (downers), with heroin being in the latter category. There is a consensus among experts about a high share of polydrug users, in particular 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). Moreover, cocaine supply is also most clearly exogenous to supply shocks in Afghanistan, as production exclusively takes place in South America and there is nearly no overlap with regard to trafficking routes (suggested by low cocaine seizures in Asia, see, UNODC, 2013b).[19] Thus, cocaine most clearly fulfills conditions 1 and 2.

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. We will also argue that the movement of prices (and expert opinions) indicate that long term price changes are more strongly driven by demand-side factors, which also alleviates concerns about omitted variables and their suitability-specific effect on opium supply and prices.[20]

C. International prices, local prices, and local revenues

In the following, we (i) discuss the movements of prices over our sample period, (ii) show that international prices of complements correlate positively with the international heroin price, (iii) international prices translate into economically relevant changes in the local price in Afghanistan and, (iv) that they affect opium revenues at the district level in Afghanistan. Figure 3 displays the variation in the international prices of heroin, cocaine, the complement index, as well as the Afghan price in constant 2010 Euro per gram. The local opium farm-gate prices at harvest time in Afghanistan are the ones most likely to be driven by opium supply side effects in Afghanistan. The international heroin price is a

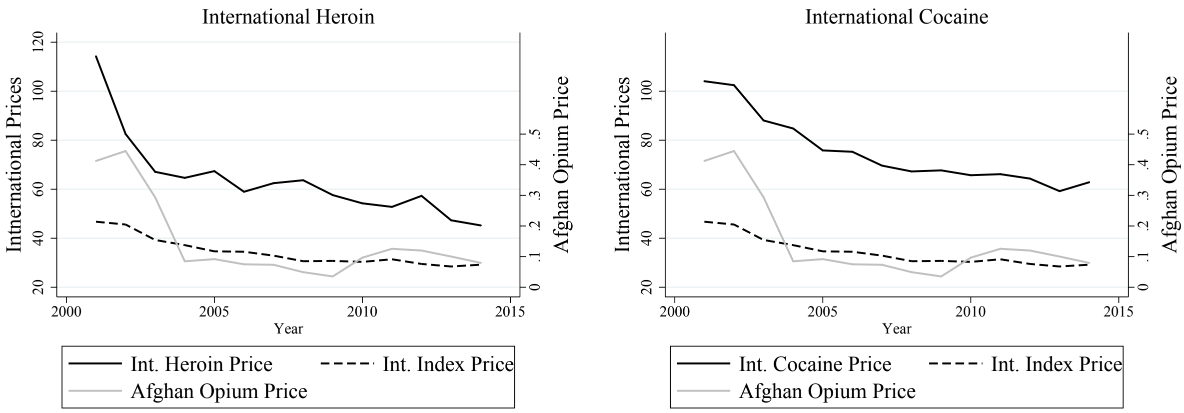
[19] There is also no evidence suggesting that ecstasy and amphetamines are produced in Afghanistan, but there is vague evidence on amphetamine-type stimulants (ATS) being seized in the Middle East (UNODC, 2013b). Afghanistan is never mentioned in this regard and not included in the list of countries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

[20] 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.

result of demand and supply in both the world market and within Afghanistan. Finally, the complement index captures shifts in demand for the three complementary drugs and largely eliminates individual supply shocks by using the average.

The graph provides several important insights. First, there are variations between the years, but overall all prices decline over time. The common pattern suggests that on average the development of prices over time is more strongly driven by common demand factors, and not by a shock to an individual drug. Interviews with experts at EMCDDA also support this view. Second, there is an overall positive correlation between the international heroin price, the complement index and the cocaine price (significant at the 1% level), validating our assumption of the cross-price elasticity being sufficiently high. As expected, the index exhibits less variation than the cocaine price. Third, local Afghan prices also correlate positively 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 at the country of origin.

FIGURE 3
Variation in international and local prices over time



After showing that the international heroin price is positively correlated with the international complement price index and with the local opium price, we proceed and quantitatively test whether international price changes translate into changes in actual opium revenues at the district level.[21] Some reports indicate that an amount of opium worth 600 US Dollar can have a street value of more than 150,000 US Dollar.[22] Consequently, we want to see whether market consumer price changes have a statistically and economically significant effect at the local level. We therefore run the empirical model as defined in Equation 1 but with the actual revenues from opium cultivation as the dependent variable (in logarithms). Opium revenues are defined as the production in

[21] In Appendix F in Table 26 we replace revenues with opium cultivation in hectares.
[22] See http://www.rollingstone.com/politics/news/afghanistan-the-making-of-a-narco-state-20141204, accessed June 14, 2018.

kg multiplied with the Afghan opium farm-gate price at harvest in constant 2010 EU/kg. Table 1 presents the results considering lagged effects in column 1. In column 2 we consider both lagged and contemporaneous effects by taking the moving average over (t) and (t-1).

TABLE 1
Effect of international price changes on opium revenues, 2002-2014

	Outcome: (t)	**Outcome: (t) + (t-1)**
	(1)	(2)
Opium Profitability (t-1)	2.336***	2.489***
	(0.827)	(0.749)
Wheat Shock (t-1)	-0.406	-0.123
	(0.460)	(0.418)
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 international heroin drug 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.

We see that external price shocks, measured by the interaction of international heroin price with the suitability to grow opium, in line with our proposed mechanism lead to an increase in local opium revenues in the same and following year (compared to Figure 2). These results are significant at the 1% level in columns 1 and 2. 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.[23] As a placebo test, it is reassuring that despite a positive correlation in the two suitability indices, the wheat shock has no effect on opium revenues.

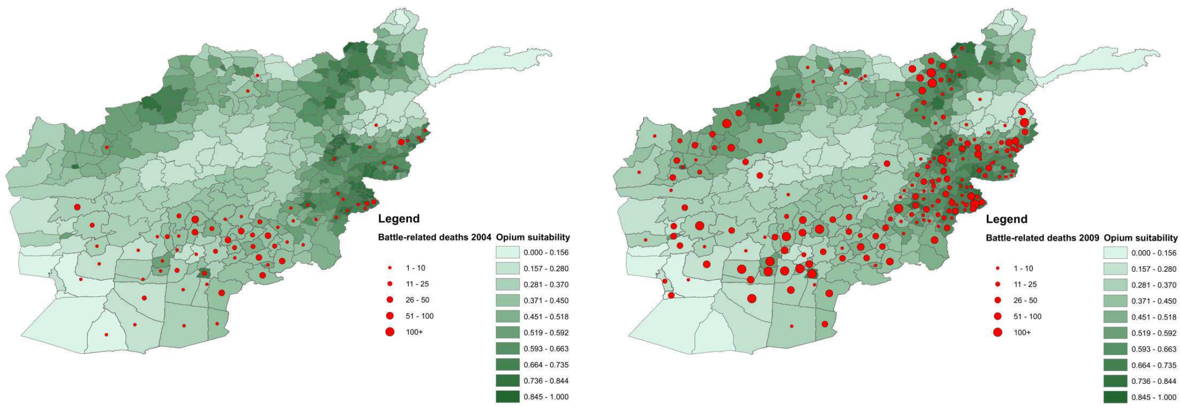
D. Visualizing the identification strategy

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- 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

[23] This estimation does not include province-times-year-fixed effects as the actual cultivation data, from which revenues are calculated, is gathered at the province level and district level data are estimated based on these underlying data (like any other estimation using cultivation data).

are more suitable to grow opium compared to districts with a low suitability. Figure 4 illustrates this with two maps showing the district level opium suitability overlaid with the distribution of conflict across Afghanistan for two selected years. 2004 is (and follows) a year of high prices and thus higher opium profitability (left graph) and 2009 a year of lower prices (right graph). It becomes immediately clear that lower prices are associated with more widespread and more intense conflict, and higher prices with less conflict, indicating support for the opportunity cost hypothesis at the country level. Our identification, however, relies on within-district variation over time conditional on suitability. This 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.

FIGURE 4
Intensity of conflict in districts with high and low opium suitability



(A) Conflict (2004): High opium prices (t/t-1) (B) Conflict (2009): Low opium prices (t/t-1)

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), and panel C and D report results using the complement price index and for robustness the international cocaine price. All regressions include only wheat shock 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 different specifications. Turning to the results, the regression coefficients are very much in line with our graphical inspection in Figure 4. Already when using the local opium prices, which introduces 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. Note that 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 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 the main legal alternative crop – wheat – 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 and Fishstein, 2016) and are thus negatively affected by price increases could explain the positive coefficients.[24]

[24] Chabot and 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.

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

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(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)
Wheat Shock (t-1)	0.366***	0.100***	0.095***	0.047	-0.013
	(0.120)	(0.037)	(0.035)	(0.031)	(0.017)
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)
Wheat Shock (t-1)	0.307**	0.088**	0.077**	0.034	-0.010
	(0.123)	(0.039)	(0.036)	(0.031)	(0.019)
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)
Wheat Shock (t-1)	0.221*	0.063	0.060	0.016	-0.023
	(0.128)	(0.040)	(0.037)	(0.033)	(0.020)
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)
Wheat Shock (t-1)	0.305**	0.087**	0.078**	0.033	-0.010
	(0.120)	(0.038)	(0.035)	(0.030)	(0.018)
Adjusted R-Squared	0.650	0.502	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. 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.

B. Instrumental variable

In a next step, we use IV regressions, where we instrument the endogenous variable (opium revenues) with two different IVs, opium profitability and a measure for climate conditions, the vegetation health index (VHI) (similar to Miguel et al., 2004; Nillesen and Verwimp, 2009). While the reduced form approach in Table 2 presents the ITT effect, we identify the LATE for compliers in Table 3. 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, as the data on opium cultivation and thus revenues are estimates only and there 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 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 A, significant at the 10% level in columns 1 and 2 as well as close to significance at conventional 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 and Stock (1997). Parallel to panel A, we instrument opium revenues with the VHI in panel B and find our results to remain robust. In particular for columns 1 to 3 coefficient estimates are very close across both panels, indicating that the LATEs are very similar. In panel C we use both instruments jointly and again find quantitatively comparable effects. Results turn out to be significant in columns 1 to 4. The three estimates reported in column 1 across all panels show that an increase of opium revenues by 10% leads to a decrease in the number of battle-related deaths of about 2%.

The last specification with two instruments allows us to conduct an overidentification test, which helps to assess the validity of the instruments. The Hansen over-identification test-statistics support the validity of the instruments in all columns. Panel D presents corresponding first stage results. While opium profitability positively affects opium revenues as we already know from Table 1, the VHI negatively affects revenues, which is reasonable as droughts deteriorate cultivaton and yield of opium.

To sum up, we get very similar results using two rather different sources of exogenous variation. This is reassuring regarding the quantitative size of the IV estimates, as well as for the validity of our main identification strategy. What is more, in Appendix F we show that this finding holds when using a further IV, which is based on changes in legal opioid prescription in the United States (Table 30). Different combinations of the three instruments point to very similar results. We also show IV results for a different timing and for opium cultivation in Appendix F.

Table 3

First and second stage IV results for opium revenue (t-1), 2002-2014

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(5)
			Panel A: 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
			Panel B: VHI (t-1) as IV		
(log) Revenue (t-1)	-0.184*	-0.049	-0.049	-0.052*	-0.016
	(0.107)	(0.032)	(0.031)	(0.027)	(0.014)
Kleibergen-Paap F stat.	9.634	9.634	9.634	9.634	9.634
			Panel C: Opium Profitability & VHI (t-1) as IV		
(log) Revenue (t-1)	-0.162**	-0.045**	-0.042**	-0.027*	-0.007
	(0.071)	(0.021)	(0.021)	(0.016)	(0.008)
Kleibergen-Paap F stat.	11.753	11.753	11.753	11.753	11.753
Hansen J p-val.	0.800	0.896	0.806	0.226	0.371
			Panel D: First stage results		
	Panel A		**Panel B**		**Panel C**
Opium Profitability (t-1)	2.922***				2.798***
	(0.722)				(0.721)
VHI (t-1)			-0.013***		-0.012***
			(0.004)		(0.004)

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 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.

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 and Couttenier (2015) and they support the conclusions in Dube and 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 and Restrepo (2015) that an income shock for an illegal resource is related to more conflict. While coca has a similar labor intensity as the alternative crops cacao, palm oil, and sugar cane in Colombia (Mejia and Restrepo, 2015), opium cultivation is much more labor-intensive than all alternative crops. 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, a second important question is to what degree individual households and farmers actually benefit from a higher opium profitability. To exploit 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 households' 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 5 plots the coefficients for opium profitability for seven different regression models with the outcome variable indicated in the legends. We find evidence that the dietary diversity increases when households experience a positive opium profitability and that more households are food secure. The positive effect of a higher profitability of opium is also visible when we consider food expenditures.[25]

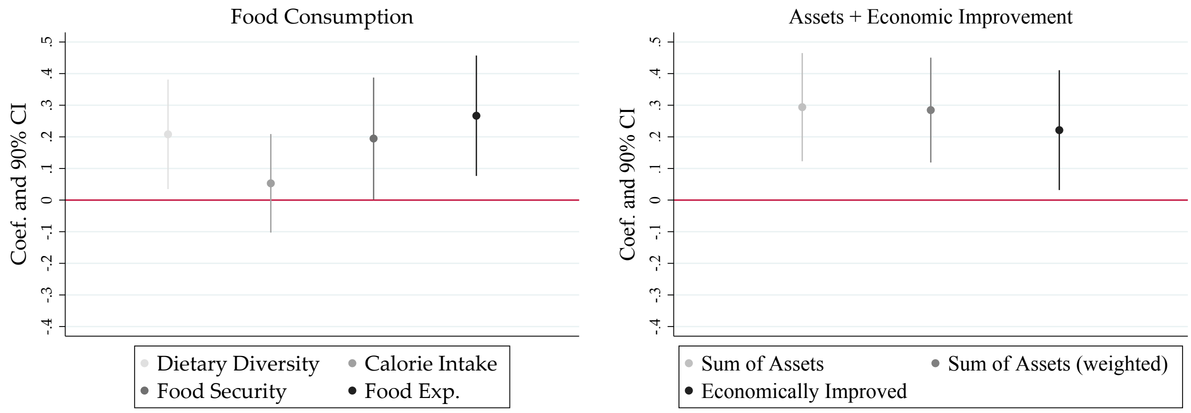
We turn to indicators that are not as volatile as food consumption. In years following high opium prices, households in districts with a higher opium suitability benefit more from the price increases also in terms of assets that they hold. The last indicator "Economically Improved" is a self-reported 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 18.[26] In line with our main findings at the district level and our hypothesized mechanisms, the household level opportunity costs of fighting increase with a higher opium profitability. We do not think it is feasible to distinguish whether factors at the household or group level are more important. Rather we provide support for mechanisms at both levels.

[25] 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. Results are robust to this choice as can be seen in Table 18.

[26] Results are also robust when accounting for household survey weights as presented in Figure 14.

Figure 5

Effect of opium profitability (t-1) on living standard indicators in year (t)



B. Opportunity costs and group competition at the district level

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.

