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Working paper 2/2011

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Drugs and Violence in Afghanistan: A Panel VAR with Unobserved Common Factor Analysis

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Abstract

This paper addresses the relationship between the level of violence and the opium market in Afghanistan's provinces. We first provide an overview of the nature and extent of the Afghan drug trafficking. This is followed by a VAR analysis of the nexus opium-insurgency activities using monthly time-series data on opium prices and the number of security incidents for 15 Afghan provinces over the period 2004-2009. We use a multifactor error structure, the Common Correlated Effect (CCE), to include unobservable common factors; Impulse Response functions to describe the time path of the dependent variables in response to shocks; and the Mean Group Estimator to summarize our results across the provinces. Results suggest a conflict-induced reduction in opium prices, while the reverse opium-violence mechanism is mostly negligible. Moreover, unobservable common factors are the main drivers of opium prices and violence.

Keywords: Conflict, Opium, Afghanistan
JEL Classification : D74, H56, K42

1) Introduction

The magnitude and importance of Afghanistan's opium economy are unique in global experience. The country has been devastated by internal wars and external military intervention for decades. These war years have seen Afghanistan emerging as the global leader in opium production. This may be explained by the destruction wrought by the war, which has resulted in the collapse of economic infrastructures across the country, relegating Afghanistan among the poorest economies in the world and at the lowest levels of global human security and development. Despite international external assistance (i.e. UN Assistance Mission in Afghanistan - UNAMA), and a long-lasting western military intervention in the country (i.e. The International Security Assistance Force -ISAF), unemployment rates remain alarming and less than 10% of the population has access to basic services such as electricity. Therefore poverty and economic stagnation, combined with an almost collapsing state, have been driving ordinary citizens to take the risks associated with the production, processing and transportation of drugs. Opium is a labor-intensive crop, particularly suitable for a labor-rich and capital-poor country. It generates jobs in on-farm casual work (e.g. weeding and harvesting) and in the non-farm rural sector (5.6 jobs per

† We are grateful to the UNODC Statistics and Survey Section for generously providing the dataset on opium prices. We wish to thank Ron Smith for helpful advices and Tilman Brück, Antonio Giustozzi, Kristian Skrede Gleditsch, and Marijke Verpoorten for their insights. We also thank HiCN's Workshop participants at the Universidad de los Andes, seminar participants at the Institute of Development Studies, conference participants at the Global Economic Costs of Conflict Conference, CSAE Conference 2011 and CESifo Venice Summer Institute for their comments. Financial support from the AXA Research Fund is greatly acknowledged. The usual disclaimer applies.

hectare, according to UNODC, 2009a). Thus, opium sustains the livelihoods of millions of rural Afghans.

Yet, it also generates income outside the rural sector. The number of people engaged in the opium trade is startling and has been increasing in recent years. In Helmand province alone, the estimated number of traders is between 600 and 6,000. Between 2003 and 2009, Afghan farmers earned more than US$ 6.4 billion from opium poppy cultivation, and Afghan traffickers approximately US$ 18 billion from local opiate processing and trading (UNODC, 2009a, 2009b). Today, Afghanistan provides 93% of the global supply of opium - and over 90% of the heroin trafficked into the UK - despite increasing efforts by the international community, and ISAF forces, to eradicate the cultivations of poppy.

The economic theory on conflict suggests two opposite relations between income and violence. Wage and income shocks increase the incentives for peace through the reduction of labour supplied to conflict activities. The higher the returns to productive activities relative to the returns to fighting activities, the higher the amount of citizens' time devoted to peaceful activities (Grossman, 1991). This opportunity-cost effect motivates civil wars (Fearon, 2008). The contest model suggests that the greater the national wealth, the greater the effort devoted to fighting relative to production (Hirshleifer, 1995; Garfinkel & Skaperdas 2007). The nexus between income and violence is not so clear cut also in the empirical evidence (e.g. Collier & Hoeffler, 2004; Fearon, 2005).

More recently, Besley *et al.* (2008) show that positive price shocks to imported and exported commodities make civil war more likely; in contrast, Bruckner & Ciccone (2010) find that a civil war is more likely in those Sub-Saharan countries where the value of export commodities is decreasing. However, the cross-country analysis has a number of severe shortcomings, and should be regarded with caution (Blattman & Miguel, 2010). A small and persuasive number of works on the Colombian conflict and the drug-violence nexus finds a positive effect of coca production on conflict both through a micro-econometric (Angrist & Kugler, 2008) and a macro-econometric approach (Gonzales & Smith, 2009). Finally, Dube & Vargas (2008) find that both a price-drop in labour-intensive activities (e.g. coffee production) and a rise in capital-intensive commodities (e.g. oil) have the same effect of intensifying attacks by Colombian guerillas.

Although the link between income and violence is among the most robust in the empirical literature, the direction of causality remains a serious concern. The recent literature has focused on addressing the causal identification problem, in a search for exogenous measures (e.g. Miguel *et al*., 2004). In 2006, UNODC published a study on the socio- economic and psychological factors influencing the variations of poppy cultivation in Afghanistan (UNODC, 2006). The survey found that main motivations for opium cultivation were (i) a lack of rule of law; (ii) insecurity; (iii) lack of employment; (iv) lack of water and agricultural infrastructure; (v) provision of basic needs and (vi) external pressure from traffickers and traders. Therefore we do not only question the ability of the Taliban-led insurgency to finance war expenditures through the drug economy; we also investigate whether the (perceived) lack of security makes illegal activities more profitable. Lind *et al*. (2011) show that ISAF hostile casualties - their tentatively exogenous proxy for conflict- have a significant impact on annual opium production. However, a suspicion of endogeneity (e.g. the placement of soldiers endogenous to opium production and ISAF eradication activities[1]) still remains. We will use monthly opium prices at the farm gate level to test these two dynamics.

Our baseline analysis assumes the endogeneity of the variables; therefore we use a vector autoregression, VAR, to estimate a system in which both income and violence are functions of their own lag, and the lag of the other variable in the system. Our VAR is augmented through an unobserved common factor. We explore whether opium prices induce subsequent violence and whether a reverse mechanism coexists. To this end, we have gathered a unique dataset with monthly information on opium prices and security incidents from 15 Afghan

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[1] In fact, the bulk of ISAF's forces are in the insurgency-wrecked South and East of the country, especially in the provinces of Helmand and Kandahar, where cultivation is concentrated.

provinces over the period 2004-2009. The geographic disaggregation of our data enables us to exploit variations across provinces and over time. Section 2 provides an overview of the nature and extent of the Afghan drug trafficking in an historical perspective. Section 3 describes the data and deals with the difficulties of identifying a clear pattern between opium and violence. Section 4 describes the methodology and presents our empirical evidence and Section 5sums up the findings from the paper and provides some policy implications.

2) Background

The nature and extent of the Afghan drug trafficking have been always shaped by military factors. Before the outbreak of war - from 1950s to 1970s - Afghanistan was a sort of rentier or "allocation" state, deriving over 40% of its revenue from resources accruing directly from abroad, which were used to create basic infrastructure and to pay a police force and army. These revenues included both foreign aid and sales of natural gas to the USSR (Rubin, 1992). The rural community was isolated from the central state and dependent on agricultural production. In the mid-1970s, following the disruption of opium production in Iran, poppy production became a significant staple in the country's rural economy. By the late 1970s, poppy was cultivated in half of the provinces (Goodhand, 2005). In 1978, the communist coup d'état and the Soviet occupation of the country were accompanied by a continued expansion of poppy cultivation. Opium was used as a source of funding for the Mujahedeenan, an islamist guerrilla. Along with an increasing production in Pakistan, Afghanistan developed into a major producer of opium, accounting for more than one-third of the global production by the mid-1980s. After 1992, when the Mujahedeen took Kabul, the local warlords fought each other to consolidate their economic activities, fragmenting the country in a series of sub-conflicts. The further deterioration of the central authority saw a rapid expansion of cross-border smuggling and the production of narcotics. In the mid-1990s, the disintegration of the country and the dissatisfaction among the population about greedy "warlordism" encouraged the rise of the Taliban. From their stronghold in the South, in the Kandahar province, the Taliban conquered the country. By September 1996 they had captured Afghanistan's capital.

The Taliban's relationship with opium has been uneven over time. When in power, the smuggling network proved to be an important source of revenue for the new regime, which facilitated its export. In 1997 total production was 2,700 metric tons, showing a 43% increase over the previous year, with cultivation spreading to new provinces. Through a direct taxation on farmers (*ushr*), a 10% "agricultural tax", they generated about $75-100 million per year between 1995 and 2000, to fund a regime without alternative sources of foreign exchange (Thachuk, 2007). In 1999 the production peaked at 4,500 metric tons, three-quarter of the global supply (UNODC, 2009a). The most damaging drought in three decades struck the rural economy, already devastated by years of conflict. In the summer of 2000 Mullah Omar banned opium cultivation, the reasons for which are still debated - he appealed generically to religious sentiments to justify the ban. The Taliban decree (*fatwa*), reduced the overall production, although the cultivation continued in areas outside the Taliban reach, particularly the North-East provinces. Also, while the opium ban concerned opium poppy cultivation, no policy toward opium trading and heroin manufacture was enunciated and the Taliban continued to levy taxes on these activities (Buddenberg & Byrd, 2007).

Following the end of the regime, poppy production returned to previous levels by 2005. Ever since their return as insurgents into Southern Afghanistan in 2005, the Taliban - and other anti-government forces - have derived enormous profit from the opium trade. In 2007 the production peaked at 8,000 metric tons, the highest level ever recorded. Today opium is the country's biggest export and one in seven Afghans is reportedly involved in some aspect of the trade, with 6.5% of the population involved in growing poppy (UNODC, 2009b). In areas such as Helmand, where cultivation is concentrated, this share rises to a staggering 80%. Although the magnitude is subject to debate, the total drug-related funds accruing to insurgents and warlords were estimated at $200- 400 million in 2006-2007 and at $450-600 million between 2005 and 2008 (UNODC, 2009b). These estimates included incomes from four sources: levies on opium farmers; protection fees on lab processing; transit fees on drug convoys; and taxation on imports of chemical precursors. At the same time, Afghanistan's opiate economy has moved towards a greater share of refined products (at present 2/3 of the raw opium output is turned into heroin and morphine). This has allowed the Taliban to tax higher value-added commodities and other drug-related activities.