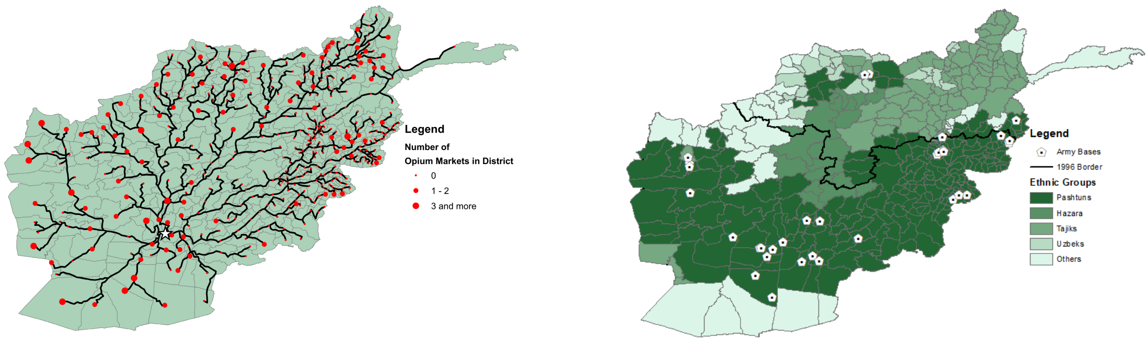
For this endeavor, we georeference data on whether a district contains a heroin or morphine lab, an opium market (major or sub-market) or whether it is crossed by potential drug trafficking routes. Figure 6 shows some of the data, and Appendices A and H provide all sources. The information is to a large extent based on UNODC reports. Profit margins are higher further up the production chain, markets create additional jobs and revenue, and trafficking routes allow raising income through some form of taxation or road charges. 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.

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 and 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) 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 (or 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 (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 and 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 driven by opportunity costs. It also further suggests that there is no large scale violent group competition about the most profitable districts.

There are at least two possible explanations. First, if the producers are at the same time the local leaders of a rebel group (the Taliban) they are facing a trade-off between

FIGURE 6
Mechanisms and channels



(A) Market access using opium markets (B) Ethnicities, military & Taliban (1996)

Notes: On the left hand side, the dots indicate district-specific centroids, and the black lines are the shortest road 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).
The right hand side map shows the four major ethnic groups in Afghanistan (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 Appendices A and H.). The area south of the thick black line was controlled by the Taliban prior to 2001 (Dorronsoro, 2005).

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. 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).

C. Mechanisms at the group level

The existing qualitative academic literature as well as reports, newspaper articles, and our previous results suggest no large scale (violent) competition amongst suppliers in Afghanistan.[27] Areas and the respective drug production as well as the trafficking process are either controlled by the Taliban and the local elites cooperating with them, or by the (internationally recognized) government, the Western forces and other groups associated

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

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

	(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 Prof. (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		**Luminosity**	
	2D	**3D**	**2D**	**3D**
Opium Profitability (t-1)	1.489	1.496	-0.902**	-0.899**
	(1.140)	(1.130)	(0.434)	(0.433)
Opium Prof. (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 prices (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 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

with it. We hypothesize that the degree of violent supplier (group) competition is decisive in moderating the relationship between resource profitability and instability. This also helps explain why our results point in the opposite direction than those from Angrist and Kugler (2008) and Mejia and Restrepo (2015) in the Colombian setting. Rather than the *de jure* legal status in its own right (as suggested in Mejia and Restrepo, 2015), local monopolies of violence and the actual enforcement of the law matter.

There are no reliable time-varying data about Taliban-dominated territory or actual government or Western military control for our whole sample period. Nevertheless, using a variable estimating contemporaneous group control would be endogenous anyway, and thus be problematic as part of an interaction term. We thus prefer to rely on time-invariant and pre-determined variation prior to the start of our sample period. To approximate the strength of government institutions and the presence of Western military (and law enforcement), we compute distances to the seat of government and assemble information about foreign military bases. Michalopoulos and Papaioannou (2014) also use distance as a measure of government influence, and Lind et al. (2014) uses distance to Kabul as an indicator for low law enforcement and weak state institutions.

In order to proxy for Taliban control, we also 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). In both types of districts, government influence is potentially less strong. Trebbi and Weese (2016, p. 5) argue that support for the Taliban as the main insurgent group is best explained by ethnic boundaries. Anecdotal evidence and personal conversations with experts indicate that ethnic institutions are more relevant compared to the official government in Pashtun areas. 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, to American military data, satellite images and newspaper reports. Figure 6 visualizes the data, and 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, the more so the higher 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."[28] Other 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."[29] 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."[30] Trebbi and Weese (2016, p. 5) also suggest that "insurgent activity in Afghanistan is best represented by a single organized group."

Drug producers apparently have little to fear from the government. Researchers describing their fieldwork in Badakhshan "observed neither restrictions to poppy farmers nor any repercussions or a need to hide the fields from outsiders" 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."[31] This suggests

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

[29] 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/, both accessed June 14, 2018.

[30] 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.

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

that the Taliban have an active interest in an undisturbed drug production process, and that the government has little power or interest to engage in the enforcement against the *de jure* illegal production.

Table 5, panel A shows that the conflict-reducing effect is actually stronger in districts that are more likely to be under Taliban control (columns 1-3). Columns 4 and 5 suggest that whether a district is ethnically mixed or features a large number of ethnic groups does not influence the relationship between opium and conflict.[32] This is also the case when we consider districts that in 1996 were partly controlled by the Taliban and partly under the control of a member group of the Northern Alliance (column 6). Panel B shows results for interactions with military bases, and several approximations for government influence using the distance to Kabul. None of the interaction coefficients in panel B turns out to be significant. That we also find no significant effect for any of the distance measures could be due to the fact that the relation is not linear. In Table 6 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. This suggests that the influence of the Afghan government seems indeed to be confined to districts within a small radius of 75 km or approximately two hours driving distance to Kabul.

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 7 does not indicate such a mechanism at the large scale. On average, an increase in opium revenue correlates with a decrease in casualties. We also show a regression aggregating all our data at the provincial level and again find a negative coefficient for opium profitability (see, Table 17). We would have expected the opposite pattern if higher revenues in one district shifted conflict to neighboring districts or to other provinces in the country.

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.

[32] In Appendix F we reconstruct measures on ethnic groups and in particular 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 38).

TABLE 5
Territorial control and ethnic groups, 2002-2014

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Taliban control & ethnic groups					
	Pashtuns	**Taliban Territory 1996**		**Ethnic Groups**		**Mixed**
		All Regions	**No North**	**1 if Mixed**	**Number**	**Territory 1996**
Opium Profitability (t-1)	0.312	-0.207	-0.221	-0.763**	-0.695**	-0.977*
	(0.365)	(0.372)	(0.365)	(0.370)	(0.298)	(0.568)
Opium Prof. (t-1)*X	-1.723***	-1.013**	-1.063**	0.130	-0.265	0.114
	(0.412)	(0.477)	(0.491)	(0.421)	(0.977)	(0.280)
	Panel B: Presence of government & 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 Prof. (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)

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 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 see Appendix A. The number of observations is 5174 in every regression, the adjusted R-squared varies between 0.649 and 0.653. Standard errors are in parentheses (clustered at the district level). Significance levels: * 0.10 ** 0.05 *** 0.01

Table 6
Government control, 2002-2014

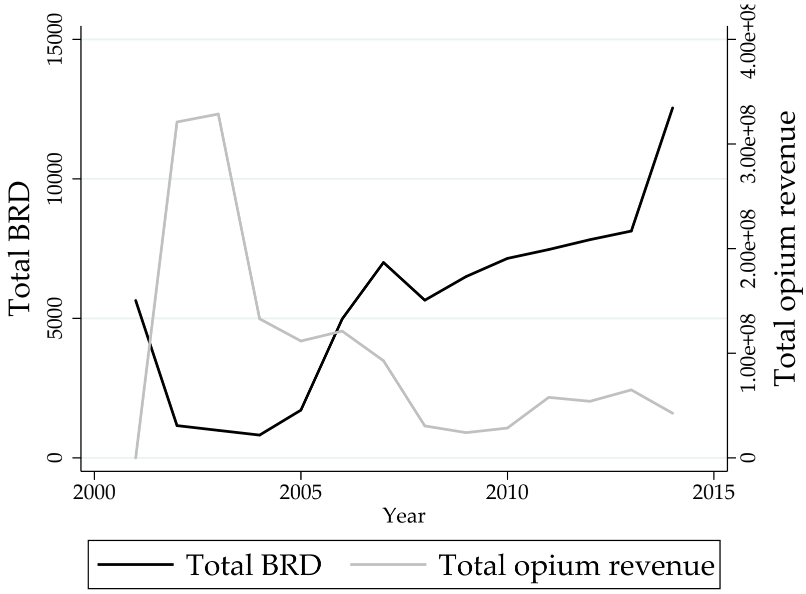
	Linear Distance		Travel Time 3D	
	1 if < 75	**1 if < 100**	**1 if < 2**	**1 if < 3**
	(1)	(2)	(3)	(4)
	Panel A: Proximity to Kabul			
Opium Profitability (t-1)	-0.826***	-0.782**	-0.893***	-0.826**
	(0.308)	(0.313)	(0.314)	(0.325)
Opium Profitability (t-1)*X	1.693**	0.712	1.685**	0.588
	(0.800)	(0.667)	(0.671)	(0.508)
	Panel B: Proximity to other main cities			
Opium Profitability (t-1)	-0.685**	-0.535	-0.576*	-0.557
	(0.327)	(0.345)	(0.319)	(0.343)
Opium Profitability (t-1)*X	-0.014	-0.463	-0.435	-0.308
	(0.527)	(0.456)	(0.564)	(0.507)

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 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 in X see Appendix A. Other main cities are Kandahar, Kunduz, Jalalabad, Hirat and Mazari Sharif. The number of observations is 5174 in every regression, the adjusted R-squared varies between 0.650 and 0.651. Standard errors are in parentheses (clustered at the district level). Significance levels: * 0.10 ** 0.05 *** 0.01

D. Exogenous change in policy

Finally, we exploit 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 section 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. (2011) for Iraq and Dell and 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

Figure 7
Variation in total opium revenue and total battle-related deaths



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 and support to the militias and many trained and armed men lost their main source of income (Giustozzi, 2009, p. 94 ff.). This change in strategy also coincides with the resurgence of the Taliban.

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, 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."[33]

We want to test whether the policy change created similar problems in Afghanistan, especially because the coalition forces at the same time repeatedly declared their aim to fight opium production (e.g., UNSC Resolution 1563). Dissolving the militias eliminated many reasonably paid jobs, which should increase the reliance on income from the opium economy. We exploit the approximate timing of this change in Table 7 and Figure 8, which show that the connection between drug profitability and conflict becomes much

[33] 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.

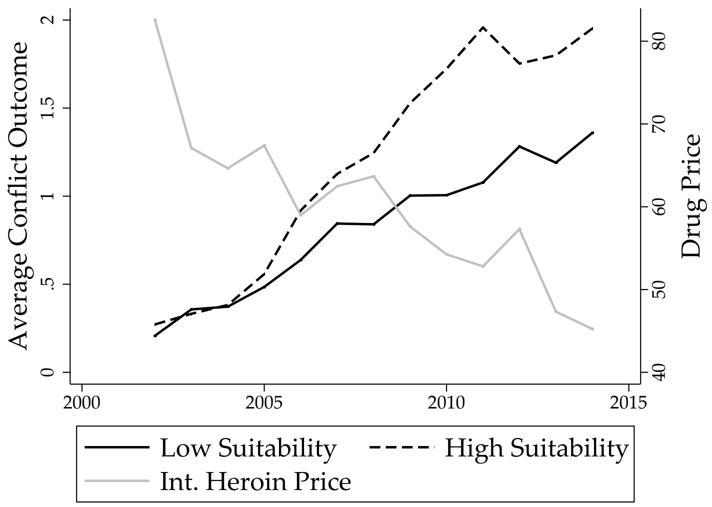
stronger following 2005. This highlights an important trade-off between "cleaning" the state and non-state armed groups as well as fighting the production of an illegal resource at the same time. In contrast to Berman et al. (2011), who rely on survey results about unemployment for just two years of observations, we thus find further evidence of an opportunity-cost-based mechanism.

TABLE 7
Before and after 2005, 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)	0.169	0.039	-0.029	0.012	0.067*
	(0.250)	(0.082)	(0.082)	(0.071)	(0.037)
Opium Prof. (t-1)*After 2005	-0.489***	-0.123***	-0.094**	-0.092**	-0.063***
	(0.162)	(0.045)	(0.044)	(0.042)	(0.024)

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 heroin prices (in logarithms) and the suitability to grow opium. After 2005 is a binary indicator taking the value of 1 for years after 2005. The number of observations is 5174 in every regression, the adjusted R-squared varies between 0.311 and 0.650. Standard errors are in parentheses (clustered at the district level). Significance levels: * 0.10 ** 0.05 *** 0.01.

FIGURE 8
Variation in conflict across high and low suitability districts over time



Notes: To assign a district to low or high suitability, we use a cut-off of 0.4. See Appendix F, Figure 18 for an alternative cut-off of 0.3. Inferences do not depend on this choice.

7. Further results and sensitivity analysis

This section explores further results and the sensitivity of our main findings to different specification choices. All tables and figures related to the results discussed in this section are reported in Appendices E and F.

Timing of shocks: In a first step, we consider different lag structures in our main analysis. We do so by first including opium profitability in periods $t + 1$, t, and $t - 1$ at the same time in Table 13, with $t + 1$ testing for pre-trends. Second, we compare our main findings for contemporaneous and lagged effects separately in Table 14. Table 13 shows, as we hypothesize, that opium profitability in t and $t - 1$ indicates the conflict-reducing effect, while international opium prices in *t+1* interacted with the suitability to grow opium have no significant effect on conflict. This is reassuring and supports the causal order and mechanism that we hypothesize. Table 14 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: To better understand the types of violence and the actors involved, Table 9 presents descriptive statistics. As can be seen, almost all events reported by UCDP are conflicts between the Taliban and the Afghan government, i.e., two-sided violence involving the state. Table 15 reports our baseline results for all battle-related deaths in column 1 and compares these to a more distinct analysis of who is fighting by looking at the actors and deaths per conflict side. Column 2 considers all casualties that are caused by Taliban violence against civilians. Results on this type of violence – that represents only 4% of all casualties – show a smaller and statistically insignificant negative coefficient. Columns 3 to 5 cover the majority of violent events, those between Taliban and government. In all specifications, irrespective of whether we look at total casualties (column 3) or only casualties on one side (column 4 and 5), we find a persistently negative effect. This exercise provides evidence for a robust conflict-reducing effect of opium income on two-sided violence throughout our observation period.

Empirical model: First, we show our main results with a less restrictive set of fixed effects in Table 19 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 larger effects in absolute terms in our baseline results (Table 2) with province-times-year-fixed effects suggest that these succeed in eliminating biasing variation.