The relation between the opiate business and the insurgency in Southern Afghanistan is amplified by the role played by tribalism in both drug trafficking and insurgent networks. The strongest overlap between the insurgency, tribal networks and the drug trade is found in the Southern and Eastern parts of the country, and extends into Pakistan's tribal areas across the Afghan border.

The literature on economic conditions and warfare surveyed above highlights the role of the illegal returns in the decision to fight: an increase in the return to crime increases the labour supplied to criminals, therefore increasing the level of violence. Thus, the opportunity-cost effect is a main factor motivating civil wars. In principle, in Afghanistan individuals may choose between opium cultivation and joining an anti-government group (e.g. Taliban, insurgency linked to Al-Qaeda or non-ideological organized crime).

Theoretically, there may also be a revenue-appropriation mechanism, or “greed” effect (Collier, 2004), especially on lootable resources (Snyder, 2006): violence might be over the opium cultivation and controlling the plantation can finance the insurgency. In practice, the narcotic trade seems to be crucial in supporting Anti-Government Elements. Extortion fund AGE through two form of local-levied taxes: not only the above-mentioned *ushr*, a 10% tax on agricultural products, but also the *zakata*, a 2.5% wealth tax applied to traders (Kalfon *et al.*, 2005). According to UNODC (2007), almost all the farmers in the Southern and Western regions pay the *ushr*. Between 2005 and 2008, the total estimated farm-gate value of opium produced in those regions was US$ 2 billion. That means approximately US$ 200 million paid as *ushr* by farmers. In the period 2003-2009, UNODC estimated that the total farm-gate value of the total opium produced in Afghanistan was almost US$ 6 billion. 2.2 billion went to Helmand farmers and 874 million to Nangarhar farmers. Taliban also levy taxes on laboratories producing morphine and heroin (UNODC, 2009a). To investigate the extent to which regional instability and insurgency is fuelled by the Afghan opiate industry, we start by exploring our dataset and by providing some descriptive patterns.

3) Data and Patterns

We use monthly time-series data on opium prices and security incidents for 15 Afghanistan provinces over the period 2004-2009. The provinces with available data are Nangarhar, Laghman, Kunar, Helmand, Kandahar, Badghis, Herat, Ghowr, Farah, Nimroz, Takhar, Badakhshan, Faryab, Kunduz and Balkh. We believe that it is possible to generalize our results to the whole country, given that these provinces are very heterogeneous in terms of i) area under poppy cultivation, ranging from poppy-free provinces like Kunduz, Balkh and Ghowr to Helmand and Kandahar, the last two accounting for 80% of the production; ii) population, from more densely populated areas like Balkh to less densely populated areas like Badghis and iii) geographic location, since our provinces cover all the regions of the country.[2]

Monthly prices of opium were provided by the *UNODC Global Illicit Crop Monitoring Programme, Statistics and Survey Section*. These price data are based on inquiries in major opium producing areas (interviews with some 170 farmers and 160 traders) on a monthly basis. They have recorded farmer and trader price of dry and fresh opium. Farmer refers to farm-gate price of opium, trader refers to local trading level, dry opium refers to air-dry opium, and fresh opium to "wet" opium shortly after harvest - or kept "fresh" by plastic wrapping to avoid moisture loss. Prices are subject to seasonal variations, with lower prices during the harvest season. This is particularly true for fresh ("wet") opium prices, as fresh opium is available in the harvest period. For this reason we use dry opium prices. We choose the farm-gate level because reflects supply factors and risk premia. Data are broken down at

[2] According to the UN classification, we have 1 province in the Central region; 3 in the Eastern region; 3 in the North-Eastern; 2 in the Northern region; 2 in the Southern; and 5 in the Western region.

the level of 15 provinces. Opium production is also based on data from the UNODC, but available online. They provide annual data on the location and extent of opium cultivation and opium eradication efforts. Data are based on satellite image acquisition (for the methodological aspects, see UNODC, 2010)

Our data on the Afghan conflict comes from the *Worldwide Incidents Tracking System (WITS), US National Counterterrorism Center*. This dataset is event-based, and includes information on the event type, date and location.[3]

Data on opium production show that from 2004 there has been tangible progress in the increasing number of poppy-free provinces and decreasing opium poppy cultivation, especially in the last three years. In 2004, poppy cultivation was observed in 30 provinces (out of 34) and occupied 131,000 hectares. In 2009, opium poppy was cultivated in 14 provinces, and production decreased by 6% (123,000 ha) compared to 2004. Comparing 2004 and 2009, opium poppy cultivation increased in the Southern and western regions and decreased in all the other regions. The production has further concentrated and consolidated in the Southwestern provinces of Afghanistan, which now produce 90% of the national production compared to 50% few years ago. Despite an increase in "poppy free" provinces and a slight reduction in the overall crop production, the opium problem remains massive, and exacerbated by its concentration in areas where the Taliban are strong. At the same time there has been a notable extension of the area under insurgent control, particularly along the restive Pashtun tribal belt on the Afghanistan-Pakistan border (see Figure 1).

By most measures, insecurity in Afghanistan has dramatically increased in the last 7 years. This is primarily a result of the insurgency's growing strength. The Afghan National Army, the Afghan National Police and ISAF forces are the most frequent targets, but there have also been a substantial number of civilian casualties. In 2008 and 2010, many of Afghanistan's provinces registered a record number of attacks (Figure 2), ranging from suicide bombings to coordinated assaults on military compounds to kidnapping of government officials and contractors. Much of the violence occurred in Southern Afghanistan (e.g. Kandahar, Helmand, Zabol), but insecurity has also spread eastwards, to cover the majority of Afghan provinces, such as Balkh and Faryab.

Although it is commonly assumed that areas of opium cultivation and insecurity correlate geographically - particularly by the UN Office on Drugs and Crime (UNODC) and by NATO - there are too many exceptions. Firstly, they fail to consider the magnitude of opium cultivation per province. In the period 2004-2009, 80% of the opium was produced in six Afghan provinces (Helmand, Nangarhar, Kandahar, Badakshan, Uruzgan and Farah). Badakshan and Nangarhar aside, the bulk of the production took place in only four provinces in Southern Afghanistan. And almost half of all opium was produced in Helmand province. The next provinces in order of importance were Kandahar and Nangarhar (see Figure 3).[4]

On the other side, most of the Afghanistan provinces have been experiencing increasing level of violence (see Figure 2). Moreover, Figure 4 shows a number of relatively insecure provinces, such as Ghazni, Paktia and Paktika, with a negligible level of opium cultivation as percentage of the total. This should be hardly surprisingly since cultivation is more likely to occur in remote areas, where the presence of government and coalition forces is weaker or totally absent. Thus, the expected punishment decreases. Other areas, such as Badakhshan, have a steady level of violence and a decreasing number of insurgency's attacks. Another point of caution must be attached to the concept of "poppy-free" provinces. Thanks to the eradication activities, many provinces show low levels of poppy cultivation. However, if those provinces currently experience almost no production, they are not necessarily free from opium-related activities, especially trafficking and smuggling as it is the case in the Northern

[3] The dataset is available at http://www.nctc.gov/wits/witsnextgen.html.

[4] Figure 3 presents the opium-producing provinces (those where the cumulative area under poppy cultivation is more than 80% of the country total). All the other provinces have a negligible level of cultivation and therefore are omitted.

and western border regions, which are crossed by important heroin smuggling routes. In particular, UNODC estimates that every year around 110 tons of heroin are exported to the European market, about 100 tons to Central Asia (the majority destined for the Russian Federation), some 25 tons to Africa, 15-17 tons the potentially large market in China, and some 15-20 tons to the USA and Canada. Heroin is trafficked through the Afghanistan's neighbors, Pakistan (40%), Iran (30%) and the Central Asian countries of Tajikistan, Uzbekistan and Turkmenistan (25%). The remaining 5% is likely to be smuggled into India (UNODC, 2009a).

Secondly, the overall level of opium revenues in the Afghan economy is determined also by the opium price (Fugure 5). Since 2004, there has been a notable increase in the number of security incidents in Afghanistan in parallel with a decrease in opium prices. This suggests that there is a negative correlation between opium prices and violence, although at this level of aggregation we cannot say anything about causation. As can be seen from Figure 5, opium prices exhibit considerable volatility. This is because opium production - and consequently opium prices - has a strong seasonal component. Opium poppy is an annual crop with a six to seven month planting cycle. It is planted between September and December and flowers approximately three months after planting. After the flower's petals fall away, between April and July, the opium, a sap found in the seed capsule, is harvested. The sap can then be refined into morphine and heroin. The timing of the price drop usually coincides with the opium harvest (UNODC, 2009b). Weather conditions have an impact on yields and hence on overall supply, therefore influencing the prices; also, the final consumption demand in OECD markets might cause changes in prices. We explore an alternative factor affecting the prices: the political/military situation. An important question is to what extent increasing criminalisation has induced higher prices through higher risk premia. Do security incidents affect prices? Also, we will test the reverse mechanism: does opium foster violence?

4) Estimates

We analyze the relationship between security incidents and opium prices by using a vector autoregressive model (VAR). It provides a flexible framework for the analysis of the dynamics and interactions between these two variables, mainly because it does not require any presumption about the direction of the causal relationship.

Before discussing the estimation strategy and our results, we briefly comment on some preliminary tests. In particular, we check whether the series follow a unit root process, and whether the series are cross-sectional dependent and/or spatially correlated.

We run the 1st and 2nd generation panel unit root test by pooling the provinces together.[5] In particular we perform the Maddala and Wu (1999) (MW) and the Pesaran (2007) (CIPS) tests. The MW test assumes heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression and ignores cross-section dependence in the data, treating them as nuisance parameters. On the opposite, the CIPS test assumes heterogeneity in the autoregressive coefficient of the Dickey-Fuller (DF) regression and allows for the presence of a single unobserved common factor with heterogeneous factor loadings in the data. The statistic is constructed from the results of panel-specific DF regressions where cross-section averages of the dependent and independent variables are included in the model. The averaging of the group-specific results follows the procedure *a la* Im *et al* (2003).