Next, we consider heterogeneous effects of opium profitability on onset and ending of conflict events. Acemoglu and Wolitzky (2014) and 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.[34] Thus, we also measure the effects for conflict incidence (panel A), onset (panel B), and ending (panel C) in separate models. Results are presented in Table 20. 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.

Modifications of the treatment variable: We use multiple modifications of our treatment variable, both by replacing the drug prices and the 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 3. 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 shock 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.

[34] Berman and Couttenier (2015), for instance, argue that conflict persistence is very low at their level of analysis (a cell equivalent to 55 times 55 kilometers at the equator) compared to country level data. Consequently, they do not include the lagged dependent and rather estimate separate models for onset and ending. We report transition probabilities of the different conflict intensities from peace to war in Table 11.

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

Across all columns, the results are robust to this adaption.

Outcome and timing (reduced form and IV): In sections 4 and 5 we show that there is a strong effect on opium revenues. We now replace opium revenues with opium cultivation in hectares. Table 26 supports the positive effect of a higher opium profitability on opium cultivation, 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 produced quantity, and cultivation only by the latter.

We then turn to the IV results. Table 27 shows IV results when replacing the endogenous variable revenue in $t-1$ with cultivation in $t-1$. Both panel A reporting second stage results and panel B reporting the corresponding first stage results support our findings. To account for the different timing as shown in Figure 2, 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 Tables 28 and 29. The two IVs, opium profitability and VHI, are again strong as indicated by the F-statistic. The overidentification test cannot be rejected, supporting the validity of the instruments. Lastly, we show different combinations of the two main instruments in tandem with the time-varying legal opioid prescription (interacted with opium suitability) as a third instrument (see Tables 30 and 31). Legal opioids can theoretically increase heroin demand through addictions or substitute the illegal drug. The negative coefficient in the first stage shows that more legal prescriptions are linked to a lower opium price. Climate conditions are useful as they are exogenously assigned and do not follow a clear trend, and legal prescriptions are useful as they are mostly driven by US-specific factors clearly unrelated to Afghanistan (Dart et al., 2015). All different combinations lead to highly comparable second stage results and both the F-statistics and over-identification tests support the power and validity of the instruments. 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.

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 32 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 and 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 shock and different fixed effects as covariates. It is natural to first compare these results to not including this main covariate. In Table 33 we find our results to remain robust to excluding the wheat shock, with coefficients slightly increasing. 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 34). In Table 35 (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 these time-invariant 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, changing 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 36 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.

[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).

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 at the time. All coefficients remain stable and within a narrow band.

Randomization: One of the important points raised by Barrett and Christian (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 (detrended, log vs. non-log). To further rule out that the results are driven by non-linear trends, we implement further randomization 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.

Taken together, our results (i) do not depend on the choice of a linear or non-linear model or (ii) on the level at which we cluster standard errors, (iii) are robust to several modifications of the treatment and outcome variable, (iv) are barely affected and actually more negative when accounting for comprehensive sets of covariates, (v) are not driven by obvious outliers or particular provinces, and (vi) survive randomization placebo tests.

8. Conclusion

This paper provides new evidence on the conflict-resource-curse and the effects of resource-related income shocks (e.g., Van der Ploeg and Rohner, 2012; Berman and Couttenier, 2015; Morelli and Rohner, 2015; Berman et al., 2017) by shedding light on the micro-foundations of the underlying mechanisms. For this purpose, we focus on Afghanistan, which is a practical case from a researcher's perspective for at least three main reasons. First, despite the high intensity of conflict, we were able to collect a rich dataset including household level information. Second, different conflict actors can be identified and distinguished. Third, the country is characterized by a high variation across space with regard to resources, the distribution of ethnic groups and government influence. Although any conflict is distinct, we believe this case provides important lessons for other settings. Many conflict-ridden countries struggle with weak government enforcement, are ethnically diverse with difficulties in forming stable coalitions, feature a weak labor market with heavy reliance on one specific product, and often face obstacles in nation-building associated with foreign interventions.

Overall our reduced-form results show that, on average, a 10% increase in opium prices decrease the number of battle-related deaths by about 7% in districts with the highest possible suitability to grow opium. These results are robust to using different international and local prices and to exploiting the relationship between opium and complement drugs. It seems 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. The reduced-form results using international prices are quantified using IV results that also exploit exogenous weather changes (like e.g., Brückner and Ciccone, 2010) and legal opioid prescriptions in the United States. All IVs yield local average treatment effects that are comparable in size. Finally, several robustness tests address the potential risk that the overall downward trend in drug prices correlates with suitability-specific trends in other variables (Barrett and Christian, 2017).

The results add to the literature in several important ways. First, they augment the scarce literature on the effect of illegal resource-shocks (Angrist and Kugler, 2008; Mejia and Restrepo, 2015), and document that these shocks need not necessarily induce conflict. Second, by comparing the effects of opium- to wheat-related shocks we support Dube and Vargas' (2013) seminal study for Colombia by showing that labor intensity matters in determining the effect of resource-related income changes. Third, we verify the relevance of opportunity costs as a mechanism both by relying on district- and household level data. We thus emphasize the degree to which a high share of Afghans indeed rely on "illegal" income sources in satisfying basic needs.

Fourth, we highlight the importance of market structures, group competition and monopolies of violence for analyses of resource-related shocks. This is particularly relevant for illicit products, where the *de jure* illegality pushes up margins and supports the creation of rival cartels, which are willing to accept the related risks and exploit the potential for profits. The conflict in Afghanistan after 2001 is largely between two factions, the government plus associated groups on one side and the Taliban on the other side (see Trebbi and Weese, 2016). Consequently, we assess whether a district is likely to be under Taliban or government control. We find that in districts where the Taliban are more likely to have a monopoly of violence, the conflict-reducing effect is stronger. This supports qualitative evidence that the rebel group has given up its prior anti-drug stance and is actively involved in the drug trade, acting as a kind of stationary bandit (De La Sierra, 2015).

Fifth, we highlight the role of government enforcement. The reduction in conflict caused by a higher opium profitability is partly explained by the apparently loose enforcement of the "illegality" of opium production. Enforcement could be driven by both the willingness and the ability of the government. Our results suggest that the only areas where government control is sufficiently strong to engage in enforcement are within a limited area around the capital Kabul (comparable to Michalopoulos and Papaioannou, 2014, for Africa). If the government enforces the rules, farmers have an incentive to support the Taliban in exchange for protection of their opium-related activities. This in turn leads to a higher potential for conflict with pro-government groups. In line with our theoretical considerations, we find no conflict-reducing effect in those districts that are close to Kabul.

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 and Elia, 2013; Lyall et al., 2013; Lind et al., 2014; Condra et al., 2018). Although we cannot make strong claims beyond our observation period, the findings are in line with the spread of conflict in Afghanistan in the last years that featured falling prices and lower opium profitability. We use results at the province- and country-level to verify that higher opium revenues do, on average, not seem to spill-over and create conflict in other parts of Afghanistan. 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. At the same time, it is, of course, also too simplistic and naive to conclude that opium production is "good" and 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 that consider the "unseen" or unexpected indirect consequences of those choices. Our results suggests that the dissolving of militia groups, which provided employment and income sources for many Afghans, intensified the reliance on opium as an income source. There are, of course, good reasons for demilitarizing societies as well as for tackling illicit economies in attempts of nation-building (relating to Berman et al., 2011; Dell and Querubin, 2018). Nonetheless, if there are no attractive and feasible alternatives, both aims are hard to achieve individually and even more so simultaneously.

References

Acemoglu, D., D. Cantoni, S. Johnson, and J. A. Robinson (2011). The Consequences of Radical Reform: The French Revolution. *American Economic Review 101*(7), 3286–3307.

Acemoglu, D. and A. Wolitzky (2014). Cycles of Conflict: An Economic Model. *American Economic Review 104*(4), 1350–1367.

Angrist, J. D. and A. D. Kugler (2008). Rural Windfall or a New Resource Curse? Coca, Income, and Civil Conflict in Colombia. *The Review of Economics and Statistics 90*(2), 191–215.

Angrist, J. D. and J.-S. Pischke (2008). *Mostly Harmless Econometrics: An Empiricist's Companion*. Princeton: Princeton University Press.

Barrett, C. and P. Christian (2017). Revisiting the Effect of Food Aid on Conflict: A Methodological Caution. World Bank Policy Research Working Paper No. WPS 8171.

Bazzi, S. and C. Blattman (2014). Economic Shocks and Conflict: Evidence from Commodity Prices. *American Economic Journal: Macroeconomics 6*(4), 1–38.

Berman, E., J. H. Felter, J. N. Shapiro, and M. Callen (2011). Do Working Men Rebel? *Journal of Conflict Resolution 55*(4), 496–528.

Berman, E., J. N. Shapiro, and J. H. Felter (2011). Can Hearts and Minds Be Bought? The Economics of Counterinsurgency in Iraq. *Journal of Political Economy 119*(4), 766–819.

Berman, N. and M. Couttenier (2015). External Shocks, Internal Shots: The Geography of Civil Conflicts. *Review of Economics and Statistics 97*(4), 758–776.

Berman, N., M. Couttenier, D. Rohner, and M. Thoenig (2017). This Mine is Mine! How Minerals Fuel Conflicts in Africa. *American Economic Review 107*(6), 1564–1610.

Besley, T. and M. Reynal-Querol (2014). The Legacy of Historical Conflict: Evidence from Africa. *American Political Science Review 108*(02), 319–336.

Blattman, C. and E. Miguel (2010). Civil War. *Journal of Economic Literature 48*(1), 3–57.

Bluhm, R., M. Gassebner, S. Langlotz, and P. Schaudt (2016). Fueling Conflict? (De) Escalation and Bilateral Aid. CESifo Working Paper No. 6125.

Bove, V. and L. Elia (2013). Drugs and Violence in Afghanistan: A Panel VAR with Unobserved Common Factor Analysis. *Defence and Peace Economics 24*(6), 535–554.

Brückner, M. and A. Ciccone (2010). International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa. *The Economic Journal 120*(544), 519–534.

Cameron, A. C., J. B. Gelbach, and D. L. Miller (2011). Robust Inference with Multiway Clustering. *Journal of Business & Economic Statistics 29*(2), 238–249.

Cameron, A. C. and D. L. Miller (2015). A Practitioners Guide to Cluster-Robust Inference. *Journal of Human Resources 50*(2), 317–372.

Caselli, F. and G. Michaels (2013). Do Oil Windfalls Improve Living Standards? Evidence from Brazil. *American Economic Journal: Applied Economics 5*(1), 208–238.

Caulkins, J. P., M. Kleiman, and J. D. Kulick (2010). *Drug Production and Trafficking, Counterdrug Policies, and Security and Governance in Afghanistan.* New York University Center on International Cooperation.

Chabot, P. and P. A. Dorosh (2007). Wheat Markets, Food Aid and Food Security in Afghanistan. *Food Policy 32*(3), 334–353.

Collier, P. and A. Hoeffler (2004). Greed and Grievance in Civil War. *Oxford Economic Papers 56*(4), 563–595.

Condra, L. N., J. D. Long, A. C. Shaver, and A. L. Wright (2018). The Logic of Insurgent Electoral Violence. *American Economic Review , forthcoming.*

Croicu, M. and R. Sundberg (2015). UCDP Georeferenced Event Dataset Codebook Version 4.0. *Journal of Peace Research 50*(4), 523–532.

CSO (2005, 2007/08, 2011/12). National Risk and Vulnerability Assessment. Kabul, CSO.

CSO and The World Bank (2011). Setting the Official Poverty Line for Afghanistan. Technical report.

Dart, R. C., H. L. Surratt, T. J. Cicero, M. W. Parrino, S. G. Severtson, B. Bucher-Bartelson, and J. L. Green (2015). Trends in Opioid Analgesic Abuse and Mortality in the United States. *New England Journal of Medicine 372*(3), 241–248.

De La Sierra, R. S. (2015). On the Origin of States: Stationary Bandits and Taxation in Eastern Congo. HiCN Working Paper No. 194.

Dell, M. (2015). Trafficking Networks and the Mexican Drug War. *The American Economic Review 105*(6), 1738–1779.

Dell, M. and P. Querubin (2018). Nation Building Through Foreign Intervention: Evidence From Discontinuities in Military Strategies. *The Quarterly Journal of Economics 133*(2), 701–764.

Donaldson, D. and R. Hornbeck (2016). Railroads and American Economic Growth: A Market Access Approach. *The Quarterly Journal of Economics 131*(2), 799–858.

Dorronsoro, G. (2005). *Revolution Unending: Afghanistan, 1979 to the Present.* Columbia University Press.

Dube, O. and J. F. Vargas (2013). Commodity Price Shocks and Civil Conflict: Evidence from Colombia. *The Review of Economic Studies 80*(4), 1384–1421.

Eck, K. (2012). In Data we Trust? A Comparison of UCDP GED and ACLED Conflict Events Datasets. *Cooperation and Conflict 47*(1), 124–141.

EMCDDA (2016). *European Drug Report - Trends and Developments.* Luxembourg:

Publications Office of the European Union, 2016.

Esteban, J., L. Mayoral, and D. Ray (2012). Ethnicity and Conflict: Theory and Facts. *Science 336*(6083), 858–865.

Esteban, J. and D. Ray (2008). Polarization, Fractionalization and Conflict. *Journal of Peace Research 45*(2), 163–182.

Fearon, J. D. and D. D. Laitin (2003). Ethnicity, Insurgency, and Civil War. *American Political Science Review 97*(1), 75–90.

Felbab-Brown, V. (2013). Counterinsurgency, Counternarcotics, and Illicit Economies in Afghanistan: Lessons for State-Building. *MM Jacqueline Brewer, Convergence: Illicit Networks and National Security in the Age of Globalization*, 189–212.

Gehring, K. and S. Schneider (2016). Regional Resources and Democratic Secessionism. ETH and University of Zurich CIS Working Paper Series No. 90.

Giustozzi, A. (2009). *Empires of Mud: The Neo-Taliban Insurgency in Afghanistan 2002-2007*. Columbia University Press.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2018). Bartik Instruments: What, When, Why, and How. National Bureau of Economic Research Working Paper No. 24408.

Grossman, H. I. (1991). A General Equilibrium Model of Insurrections. *American Economic Review 81*(4), 912–921.

Harari, M. and E. La Ferrara (2018). Conflict, Climate and Cells: A Disaggregated Analysis. *Review of Economics and Statistics, forthcoming.*

Henderson, J. V., T. Squires, A. Storeygard, and D. Weil (2018). The global distribution of economic activity: Nature, history, and the role of trade. *The Quarterly Journal of Economics 133*(1), 357–406.

Henderson, J. V., A. Storeygard, and D. N. Weil (2012). Measuring Economic Growth from Outer Space. *American Economic Review 102*(2), 994–1028.

Hijmans, R. J., L. Guarino, M. Cruz, and E. Rojas (2001). Computer Tools for Spatial Analysis of Plant Genetic Resources Data: 1. DIVA-GIS. *Plant Genetic Resources Newsletter 127*, 15–19.

Hirshleifer, J. (1988). The Analytics of Continuing Conflict. *Synthese 76*(2), 201–233.

Hirshleifer, J. (1989). Conflict and Rent-seeking Success Functions: Ratio vs. Difference Models of Relative Success. *Public Choice 63*(2), 101–112.

Hirshleifer, J. (1995). Anarchy and Its Breakdown. *Journal of Political Economy 103*(1), 26–52.

IMF (2005-2017). International Monetary Fund - Database. available at http://www.imf.org/external/np/res/commod/index.aspx.

Kenan, K. and K. Mack (2012). Trends in Prescriptions for Oxycodone and Other Commonly Used Opioids in the United States, 2000-2010. *Open Medicine 6*(2), e41–

e47.

Kienberger, S., R. Spiekermann, D. Tiede, I. Zeiler, and C. Bussink (2017). Spatial Risk Assessment of Opium Poppy Cultivation in Afghanistan: Integrating Environmental and Socio-Economic Drivers. *International Journal of Digital Earth 10*(7), 719–736.

Kreutzmann, H. (2007). Afghanistan and the Opium World Market: Poppy Production and Trade. *Iranian Studies 40*(5), 605–621.

La Ferrara, E. and M. Guidolin (2007). Diamonds are Forever, Wars are Not: Is Conflict Bad for Private Firms? *American Economic Review 97*(5), 1978–1993.

Leri, F., J. Bruneau, and J. Stewart (2003). Understanding Polydrug Use: rReview of Heroin and cCocaine Co-use. *Addiction 98*, 7–22.

Lind, J. T., K. O. Moene, and F. Willumsen (2014). Opium For the Masses? Conflict-Induced Narcotics Production in Afghanistan. *Review of Economics and Statistics 96*(5), 949–966.

Lujala, P. (2009). Deadly Combat over Natural Resources: Gems, Petroleum, Drugs, and the Severity of Armed Civil Conflict. *Journal of Conflict Resolution 53*(1), 50–71.

Lyall, J., G. Blair, and K. Imai (2013). Explaining Support for Combatants during Wartime: A Survey Experiment in Afghanistan. *American Political Science Review 107*(4), 679–705.

Manchikanti, L., S. H. II, B. Fellows, J. W. Janata, V. Pampati, J. S. Grider, and M. V. Boswell (2012). Opioid Epidemic in the United States. *Pain Physician 15*(3 Suppl.), 2150–1149.

Mansfield, D. and P. Fishstein (2016). Time to Move on: Developing an Informed Development Response to Opium Poppy Cultivation in Afghanistan. Afghanistan Research and Evaluation Unit.

Mejia, D. and P. Restrepo (2015). Bushes and Bullets: Illegal Cocaine Markets and Violence in Colombia. Documento CEDE Working Paper No. 2013-53.

Mejía, D., P. Restrepo, and S. V. Rozo (2015). On the Effects of Enforcement on Illegal Markets: Evidence from a Quasi-experiment in Colombia. *The World Bank Economic Review 31*(2), 570–594.

Michalopoulos, S. and E. Papaioannou (2014). National Institutions and Subnational Development in Africa. *The Quarterly Journal of Economics 129*(1), 151–213.

Michalopoulos, S. and E. Papaioannou (2016). The Long-Run Effects of the Scramble for Africa. *American Economic Review 106*(7), 1802–1848.

Miguel, E., S. Satyanath, and E. Sergenti (2004). Economic Shocks and Civil Conflict: An Instrumental Variables Approach. *Journal of political Economy 112*(4), 725–753.

Morelli, M. and D. Rohner (2015). Resource Concentration and Civil Wars. *Journal of Development Economics 117*, 32–47.

Nillesen, E. E. and P. Verwimp (2009). Grievance, Commodity Prices and Rainfall:

A Village-Level Analysis of Rebel Recruitment in Burundi. MICROCON Research Working Paper No. 11.

Nunn, N. and D. Puga (2012). Ruggedness: The Blessing of Bad Geography in Africa. *Review of Economics and Statistics 94*(1), 20–36.

Nunn, N. and N. Qian (2014). U.S. Food Aid and Civil Conflict. *American Economic Review 104*(6), 1630–1666.

OECD (2016). Organization for Economic Cooperation and Development - Consumer Price Index.

Peters, G. (2009). How Opium Profits the Taliban. Peaceworks No. 62.

Ross, M. (2004). How Do Natural Resources Influence Civil War? Evidence From 13 Cases. *International Organization 58*(1), 35–67.

Rubin, B. R. and J. Sherman (2008). *Counter-narcotics to Stabilize Afghanistan: The False Promise of Crop Eradication*. UNDP.

Sexton, R. (2016). Aid as a Tool against Insurgency: Evidence from Contested and Controlled Territory in Afghanistan. *The American Political Science Review 110*(4), 731–749.

Shaver, A. C. and A. L. Wright (2016). Are Modern Insurgencies Predictable? New Evidence from the Afghanistan and Iraq Wars. *Mimeo*.

Staiger, D. O. and J. H. Stock (1997). Instrumental Variables Regression With Weak Instruments. *Econometrica 65*(3), 557–586.

Sundberg, R. and E. Melander (2013). Introducing the UCDP Georeferenced Event Datas. *Journal of Peace Research 50*(4), 523–532.

Trebbi, F. and E. Weese (2016). Insurgency and Small Wars: Estimation of Unobserved Coalition Structures. *Yale Economic Growth Center Discussion Paper No. 1053*.

UNDCP (2000). Annual Opium Poppy Survey.

UNODC (2004). Farmers' intentions survey 2003/2004. *UNODC Report*.

UNODC (2005-2016). Afghanistan Opium Survey: Socio-Economic Analysis. *Ministry of Counter Narcotics, Afghanistan and United Nations Office for Drugs and Crime, Vienna*.

UNODC (2006-2013a). Afghanistan Opium Price Monitoring.

UNODC (2013b). World Drug Report 2013. United Nations Publication Sales.

Van der Ploeg, F. and D. Rohner (2012). War and Natural Resource Exploitation. *European Economic Review 56*(8), 1714–1729.

Van Hoolst, R., H. Eerens, D. Haesen, A. Royer, L. Bydekerke, O. Rojas, Y. Li, and P. Racionzer (2016). FAO's AVHRR-based Agricultural Stress Index System (ASIS) for Global Drought Monitoring. *International Journal of Remote Sensing 37*(2), 418–439.

Webb, M. D. (2013). Reworking Wild Bootstrap Based Inference for Clustered Errors.

Queen's Economics Department Working Paper No. 1315.

Weidmann, N. B. (2015). On the Accuracy of Media-Based Conflict Event Data. *Journal of Conflict Resolution 59*(6), 1129–1149.

Weidmann, N. B., J. K. Rød, and L.-E. Cederman (2010). Representing Ethnic Groups in Space: A New Dataset. *Journal of Peace Research 47*(4), 491–499.

Wiesmann, D., L. Bassett, T. Benson, and J. Hoddinott (2009). Validation of the World Food Programme's Food Consumption Score and Alternative Indicators of Household Food Security. IFPRI Discussion Paper No. 00870.

World Bank (2005-2016). World Development Indicators.

Wright, A. L. (2018). Economic Shocks and Rebel Tactics. *American Political Science Review , forthcoming.*

APPENDIX

A. Definition of the variables

Any Lab: The information on the existence of laboratories used for processing opium is based on UNODC reports regarding drug markets, labs, and trafficking routes (e.g., UNODC, 2006/07, 2014, 2016). As described in Appendix H, we georeference the maps in the reports to assign coordinates to the labs, and later compute district averages. For this variable, we count all type of heroin laboratories. It takes on the value 1 if there is at least one lab in a district i, and 0 otherwise.

Any Military Base: We use information from Wikipedia's GeoHack program for the more well-known bases and on news articles, and Wikimapia and Google Maps satellite data for the less well-documented ones. The approach is described in detail in Section 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. The variable takes on the value one if there is at least one open military base in a district i in year t, and 0 otherwise.

Battle-Related Deaths (BRD): The best (most likely) estimate of total fatalities resulting from an event, with an event being defined as "[an] incident where armed force was by an organized actor against another organized actor, or against civilians, resulting in at least 1 direct death at a specific location and a specific date." A direct death is defined as "a death relating to either combat between warring parties or violence against civilians." Note that UCDP/GED only includes BRD of events that belong to a dyad ("two conflicting primary parties or party killing unarmed civilians") that reached in total at least 25 BRD within 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 anymore 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. From UCDP/GED (Sundberg and Melander, 2013; Croicu and Sundberg, 2015).

Calorie Intake and Food Insecurity: The woman's questionnaire provides amounts, frequencies and sources of a large set of food items, which we use 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. The kcal values are provided by the CSO and The World Bank (2011). To get a binary indicator on food insecurity we use the reference value of 2100 calories per day as recommended by the FAO. 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: NRVA (CSO, 2005,2007/08,2011/12).

Consumer Price Index (CPI): From OECD (2016) for the Euro area (19 countries) and from World Bank (2016) for remaining countries (2010 = 100).

Dietary 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. The variable varies between zero and eight, with eight indicating a high food diversity. Source: NRVA (CSO, 2005,2007/08,2011/12).

Distance/Proximity to Kabul (capital) and Kandahar, Kunduz, Jalalabad, Hirat, and Mazari Sharif (next five largest cities): 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 Afgan 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. The first source is UNESCAP (http://www.unescap.org/sites/default/files/2.4.Afghanistan.pdf, page 14) which assumes that the speed on motorways is 90 km/h and on urban roads 50km/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 50km/h. The 3rd source is WHO (http://apps.who.int/gho/data/view.main.51421) reporting 90km/h for rural. We choose the following average traveling speeds, assuming that no strictly enforced limits and little traffic on motorways (120km/h), and accounting for some (90km/h-10km/h) and moderate traffic in cities (50-20km/h). Thus our main choice is the following. Motorways: 120km/h, rural: 80km/h, urban: 30km/h. These choices are not perfect, but we verify that our results hold with other variations as well.

For the proximity to Kabul and other main cities we also define binary indicators for the distance being smaller than 75km (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 3h.

Drug Prices (International): The data are average prices per gram in constant (2010) EU across all available countries in Europe. We use data on different drugs: amphetamines, cocaine, ecstasy, heroin (brown). To construct the average price of alternative drugs we use a mean of the three upper drugs amphetamines, cocaine, and ecstasy. For the analysis we convert all drug prices into constant 2010 EU per gram. We then normalize the prices by using a linear min-max function such that all prices vary between 0 and 1. From European Monitoring Centre 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?" 1 indicates much worse, 2 slightly worse, 3 same, 4 slightly better, and 5 much better. This is a self-reported measure of the household. Source: NRVA (CSO, 2005,2007/08,2011/12).

Ethnic Groups: We have used the GIS-coordinates of all ethnic groups in the "georeferencing of ethnic groups" (GREG) dataset Weidmann et al. (2010). It relies on maps from the classical "Soviet Atlas Narodov Mira" from 1964, and is very extensively used for the construction of ethnolinguistic fractionalization indices. GREG is a georeferenced dataset containing the coordinates of the group boundaries of 1120 ethnic groups. One advantage and disadvantage of the data is that it is capturing group locations in the 1960s. This is an advantage as it ensures that the boundaries are not endogenous to changes during our period of observation. It is partly a disadvantage if groups and countries changed over time. In Afghanistan, the country boundary did not change. Ethnic group populations certainly change to some degree over time, so that all variables more precisely capture the historic homelands of ethnic groups rather than the current settlement areas. Our variable Pashtuns is coded in the following way. The GREG polygons can contain more than one ethnic group. Our binary indicator takes on the value one if Pashtuns are present to any degree in a district i, regardless of whether they were the majority group. The idea behind this is that the Taliban are initially a Pashtun group (although not exclusively anymore), so that Pashtun presence could make it easier to establish a presence of the Taliban in a district. We also construct two measures on whether a district is ethnically mixed, first by using the the number of ethnic groups and second by generating a binary indicator, which takes a value of 1 if the number of ethnic groups is larger 1.

Ethnic Trafficking Route: This variable combines information about unofficial border crossings from UNODC with information about the homelands of ethnic groups from the (GREG) dataset (Weidmann et al., 2010). It 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 higher, if there is no need to cross the area of other ethnic groups to transport over the border.

Food Expenditures (Paasche/Laspeyres): Following the literature, we include food items from all possible sources, i.e., purchased food or food in form of gifts etc. We use the section on food consumption from the NRVA women's questionnaire as this section offers precise amounts per food item. The food items are merged to local prices, which are provided in a separate section of the NRVA, the district questionnaire. Prices vary at the district level. 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. 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 meaured 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). Source: NRVA (CSO, 2005,2007/08,2011/12).

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

Insecurity/Violence Shock: The share of sampled households per district that have experienced a shock due to insecurity/violence according to the NRVA survey (CSO, 2005,2007/08,2011/12).

Legal Opioids: The data are collected using a variety of sources. The reason is that most single publications did not cover our whole sample period, and that we want to cross-verify the numbers. A main source is the US CDC Public Health surveillance report 2017, available at https://stacks.cdc.gov/view/cdc/47832. Other important sources were Manchikanti et al. (2012); Kenan and Mack (2012); Dart et al. (2015).

Local Opium Price: Local price data on opium is derived from the annual Afghanistan Opium Price Monitoring reports UNODC. These reports include (monthly) province level dry opium prices by farmers and by traders as well as country-wide yearly data on fresh opium farm-gate prices, that are weighted by regional production. The province level opium prices of farmers and traders are highly correlated, with a correlation coefficient close to 1 (0.998). The correlation between the country level farm-gate price and the province level farm-gate price is 0.66, significant at the 1% level. While the province level prices are only available from 2006 to 2013 and for a subset of provinces, they are still very helpful in identifying whether international prices are correlated with local prices. We 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.

Luminosity: Proxy for GDP and development. 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. From 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 information on opium markets is based on UNODC reports regarding drug markets, labs, and trafficking routes (e.g., UNODC 2006/07, 2014, 2016). The first variable takes on the value one 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).

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 and 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 book by Dorronsoro (2005) provides a map indicating the territory of the Taliban in 1996 and 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. The binary indicator on Taliban Territory that we create take on the value one if a district belongs to the territory that was occupied or under the control of the Taliban in 1996. A second indicator (Taliban Territory 1996 - No North) is defined whether the district exclusively occupied by the Taliban and is characterized by no presence of the Northern Alliance. More details can be found in Dorronsoro (2005) and Giustozzi (2009).

Opium Cultivation and Revenues: 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. From the Annual Opium Poppy Survey (UNDCP, 2000) and Afghanistan Opium Survey (UNODC, 2001-2014).