Table 1 displays p-values of the two tests for 6 lagged differences and for two specifications, one with and one without a trend. The MW test rejects the null of nonstationarity for the security incidents series up until lags 2 in both specifications, whereas it rejects the null for the opium prices series up until lags 3 only when we allow for a trend. However, the results of the MW test ignore the cross-section correlation between provinces, leading to possible

[5] Augmented Dickey-Fuller for each province always rejects the null hypothesis of a unit process. Results are not reported here but available upon request.

erroneous rejection of the null hypothesis.[6] The CIPS test is more reliable since it takes into account a likely correlation among provinces.[7] In table 1, the CIPS test performs better and it rejects the null of non-stationarity for the security incidents series up until lag 4 and for the opium prices series up until lag 1.

Failing to reject the null for higher lags does not cause concern, because province-specific ADF tests are sensitive to the number of lagged difference terms and this sensitiveness may affect the outcome of the panel unit root test. Further, even if non-stationarity is an issue, including cross-sectional averages of the variables in the model is a robust procedure in presence of unit root processes (Pesaran, 2006). Nevertheless, as a precautionary measure, we also run the model with the variable in first difference (see below).

Table 2 displays the Pesaran (2004) CD test for cross-section dependence. Results indicate an important degree of cross-section correlation. The security incidents series shows a correlation of 0.35 and the opium prices series a correlation of 0.7. The test rejects the null of cross-section independence with a high level of significance. This correlation may be caused by common shocks with heterogeneous impact across provinces as well as by local spillover effects between provinces. Ignoring such dependence might lead to biased (and asymptotically inconsistent) estimates with inflated t-statistics. There are two econometric methods that can address these problems: spatial econometrics and common factor models. Both methods investigate spatial association (broadly defined as geographical or non-geographical) in the outcome variable. Spatial econometrics methods heavily rely on a known weight matrix to describe the spatial association across groups. Choosing a reliable weight matrix is not trivial: space can assume a variety of forms, and may not necessarily be based on a simple metric distance.

We specify a weight matrix in contiguity form, which defines the contiguity between provinces where measurements of prices and violence were made. Since data are collected in 15 locations, the weight matrix is a 15x15 with zeroes on the diagonal. To check for the presence of spatial correlation between provinces, we carry out two customary tests: the Moran's I (Moran 1950) tests for global spatial autocorrelation for continuous data, which is based on cross-products of the deviations from the mean, and the Geary's C statistic (Geary 1954), based on the deviations in responses of each observation with one another. Table 3 shows Moran's I and Geary's C statistics and the corresponding two-tail p-values for each variable. Both tests do not reject the null of global spatial independence.[8] Although the conclusions of the above tests are valid only with this contiguity matrix, this matrix represents the most obvious form of spatial correlation.

An alternative to the spatial approach is the factor structure approach, which assumes that the disturbance term contains a finite number of unobserved factors influencing each province at the same time. We use the Common Correlated Effects (CCE) method advanced by Pesaran (2006). The approach consists of approximating the linear combinations of the unobserved factors by cross section averages of the dependent and explanatory variables, and then running our regressions augmented with these cross section averages. A main advantage of this method is that it yields consistent estimates under a variety of situations such as serial correlation in errors, unit roots in the factors and contemporaneous dependence of the observed regressors with the unobserved factors (Pesaran & Tosseti, 2011).

To see the motivations for this procedure, consider a general model of this form

$$y_{it} = \alpha_i + \beta_i x_{it} + \gamma_i f_t + \varepsilon_{it} \qquad (1)$$

[6] As Baltagi, Bresson, and Pirotte (2007) point out, the 1st generation panel unit root tests - which do not account for cross-section dependence - can be subject to considerable size distortions.

[7] The presence of cross-section correlation is confirmed by the Pesaran (2004)'s cross-section dependence test shown in Table 2.

[8] We have also performed the test under the null of local spatial independence (results are not reported but available upon request) and even in this case we do not detect spatial dependence.

where f_t represents the unobserved factors, which may influence each unit differently and which may be correlated with the x_{it}. The average across units gives

$$\bar{y}_t = \bar{\alpha} + \bar{\beta}\bar{x}_t + \bar{\gamma} f_t + \bar{\varepsilon}_t + N^{-1}\sum(\beta_i - \bar{\beta})x_{it} \qquad (2)$$

$$f_t = \bar{\gamma}^{-1}[\bar{y}_t - \bar{\alpha} + \bar{\beta}\bar{x}_t + \bar{\varepsilon}_t + \sum(\beta_i - \bar{\beta})x_{it}] \qquad (3)$$

so the $\bar{y}_t$ and $\bar{x}_t$ provide a proxy for the unobserved factor. The covariance between $\bar{y}_t$ and ε_{it} goes to zero with N, so for large N there is no endogeneity problem. The CCE generalises to many factors and lagged dependent variables. Moreover any seasonality is captured by the means (seasonality is a common factor).

We consider opium prices for province *i* in month *t* (P_{it}) and the number of security incidents (I_{it}), such that

$$P_{it} = a^i_{11}P_{it-1} + a^i_{12}I_{it-1} + \sigma_{11}\bar{P}_t + \sigma_{21}\bar{I}_t + \varepsilon_{it} \qquad (4)$$

$$I_{it} = a^i_{21}P_{it-1} + a^i_{22}I_{it-1} + \sigma_{12}\bar{P}_t + \sigma_{22}\bar{I}_t + \varepsilon_{it} \qquad (5)$$

with $\bar{P}_t$ and $\bar{I}_t$ being the cross section averages of the opium prices and security incidents, respectively. Besides the parameters in the equation, our econometric specification includes a constant term and two lags.

Due to a lack of a large number of months (we only have a maximum of 67 time series observations for some provinces, and less than 30 for a couple of provinces), we do not consider VARs in more variables. As a robustness check, we also use a VAR in first difference.

To summarize our results we use the Mean Group (MG) estimator proposed by Pesaran & Smith (1995). The MG estimator is defined as the simple average of the coefficients a_{11}, a_{12}, σ_{11} and σ_{21}. Given a coefficient a_{11}, we compute the MG coefficients and standard errors, respectively, using the following formulae:

$$a^{MG}_{11} = \bar{a}_{11} = \frac{\sum_{k=i}^{N} a^i_{11}}{N}$$

$$se(a^{MG}_{11}) = \sqrt{\frac{\sum_{k=i}^{N}(a^i_{11} - \bar{a}_{11})}{N-1}} / \sqrt{N}$$

The MG estimator can produce consistent estimates of the average of the parameters.

Our results are reported in Tables 4 and 5. In Table 4 we have a VAR on security incidents and opium prices, with 2 lags and augmented by the CCE; Table 5 reports the same VAR but in first-difference, as a robustness check. Table 6 shows the International Organization for Standardization (ISO) code used in the columns of the subsequent tables to identify the provinces. In the first column of each table we report the results for the MG estimator. We comment mainly on the signs of the coefficients, rather than their size (i.e the magnitude of their influence), since our model is far from being saturated and the signs are the most reliable result to discuss.

Table 4 shows no substantial effect of lagged opium prices on the subsequent number of incidents. The Mean Group estimator confirms no effects: even though we achieve statistical significance - with a non-obvious interpretation, since the two lags run in opposite directions – the coefficients are very close to zero (-0.02 and 0.01 respectively). Notwithstanding the numerous surveys covered in our background section, which explain how the country's drug economy generates several hundred million dollars per year into criminal activities, we do not find any considerable impact of opium prices - and therefore revenue from illegal activities – on the intensity of the insurgency activities across the 15 provinces. This finding runs also counter to the growing economic literature on civil conflict, which demonstrates that insurgencies have the capability of exploiting drug money for funding, such as the FARC in Colombia. In this respect, Afghanistan seems to be an exception.

The strong and significant effect of the cross sectional average of the number of attacks in the equation for security incidents suggests the persistence of unobservable common factors. As one would expect, accounting for common correlated effects decreases the effect of the other variables in the equation. This may explain the lack of statistical significance of our variables in many provinces.

While we find that opium prices have a negligible impact on the level of violence, there is a strong negative effect of security incidents on opium price; the magnitude of the coefficients ranges from -0.8 to -1.52, with the only exception of Nangarhar, where it is positive. This strong insurgency's effect on the opiate business is found in particular in the Southern and Eastern parts of the country, such as in Helmand, Farah, Kandahar, Konar and Nimruz. This is not surprisingly, since in these regions the overlap drug-violence is amplified by the role played by tribal networks in both drug trafficking and insurgent networks. And the overlap extends into Pakistan's tribal areas across the Afghan borders. The Mean Group estimator also points out a negative impact of violence on opium prices. The two lags in the opium prices series negatively predict changes in insurgencies by an amount of -0.54 and -0.37 respectively. The fact that violence induces lower opium prices can be explained by two simultaneous mechanisms, a demand-side and a supply-side dynamic. On the demand side, we should expect Anti Government Elements to fight over the extraction of revenues from the opium trade, which in turn causes a disruption of the opiate business and reduces the level of demand. In fact, both government officials and anti-government elements have been ending up in second-order conflicts over the extraction of revenues from the opium trade in recent years. This might explain a conflict-induced disruption of the opium trading, which in turn results in lower opium prices. On the supply-side, conflict strengthens the level of lawlessness – indeed, opium is more likely to be cultivated where the influence of the central authority is weak – and therefore we should expect to observe higher productions in those areas and lower prices.

Common correlated effects show statistical significance and the Mean Group estimator in the equation for opium prices confirms the presence of common factors driving the dynamics of violence and opium prices. This result was expected since common correlated effects, such as the weather conditions, have an impact on yields and influence the prices; also, the final consumption demand in OECD markets might cause changes in prices.

Finally, Table 5 reports the results for the VAR in first difference: our findings are corroborated with no exceptions. The level of revenue opportunities from opium does not have a significant effect on the number of violent activities, while violence induces lower opium prices. Conflict and illicit economic activities have been always intertwined. However, our findings suggest that instability has an impact on the narco-industry, while the opium market, with all his consequences like money-laundering and collusion with government officials, does not appear to significantly undermine the security environment. Moreover, using a VAR in first difference proves to be an adequate robustness check, which in many instances reinforces the significance of the coefficients in the system.