Opium Suitability: Proxy for potential of opium production based on exogenous underlying information about land cover, water availability, climatic suitability, and soil suitability. It was developed in the context of a study in collaboration with UNODC, and is described in detail in a publication in a geographical science journal (Kienberger et al., 2017). The environmental as well as climatic suitability to cultivate opium poppy (Papaver somniferum) is characterized by different factors such as the prevailing physiogeographical 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. From Kienberger et al. (2017). 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 (our results are not significantly affected by this choice).

Population: A minimally-modeled gridded population data collection that incorporates census population data from the 2010 round of censuses. Population estimates are derived by extrapolating the raw census estimates to a series of target years and are provided for the years 2000, 2005, 2010, 2015, and 2020. We use the ipolated data from 2000 till 2015. We take the logarithm. From 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). Source: http://dx.doi.org/10.7927/H4F47M2C, accessed October 5, 2017.

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

Southern Provinces: Dummy variable which turns one 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 the 3 survey waves. This set consists of Radio/Tape, Refrigerator, TV, VCR/DVD, Sewing Machine, Thuraya (any phone), Bicycle, Motorcycle, Tractor/Thresher, 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).

Travel Time to Kabul and other main cities: Hours required to travel from district centroid to Kabul. For details about distance computation see Distances.

Vegetation Health Index (VHI): We use the Vegetation Health Index (VHI) of FAO (Van Hoolst et al., 2016). VHI is a composite index joining the Vegetation Condition Index (VCI) and the Temperature Condition Index (TCI, Kogan 1995). Low values of VHI represent drought conditions. This is a combination of low values of the observed VCI (relatively low vegetation) and higher values of the TCI (relatively warm weather). For details see Van Hoolst et al. (2016). The VHI is calculated from data of Advanced Very High Resolution Radiometer (AVHRR) sensors on board 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 $1km^2$. 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.

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

Wheat Suitability: The FAO-GAEZ (2012) model provides for each crop/Land Utilization Type (LUT) a comprehensive soil suitability evaluation for all the soil units contained in the Harmonized World Soil Database (HWSD). This is done by the use of individual soil quality ratings (SQ). Seven different SQs are calculated and are combined in a soil unit suitability rating (SR, %). The SR represents the percentage of potential yield expected for a given crop/LUT with respect to the soil characteristics present in a soil map unit of the HWSD and is depending on input/management level. 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 the website http://www.fao.org/nr/gaez/about-data-portal/

agricultural-suitability-and-potential-yields/en/, accessed October 12, 2016. Move 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 8
Descriptives: 2005-2012

	Obs.	Mean	Stand. Dev.	Min	Max
BRD					
(log) All	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	5174	0.08	0.37	0.00	4.14
(log) Taliban-Government	5174	1.05	1.52	0.00	8.20
(log) Government BRD by Taliban	5174	0.53	0.94	0.00	8.03
(log) Taliban BRD by Government	5174	0.77	1.33	0.00	6.39
(log) Opium Profitability					
Int. Heroin	5174	-1.52	0.66	-4.61	-0.00
Local Opium	5174	-1.04	0.70	-4.61	0.01
Int. Complement	5174	-1.30	0.56	-3.17	-0.00
Int. Cocaine	5174	-1.15	0.67	-4.61	-0.00
Distance to Kabul					
Linear	5148	277.05	181.54	0.00	817.64
Road 2D	5174	345.03	212.05	0.00	959.78
Road 3D	5174	347.47	213.08	0.00	964.48
Travel Time 2D	5174	7.53	5.91	0.00	28.40
Travel Time 3D	5174	7.57	5.94	0.00	28.45
Market Access					
Opium Market 2D	5174	4.47	1.10	2.24	11.23
Opium Market 3D	5174	2.63	0.69	1.33	6.93
Luminosity 2D	5174	6.51	4.86	1.85	41.26
Luminosity 3D	5174	6.47	4.84	1.85	41.24

Continued on next page

Table 8 continued					
All other variables					
(log) Wheat Shock	5174	-0.48	0.46	-2.11	0.01
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
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
Mixed Territory 1996	5174	0.04	0.20	0.00	1.00
Taliban Territory 1996	5174	0.58	0.49	0.00	1.00
Pashtuns	5174	0.74	0.44	0.00	1.00
Ethnicity - 1 if Mixed	5174	0.59	0.49	0.00	1.00
Number Ethnic Group	5174	1.93	0.97	1.00	5.00

Notes: The sample is based on the specification in Table 2, column 1.

Table 9

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 provided by UCDP GED between 2002-2014.

Table 10
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 2, column 1. To assign a districts to low or high suitability, we use a cut-off of 0.4. In Table 35 we control for an interaction of all the variables (above the separating line) with a time trend or with time-fixed effects.

Table 11
Unconditional 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: US Geological Survey (USGS) Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010), available at https://lta.cr.usgs.gov/GMTED2010, accessed June 4, 2018. Source for ADM1 administrative data is www.gadm.org, accessed June 4, 2018.

Figure 11
ADM1 level (provinces) of Afghanistan

Notes: The figure plots the 34 provinces (ADM1 level). Source: Central Statistical Office Afghanistan, available at http://afghanag.ucdavis.edu/country-info/about-afghan.html, accessed July 9, 2018.

D. Identification using complement prices

Assume that we estimate a regression

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

but the true regression is

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

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 conditional on the suitability (*suit*). $suit \sim [0, 1]$, 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.[37] 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

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

complement increases, which leads to a price 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.[38] 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

[38] 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.

bias and an iid error term ϵ^C_{t-1}, which we can treat as additional random measurement error in a regression on conflict. 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 and 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

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

and

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

$$\implies$$

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

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 12 shows these results in detail for the scenarios A to D. Based on the table and Figures 12 and 13, 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 12 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 (downward 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.[39] 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.[40]

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 13.

[39] 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.

[40] 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 12
Simulation

	A β=0 & Downward bias (1)	B β=0 & Upward bias (2)	C β=-1 & Downward bias (3)	D β=-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 5'000 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 12

Simulations with true parameter estimate β=0. A: Upward bias, left side, B: Downward bias, right side

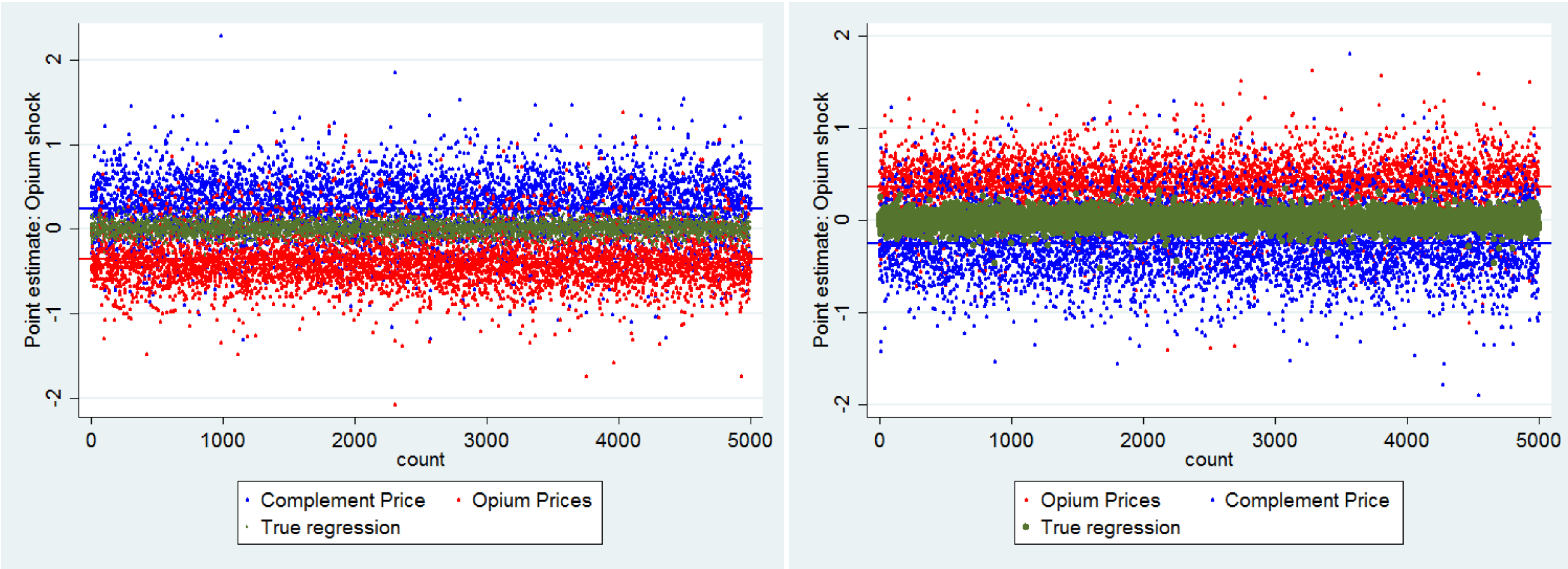
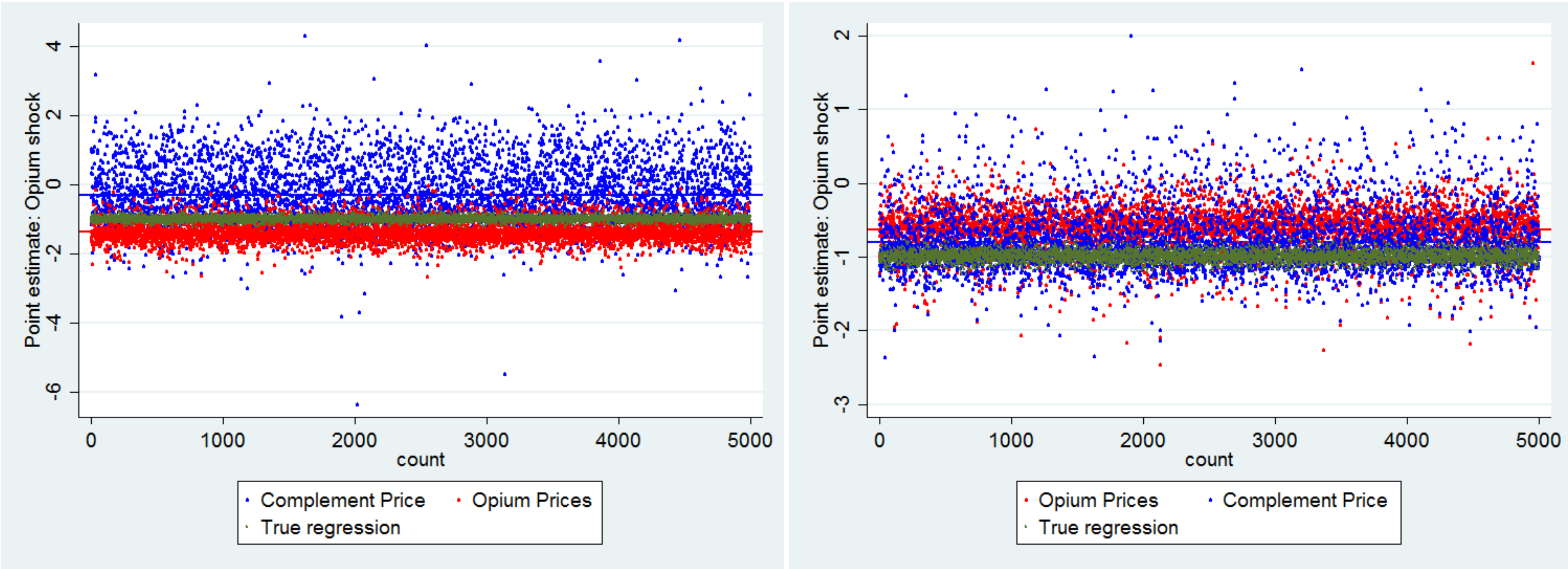


Figure 13

Simulations with true parameter estimate β=-1. C: Upward bias, left side, D: Downward bias, right side



E. Further results

Different timing of the shocks

Table 13
Leads and lags, 2002-2014

	Wheat shock: Not included (1)	**Wheat shock: (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 14
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)
Wheat Shock (t)	0.443***	0.092*	0.115***	0.064*	0.010
	(0.154)	(0.050)	(0.043)	(0.038)	(0.024)
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)
Wheat Shock (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

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 15
Types of fighting, 2002-2014

Conflict Actor:	**All**	**Taleb.-Civil.**		**Taleb.-Gov.**	
BRD:	**Any**	**Both**	**Both**	**Taleb.**	**Gov.**
	(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)
Wheat Shock (t-1)	0.307**	0.012	0.362***	0.134*	0.257**
	(0.123)	(0.026)	(0.124)	(0.079)	(0.115)
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

Regressions at the province level

Table 16
Effect of income shocks on opium revenues, province level, 2002-2014

	Outcome: (t)	**Outcome: (t) and (t-1)**
	(1)	(2)
Opium Profitability (t-1)	5.885*	5.461*
	(3.199)	(3.074)
Wheat Shock (t-1)	2.238	2.184
	(1.901)	(2.030)
Number of observations	442	442
Adjusted R-Squared	0.609	0.679

Notes: Linear probability models 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 17
Normalized drug prices, province level, 2002-2014

	Local Opium Price	**International Heroin Price**	**Complement Price**	**International Cocaine Price**
	(1)	(2)	(3)	(4)
Opium Profitability (t-1)	-0.290	-0.717	-1.101*	-0.661*
	(0.299)	(0.566)	(0.647)	(0.368)
Wheat Shock (t-1)	0.083	-0.027	-0.179	-0.105
	(0.385)	(0.404)	(0.401)	(0.409)
Number of observations	442	442	442	442
Adjusted R-Squared	0.723	0.724	0.726	0.726

Notes: Linear probability models 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.

Regressions at the household level: Living standards

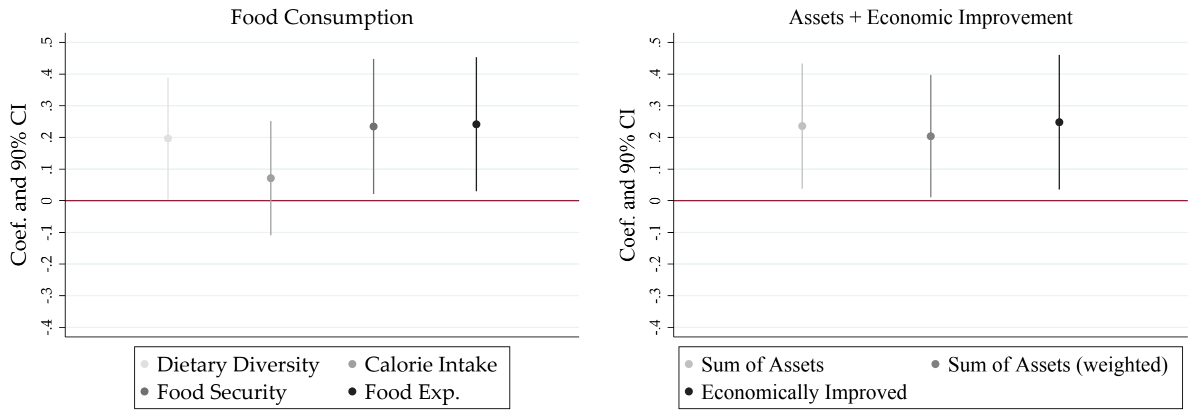
Table 18
Living standard indicators, household level, 2002-2014

	(1)	(2)	(3)
	Dietary Diversity	**Calorie Intake**	**Food Insecurity**
		Panel A: Food consumption	
Opium Profitability (t-1)	0.571**	143.915	0.182*
	(0.289)	(256.750)	(0.110)
Wheat Shock (t-1)	0.144	103.729	-0.000
	(0.124)	(98.066)	(0.035)
Number of observations	72224	71634	71634
Adjusted R-Squared	0.371	0.139	0.197
		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)
Wheat Shock (t-1)	346.351***	366.635***	263.161**
	(109.688)	(110.396)	(112.203)
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)
Wheat Shock (t-1)	-0.066	-0.015	-0.228***
	(0.112)	(0.072)	(0.082)
Number of observations	72447	66620	70670
Adjusted R-Squared	0.323	0.336	0.249

Notes: Linear probability models 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 international heroin price (in logarithms) and the suitability to grow opium. All food expenditures are in 2011 prices. Standard errors are in parentheses (clustered at the district-year level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Figure 14

Effect of opium profitability (t-1) on living standard indicators in (t), accounting for household survey weights



Notes: The figure shows results of 7 separate regressions in analogy to Table 18. 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.