As final step, we compute the impulse response functions for equations (4) and (5), to visually represent the behavior of the series. We impose the restriction that opium prices do not have a simultaneous effect on the security incidents series (e.g. insurgents need time to adapt their strategy to changes in their illegal revenue stream). Figure 6 plots the "Mean Group" impulse response functions up until $t=10$, by averaging the province-specific orthogonalized impulse response functions. Panels (a) and (c) of figure 6 show how the time paths of opium and violence respond to a one-unit shock in opium prices. As shown in panel (a), a one-unit shock in opium prices has no simultaneous effect on the security incidents series (and this is due to our imposed restrictions) but it causes following security incidents to jump moderately and shortly downward and then to return to the long-run values. The moderate jump is consistent with the close-to-zero coefficients of the two lags of opium prices in the security incidents equation in Tables 4 and 5. Panel (c) shows that a one-unit change in opium prices causes a 10 units jump in the opium series and a very quick return to zero.

The effects of a one-unit shock in the security incidents series are shown in panels (b) and (d) of Figure 6. A one-unit change in the number of security incidents causes an upward jump of 1.5 units in the security incidents series. Again, there is no simultaneous effect of incidents on the opium prices, given our restriction; but we find a strong negative effect of violence on prices, starting from the first month. This is consistent with the results of the VAR in Tables 4 and 5. Since the system is stationary the impulse responses decay.

5) Conclusions

Security incidents in Afghanistan, such as armed attacks and bombings, have been rising since 2003. Given the links between anti-government elements in the country and its drug economy, NATO forces and the UN consider poppy cultivation as of the main obstacles to the long-term security of the region. Opium poppy is a low-risk crop in a high risk environment. Even though Taliban insurgents levy taxes on all forms of trade and agriculture, opiates are the highest-value product on the market. This paper focuses on the state of insecurity in Afghanistan, which is related to the role played by the Taliban-led insurgency and supposedly fuelled by the opium trade.

We argue that both the relationship between violence and opium cultivation and the direction of causality are not at all clear cut. While in many poppy-free provinces the security conditions are worsening, in areas where poppy cultivation is a main activity, security is improving. This is because, in principle, drug production has an income effect, financing attacks, and a substitution effect, providing an alternative occupation to insurgency activities. The direction of causality is also unclear. Opium funds insurgency through taxes on production and trafficking, while violence, and the absence of law-enforcement, encourages illegal activities

Using a unique dataset with monthly time-series data on opium prices and security incidents for 15 Afghan provinces over the period 2004-2009 and a Panel VAR with multifactor error structure analysis, we explore in detail the interaction between income and insurgency activities. Overall, opium prices do not appear to play a role in exacerbating violence, at least not in the expected magnitude and significant, while a conflict-induced reduction in the level of opium trading seems to drive the prices; this dynamic implies that violence may disrupt the opium trade or increase the level of production through a demand and/or supply mechanism. We also find that unobservable common channels prevail in determining how income and conflict dynamics interact.

Since 2004, the strength of the insurgency in Afghanistan has become stronger and the transnational threat posed by the conflict more acute. Afghanistan's drug industry is a central issue for the country's state-building, security, governance, and development agenda. The opium trade has worldwide consequences. Drugs fund insurgents, criminals and terrorists in Afghanistan and abroad. Collusion with corrupt government officials undermines public trust, security, and the law, while money-laundering damages the reputation of banks in the Gulf region. Drug addiction and HIV are spreading death along opiate trafficking routes, particularly in Central Asia and Russia. In Europe, thousands are predicted to die this year from heroin overdoses, a sub-product of opium. It is therefore essential to analyze the relation between the opiate business and insurgency and to indentify a more general pattern among illegal activities, such as drug production and trafficking, and violence.

We believe that there is an important lesson to be learned: there is a simplified reading of the income-violence, and in Afghanistan of the drugs-Taliban nexus. The geographic correlation between drugs and Taliban creates the dangerous temptation to merge the war against the Taliban and the war on opium. Opium production is usually associated with insecurity, conflict and increasingly anti-government violence in Afghanistan, yet opium and violence are not intrinsically linked. Certainly in Afghanistan in the past, and currently in other parts of the country, the drugs trade has not been linked with such high levels of violence. The intensity of the conflict in the South may originate in a conjunction between politically motivated anti-government activity and local opportunistic opium production and trade that deteriorated in a spiral of violence, in which anti-government elements portray themselves as "protectors" of the security of the rural population. But there are other endemic factors, particularly corruption, which should enter into the equation as well. Our findings would recommend a more differentiated implementation of counter-narcotics vis-a-vis counter-insurgency.

We also contribute to the debate on civil war and the nexus income - violence. Most part of the scholarly research on this topic takes a generic approach, and does not recognize possible differences across regions within the same country. We stress the likely presence of heterogeneity across provinces; this knowledge can contribute to the implementation of suitable reconstruction policies. Moreover, understanding how the returns to crime and violence affect the choice between legal and illegal activities can help the government of Afghanistan to provide the right incentives to former combatants to disarm and integrate into civilian life.