F. Sensitivity analysis

Empirical model

Table 19
Normalized prices, district- and year-fixed effects, 2002-2014

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(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)
Wheat Shock (t-1)	0.318***	0.084***	0.074**	0.049*	0.010
	(0.106)	(0.032)	(0.030)	(0.026)	(0.015)
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)
Wheat Shock (t-1)	0.289***	0.080**	0.067**	0.044*	0.008
	(0.110)	(0.032)	(0.031)	(0.027)	(0.016)
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)
Wheat Shock (t-1)	0.207*	0.053	0.050	0.032	0.003
	(0.114)	(0.033)	(0.032)	(0.028)	(0.016)
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)
Wheat Shock (t-1)	0.268**	0.075**	0.065**	0.040	0.006
	(0.108)	(0.032)	(0.030)	(0.026)	(0.016)
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.

Table 20

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 Profitability (t-1)	-6.376***	-6.823***	-6.849**	-3.148
	(1.764)	(2.519)	(3.249)	(6.672)
Wheat Shock (t-1)	-0.171	2.204**	2.631*	1.154
	(1.087)	(1.117)	(1.466)	(3.084)
Number of observations	4407	3510	2431	806
Pseudo R-Squared	0.350	0.272	0.272	0.213
	Panel B: Onset			
Opium Profitability (t-1)	-4.505***	-6.076**	-5.729*	-1.719
	(1.686)	(2.375)	(3.092)	(5.601)
Wheat Shock (t-1)	1.062	2.860***	1.725	0.162
	(1.020)	(1.109)	(1.424)	(2.721)
Number of observations	2953	2739	1995	714
Pseudo R-Squared	0.170	0.136	0.149	0.149
	Panel C: Ending			
Opium Profitability (t-1)	4.053**	0.445	-0.446	-9.784
	(1.698)	(2.430)	(2.939)	(8.124)
Wheat Shock (t-1)	0.363	-0.457	-1.357	-1.915
	(1.150)	(1.558)	(2.059)	(4.696)
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. 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

Modifications of the treatment variable: Drug prices

Table 21
Non-normalized drug prices, 2002-2014

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(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)
Wheat Shock (t-1)	0.341***	0.095**	0.090**	0.041	-0.016
	(0.121)	(0.038)	(0.035)	(0.031)	(0.017)
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)
Wheat Shock (t-1)	0.289**	0.085**	0.075**	0.030	-0.016
	(0.128)	(0.040)	(0.037)	(0.033)	(0.020)
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)
Wheat Shock (t-1)	0.221*	0.065	0.062*	0.016	-0.023
	(0.130)	(0.040)	(0.037)	(0.033)	(0.020)
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)
Wheat Shock (t-1)	0.220*	0.066*	0.062	0.015	-0.023
	(0.130)	(0.040)	(0.038)	(0.033)	(0.020)
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 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(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)
Wheat Shock (t-1)	0.853**	0.250**	0.222**	0.107	-0.037
	(0.354)	(0.112)	(0.106)	(0.092)	(0.050)
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 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(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)
Wheat Shock (t-1)	0.303**	0.089***	0.080**	0.032	-0.017
	(0.122)	(0.031)	(0.036)	(0.027)	(0.020)
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 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(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)
Wheat Shock (t-1)	0.173	0.036	0.049	0.014	0.006
	(0.149)	(0.043)	(0.043)	(0.040)	(0.024)
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 DiD

TABLE 25
DiD, dyadic treatment, 2002-2014

	(log) BRD	1 if ≥ 5	1 if ≥ 10	1 if ≥ 25	1 if ≥ 100
	(1)	(2)	(3)	(4)	(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)
Wheat Shock (t-1)	0.072	0.027*	0.026*	0.007	-0.014**
	(0.051)	(0.016)	(0.015)	(0.013)	(0.006)
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)
Wheat Shock (t-1)	0.099	0.029	0.043	0.007	-0.025**
	(0.092)	(0.028)	(0.029)	(0.024)	(0.012)
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.

Outcome and timing (Reduced form and IV)

Table 26
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)
Wheat Shock (t-1)	-0.173	-0.070
	(0.171)	(0.168)
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 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.

Table 27
IVs for opium cultivation, 2002-2014

	(log) BRD	**1 if** ≥ 5	**1 if** ≥ 10	**1 if** ≥ 25	**1 if** ≥ 100
	(1)	(2)	(3)	(4)	(5)
	Panel A: Second Stages Opium Profitability (t-1) and VHI (t-1) as IVs				
(log) Cultivation (t-1)	-0.469**	-0.132**	-0.125**	-0.083*	-0.022
	(0.213)	(0.063)	(0.063)	(0.048)	(0.022)
Number of observations	5173	5173	5173	5173	5173
Kleibergen-Paap F stat.	9.947	9.947	9.947	9.947	9.947
Hansen J p-val.	0.708	0.644	0.724	0.448	0.496
	Panel B: First Stages Cultivation in (t-1)				
Opium Profitability (t-1)	0.811***	0.811***	0.811***	0.811***	0.811***
	(0.260)	(0.260)	(0.260)	(0.260)	(0.260)
VHI (t-1)	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Adjusted R-Squared	0.385	0.385	0.385	0.385	0.385

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 cultivation is in (t-1). Opium Profitability (t-1) and VHI (t-1) are used as IVs. Standard errors are in parentheses (clustered at the district level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Table 28
IVs for opium revenues, 2002-2014

	(log) BRD	1 if ≥ 5	1 if ≥ 10	1 if ≥ 25	1 if ≥ 100
	(1)	(2)	(3)	(4)	(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: VHI (t-1) as IV					
(log) Revenue:(t)+(t-1)	-0.374	-0.099	-0.099	-0.105	-0.032
	(0.299)	(0.084)	(0.084)	(0.079)	(0.033)
Number of observations	5084	5084	5084	5084	5084
Kleibergen-Paap F stat.	2.610	2.610	2.610	2.610	2.610
Panel C: Opium Price Shock and VHI (t-1) as IVs					
(log) Revenue:(t)+(t-1)	-0.193**	-0.054*	-0.051*	-0.029	-0.007
	(0.098)	(0.029)	(0.029)	(0.021)	(0.010)
Number of observations	5084	5084	5084	5084	5084
Kleibergen-Paap F stat.	6.170	6.170	6.170	6.170	6.170
Hansen J p-val.	0.374	0.464	0.413	0.079	0.266

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 first stage results for revenues (t)+(t-1), 2002-2014

	Opium Profitability	VHI	Opium Profitability, and VHI
	(1)	(2)	(3)
Opium Profitability (t-1)	2.489***		2.436***
	(0.749)		(0.748)
VHI (t-1)		-0.007	-0.005
		(0.004)	(0.004)

Notes: Linear probability models with year- and district-fixed effects. The dependent variable is opium revenues. Opium revenues is operationalized as the moving average between (t) and (t-1). 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.

Table 30
Alternative IVs for revenue (t-1), 2002-2014

	(log) BRD	**1 if ≥ 5**	**1 if ≥ 10**	**1 if ≥ 25**	**1 if ≥ 100**
	(1)	(2)	(3)	(4)	(5)
	Panel A: Opium Profitability (t-1) and VHI (t-1) as IVs				
(log) Revenue (t-1)	-0.162**	-0.045**	-0.042**	-0.027*	-0.007
	(0.071)	(0.021)	(0.021)	(0.016)	(0.008)
Number of observations	5103	5103	5103	5103	5103
Kleibergen-Paap F stat.	11.753	11.753	11.753	11.753	11.753
Hansen J p-val.	0.800	0.896	0.806	0.226	0.371
	Panel B: Legal Opioids (t-1) as IVs				
(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 C: Legal Opioids (t-1) and VHI (t-1) as IVs				
(log) Revenue (t-1)	-0.192**	-0.056**	-0.046**	-0.030*	-0.010
	(0.075)	(0.022)	(0.021)	(0.016)	(0.007)
Number of observations	5103	5103	5103	5103	5103
Kleibergen-Paap F stat.	10.431	10.431	10.431	10.431	10.431
Hansen J p-val.	0.947	0.819	0.943	0.334	0.596

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 31
Corresponding first stage results for revenues, 2002-2014

	Opium Profitability and VHI	**Legal Opioids**	**Legal Opioids and VHI**
	(1)	(2)	(3)
Opium Profitability (t-1)	2.798***		
	(0.721)		
VHI (t-1)	-0.012***		-0.011***
	(0.004)		(0.004)
Legal Opioids (t-1)		-15.384***	-14.878***
		(4.259)	(4.271)

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.

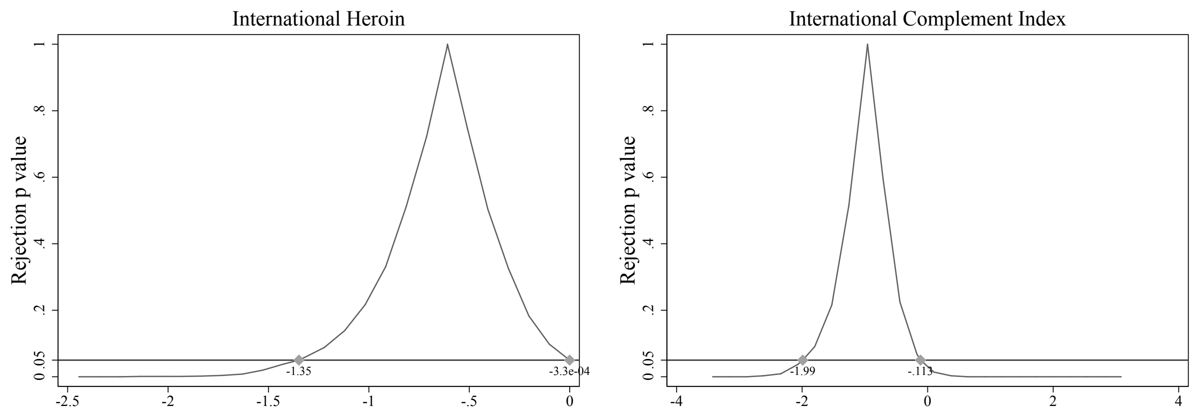
Standard errors

TABLE 32
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
	(0.365)	(0.103)	(0.103)	(0.082)	(0.044)
Wheat Shock (t-1)	0.307**	0.088***	0.077**	0.034	-0.010
	(0.105)	(0.025)	(0.030)	(0.024)	(0.016)
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 shock (t-1)	-0.675*	-0.126	-0.191*	-0.147*	-0.040
	(0.365)	(0.104)	(0.103)	(0.082)	(0.044)
Wheat shock (t-1)	0.307**	0.144***	0.077**	0.034	-0.010
	(0.105)	(0.033)	(0.030)	(0.024)	(0.016)
Number of observations	5174	5174	5174	5174	5174
Adjusted R-Squared	0.649	0.550	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-cluster bootstrap (clustered at the province level)



Notes: Figures show the distribution of bootstrap estimates. The dependent variable is the (log) of BRD. Regressions correspond to Table 2 column 1 (panels 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 33
No wheat shock included, 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)	-0.923***	-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 34
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)
Wheat Shock (t-1)	0.260**	0.083**	0.068**	0.031	-0.008
	(0.103)	(0.036)	(0.032)	(0.027)	(0.015)
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 35
Including covariates, 2002-2014

	(log) BRD (1)	1 if ≥ 5 (2)	1 if ≥ 10 (3)	1 if ≥ 25 (4)	1 if ≥ 100 (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)
(log) Wheat shock (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)
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)	-0.680**	-0.182**	-0.199**	-0.175**	-0.030
	(0.269)	(0.084)	(0.081)	(0.068)	(0.039)
(log) Wheat shock (t-1)	0.269**	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	0.002	-0.004	-0.001
	(0.020)	(0.006)	(0.006)	(0.005)	(0.003)
(log) Population (t-2)	-0.652	-0.910	-0.719	-0.232	0.910**
	(3.469)	(0.948)	(0.956)	(0.934)	(0.380)
Adjusted R-Squared	0.653	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)
(log) Wheat shock (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)
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). The number of observation is 5173 in panel A, and 5174 in panels B and C. Standard errors are in parentheses (clustered at the district level). Significance levels: * 0.10 ** 0.05 *** 0.01.

Outlier analysis

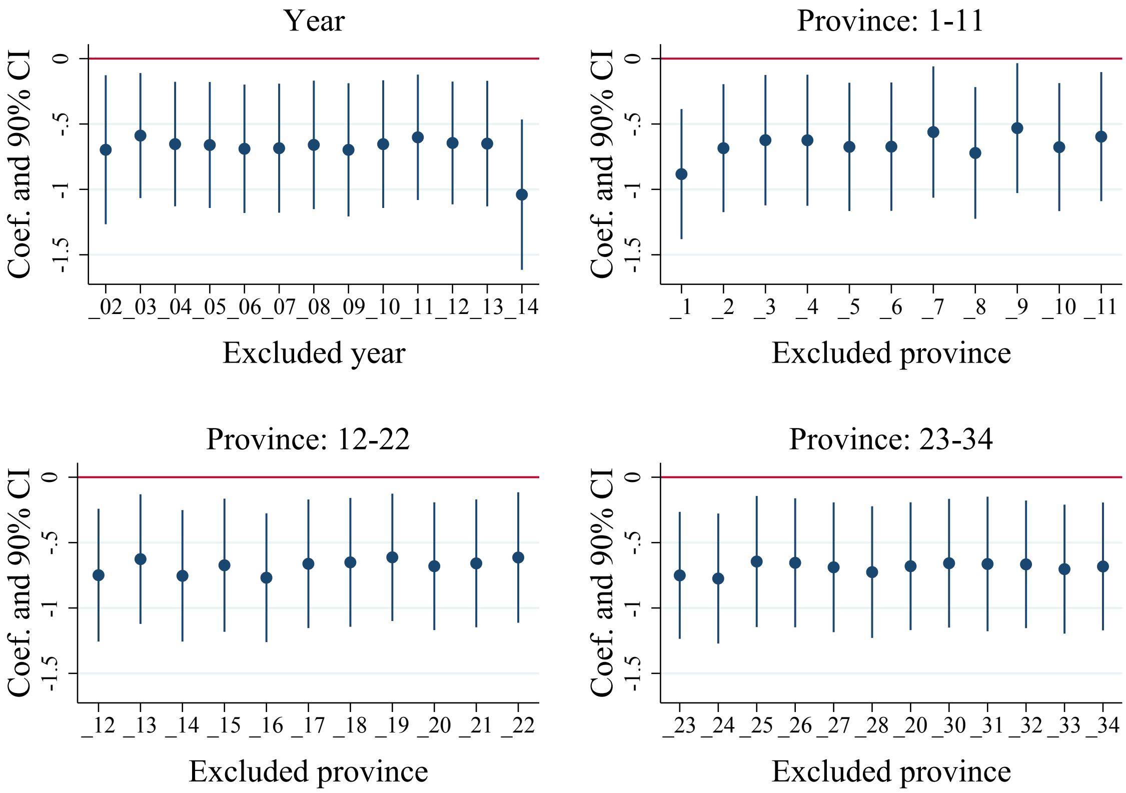
Table 36
Drop potential outliers, 2002-2014

	(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)
Wheat Shock (t-1)	0.348**	0.113**	0.106**	0.027	-0.019
	(0.167)	(0.052)	(0.050)	(0.043)	(0.027)
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)
Wheat Shock (t-1)	0.319**	0.088**	0.072*	0.033	0.003
	(0.127)	(0.041)	(0.038)	(0.032)	(0.017)
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

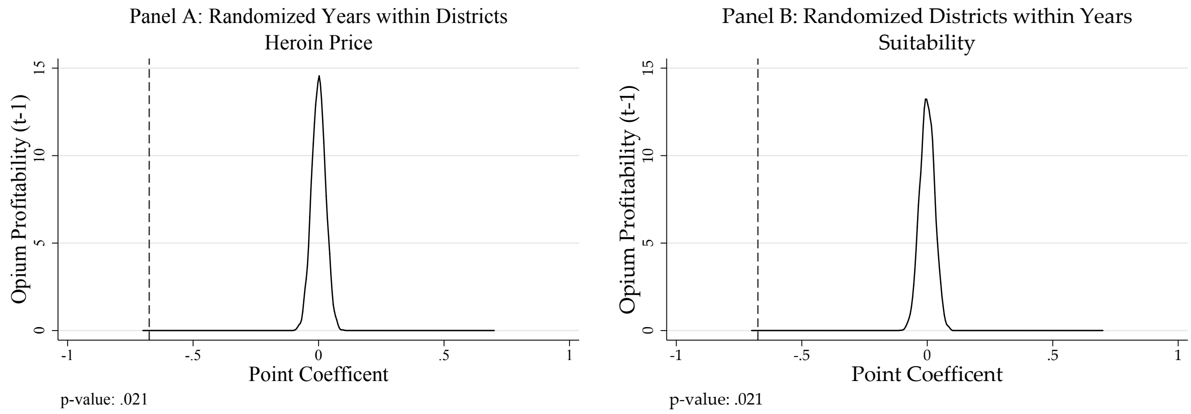
Leave one out - year and province



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.

Robustness for Table 4 and Table 5

Table 37
Opportunities costs proxied by share of value added, 2002-2014

	Market Acess Population 2D (1)	**Market Acess Population 3D** (2)	**Sum Markets and Lab** (3)
Opium Profitability (t-1)	-0.6533**	-0.6534**	-0.5368*
	(0.3027)	(0.3027)	(0.3015)
Opium Profitability (t-1)*X	-0.2188	-0.0002	-0.1882
	(0.2678)	(0.0003)	(0.1292)
Number of observations	5174	5174	5174
Adjusted R-Squared	0.649	0.649	0.650

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. Regressions include interactions of the opium profitability with a variable X as indicated in in the column heading. For definitions of the variables X see Appendix A. Standard errors are in parentheses (clustered at the district level). Significance levels: * 0.10 ** 0.05 *** 0.01

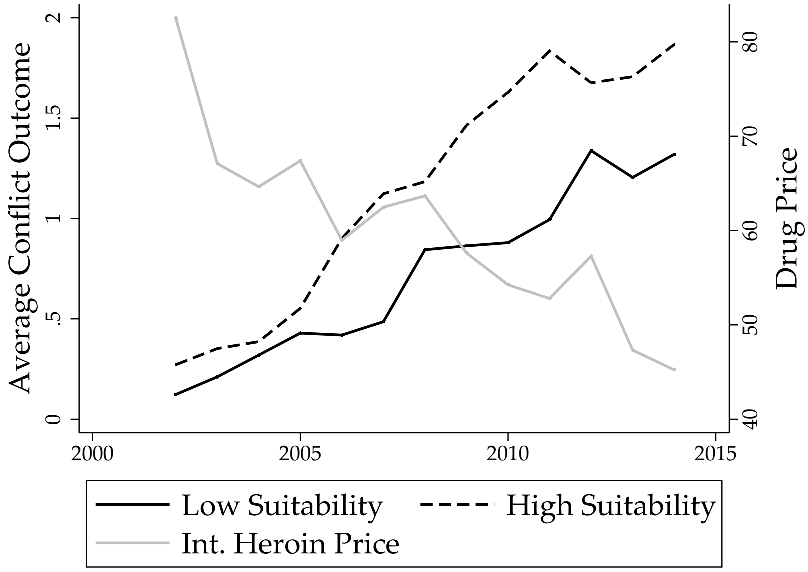
Table 38
Ethnic groups measured by NRVA, 2002-2014

	Any Pasthuns	**Share Pasthuns**	**Ethnic Groups**	
			1 if Mixed	**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 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 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 a suitable proxy for ethnic group distribution. Standard errors are in parentheses (clustered at the district level). Significance levels: * 0.10 ** 0.05 *** 0.01

Robustness for Figure 8.

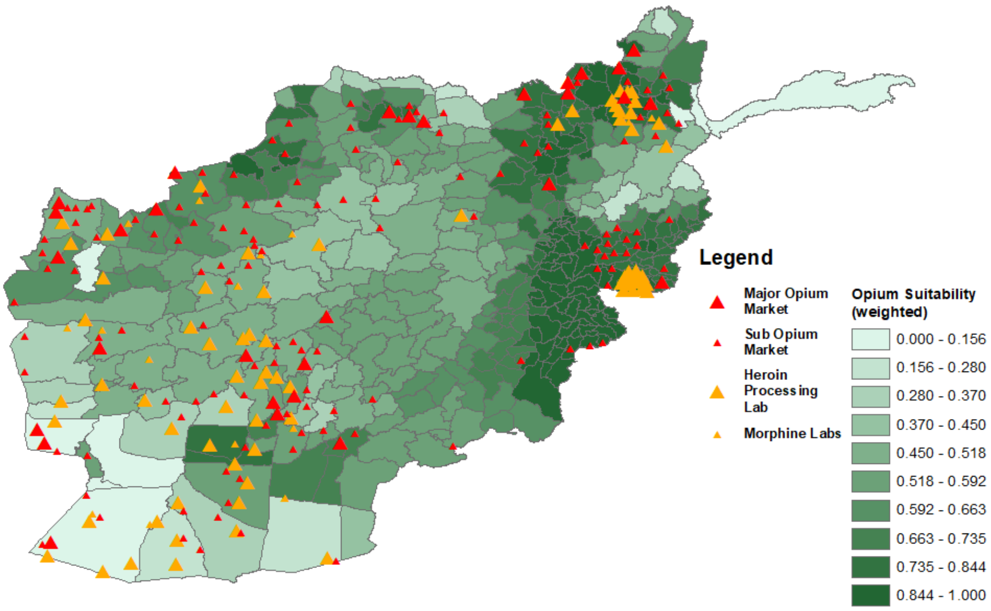
Figure 18
Variation in conflict across high and low suitable districts over time



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

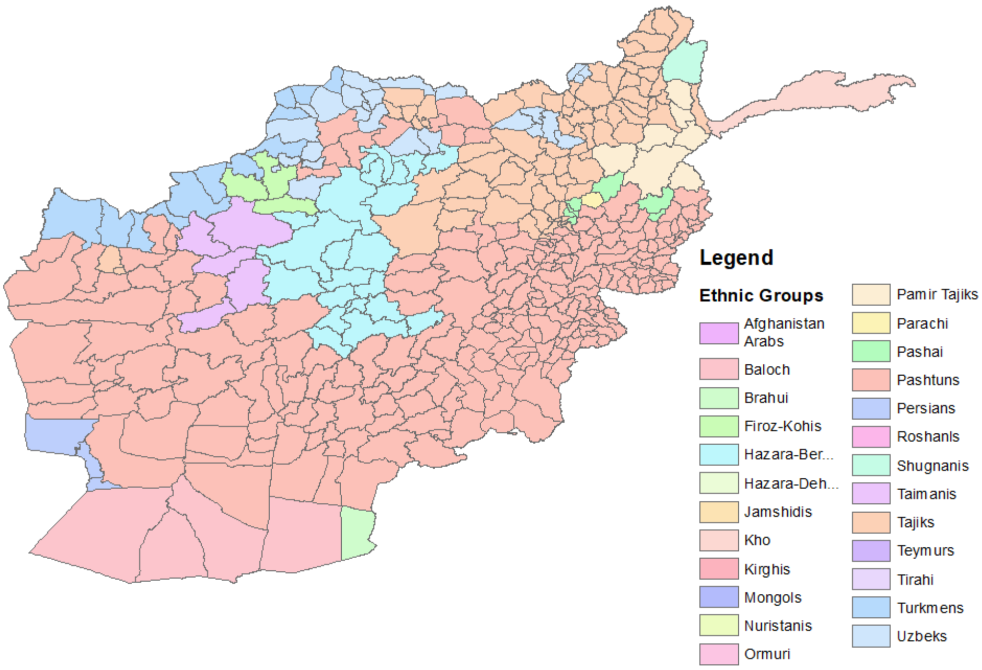
G. Additional maps

FIGURE 19
Opium suitability, opium markets, and processing labs



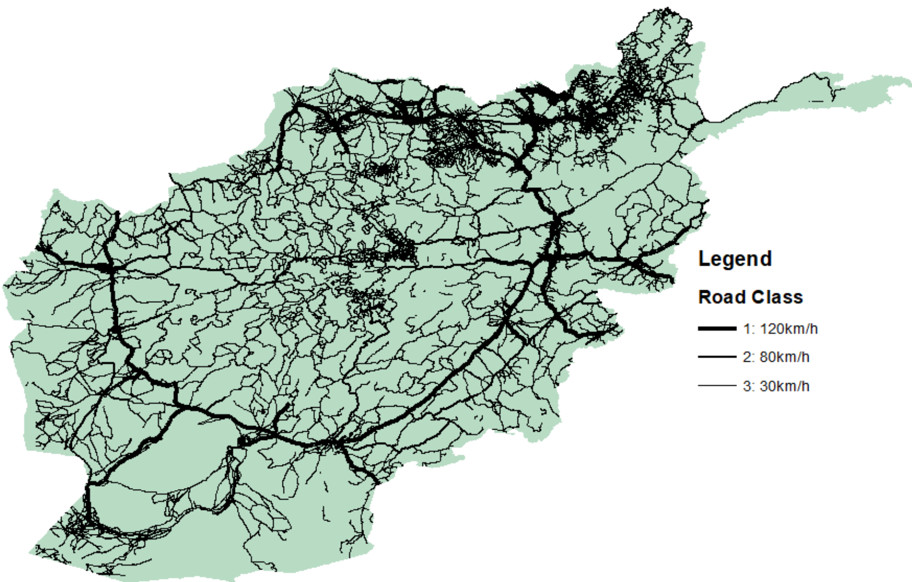
Notes: The figure plots the population weighted suitability. Market and lab information based on UNODC. Opium suitability based on Kienberger et al. (2017).

Figure 20
Ethnic groups



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).

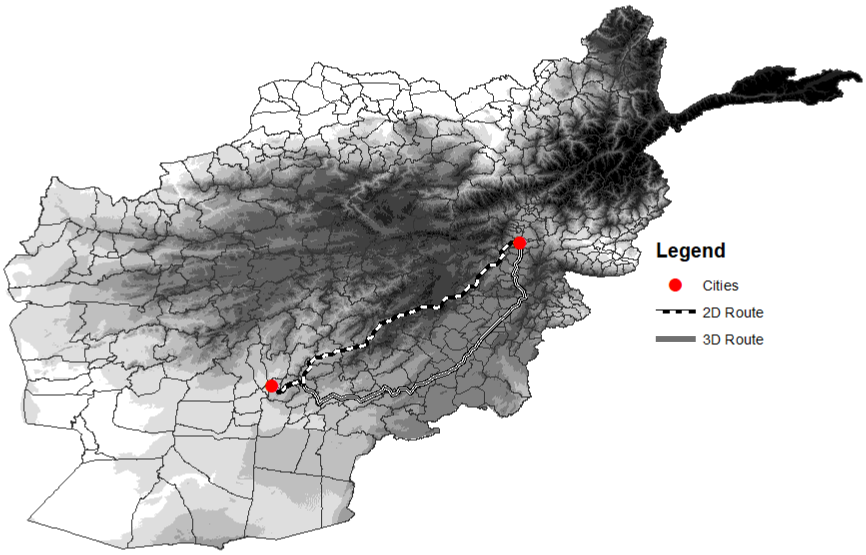
FIGURE 21
Road network



Notes: The road network in Afghanistan distinguishing in highways (assumed speed 120km/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 22

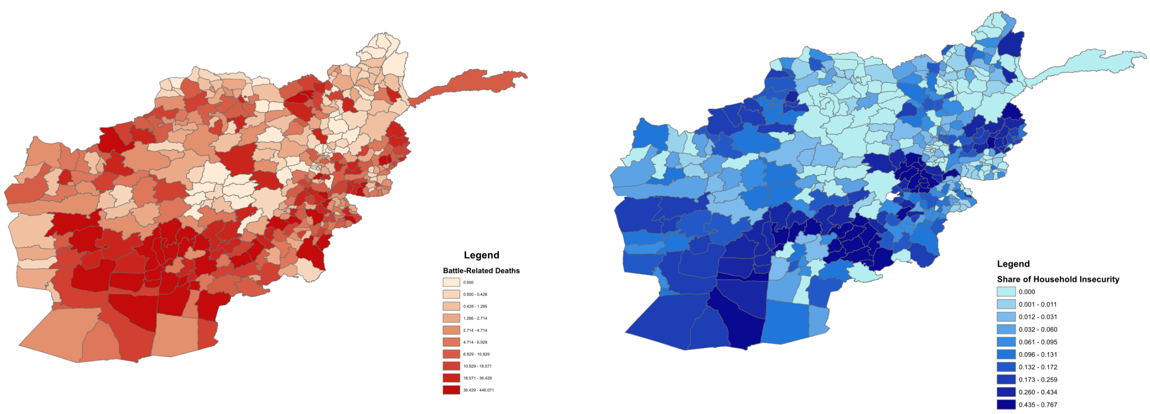
Elevation, 2D and 3D route



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.

Figure 23

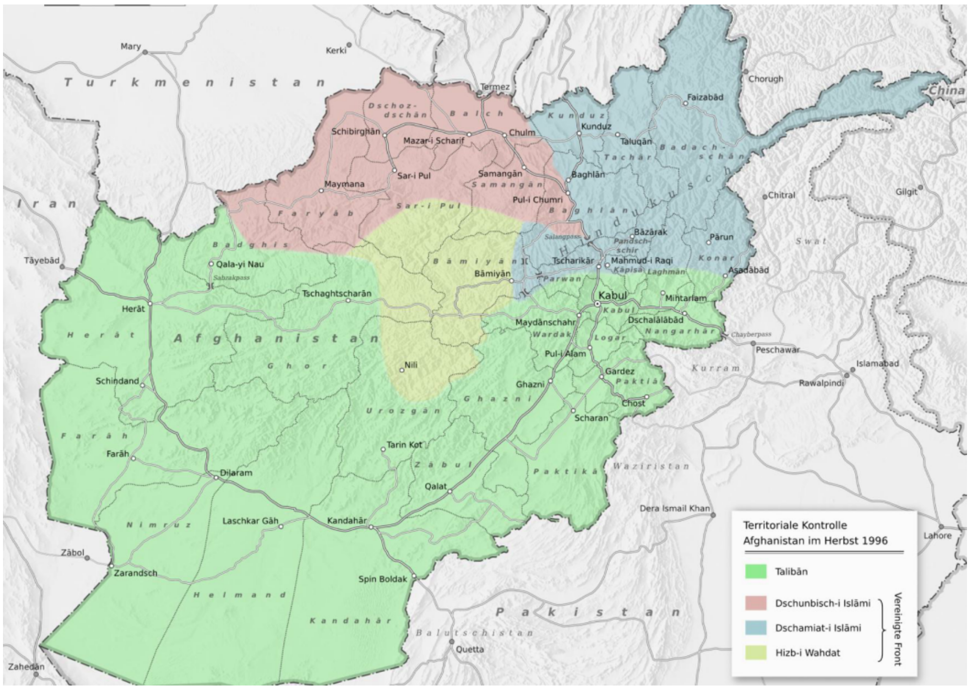
Distribution of objective and subjective conflict indicators, 2002-2014



(A) Number of battle-related deaths (UCDP GED)

(B) Share of households experiencing insecurity shock (NRVA)

Figure 24
Political control in Afghanistan in the fall of 1996



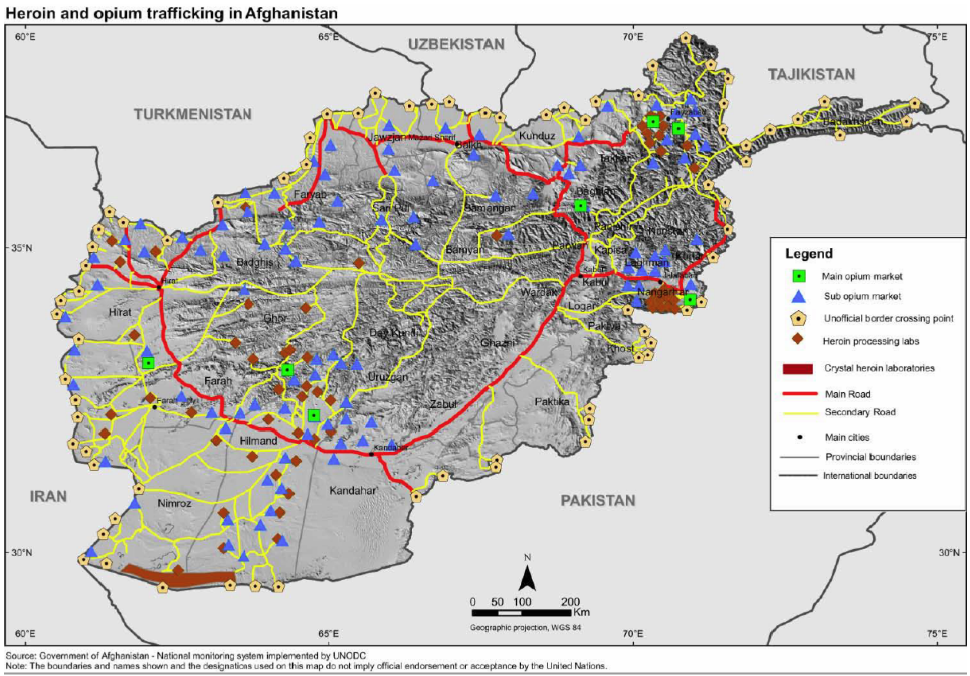
Notes: The figure is an excerpt from a book by Dorronsoro (2005). We georeference the green area as the area formerly under Taliban control, and the other three polygons as not under Taliban control.

H. Data coding and map generation

Processing and trafficking

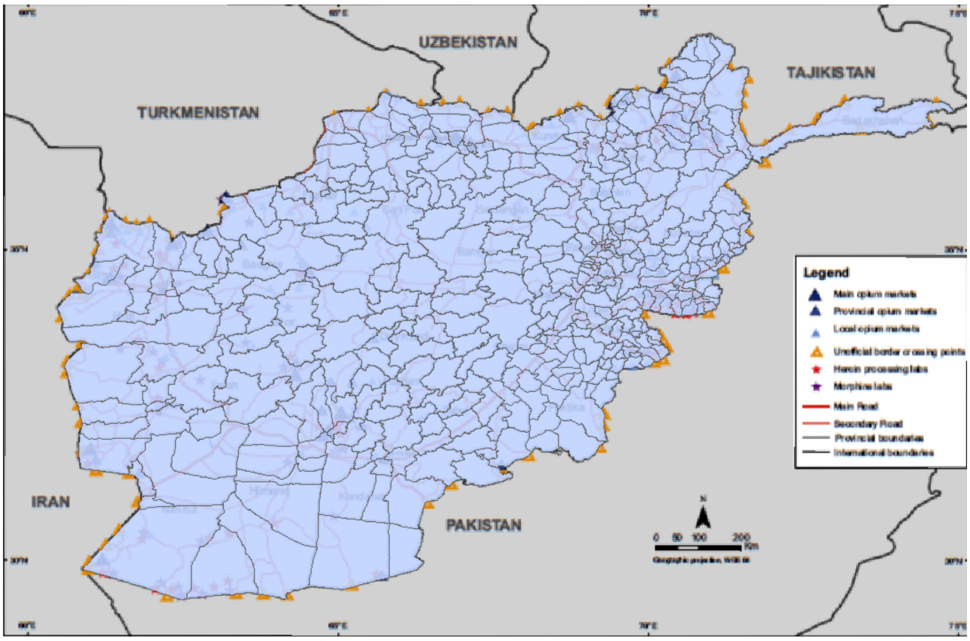
There is little to no information that is publicly available on trafficking routes that might be used to smuggle opium through and out of the country. Nevertheless, the UN Office on Drugs and Crime creates and contains spatial maps in its public reports. We were able to digitize a UNODC map from 2007 (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, heroin processing labs.

Original UNODC map (2007)



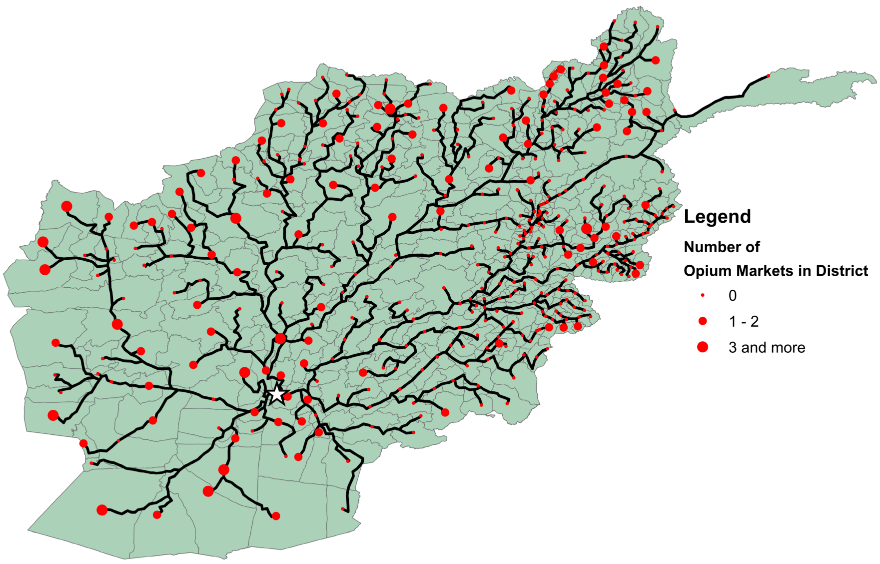
Map making process: The source of the original map comes is the UNODC's 2007 Afghanistan Opium Survey. The map depicts major and secondary roads, main cities, opium markets, border crossing points, and processing labs. We also used the 2009 Afghanistan Opium Survey to cross-validate the data points. In almost all cases, there were no changes between the two years. In case the 2009 map identifies additional markets or labs we added these as data points. Given that the location of illegal markets and labs will always contain some measurement error and could be moved over time, our aim is to code variables that measure the potential for a trafficking route, border crossing, market or lab. This means that 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



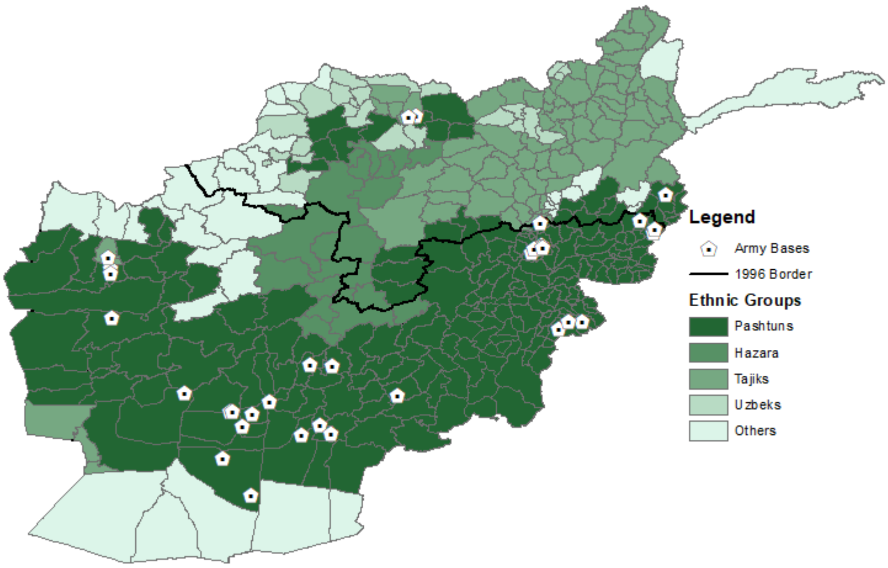
In the next step of the process, we match the borders of the image and the georeferenced (Coordinate system GCS WGS 1984) shapefile for Afghan authorities (ESOC Princeton, https://esoc.princeton.edu/files/administrative-boundaries-398-districts). This way, we are accurately overlaying the data points 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 6 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: he 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 the appendix). 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 the bases mostly 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, where exactly (latitude and longitude coordinates) these bases are (or were; many are now closed). 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.

Main bases and relevant information (1/2)

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

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), Main bases and relevant information (2/2)

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

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 Field9 for explanatory notes in these cases), and general notes of interest.

Confirming the location of these districts using satellite

This is an example of what the Wikimapia satellite imagery we used to locate bases looks like. This is an image of Base Blackhorse, which is 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 of course not the only criteria we used to determine whether or not a specific base should be represented on the map, it was important for weeding out those that are not included (for example, we included no firebases on account of their temporary 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 from Wikipedia 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.

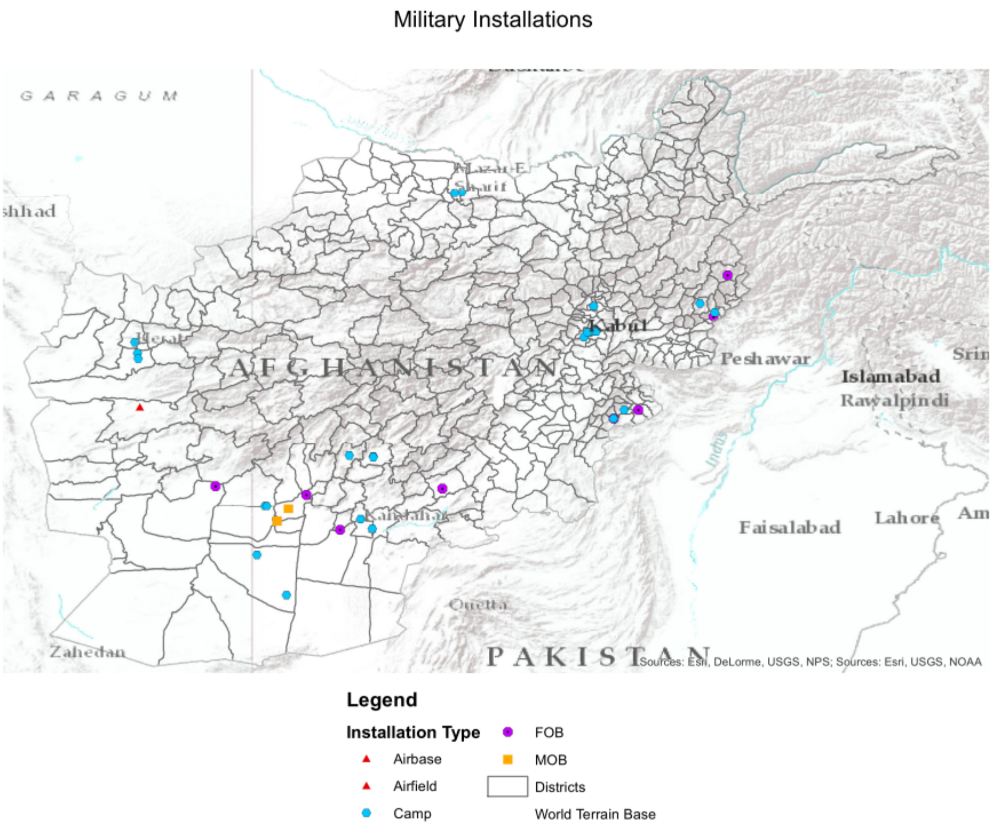
10. FOB Hamidullah located using Wikimapia satellite data. In Wikimapia, the location is described as FOB Nolay, the previous name of the base.

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.