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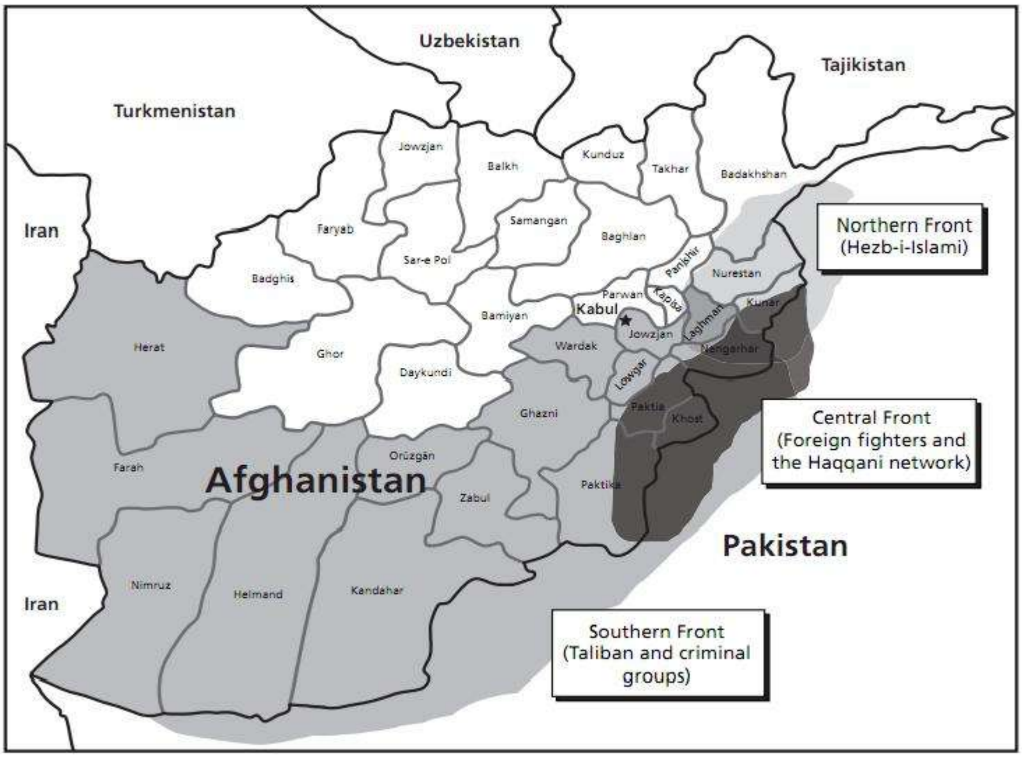


Figure 1. The Afghan Insurgent Front. Source: The Rand Corporation

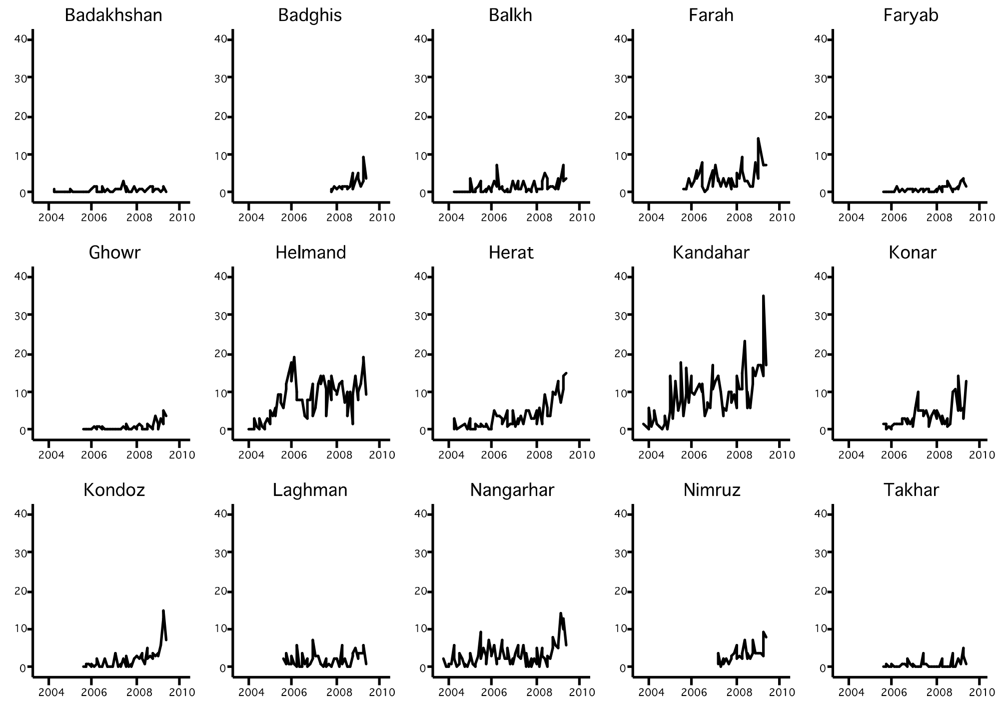


Figure 2. Number of security incidents. Author's calculation based on records from the Worldwide Incidents Tracking System, US National Counterterrorism Center, and from the UNODC Statistics and Survey Section

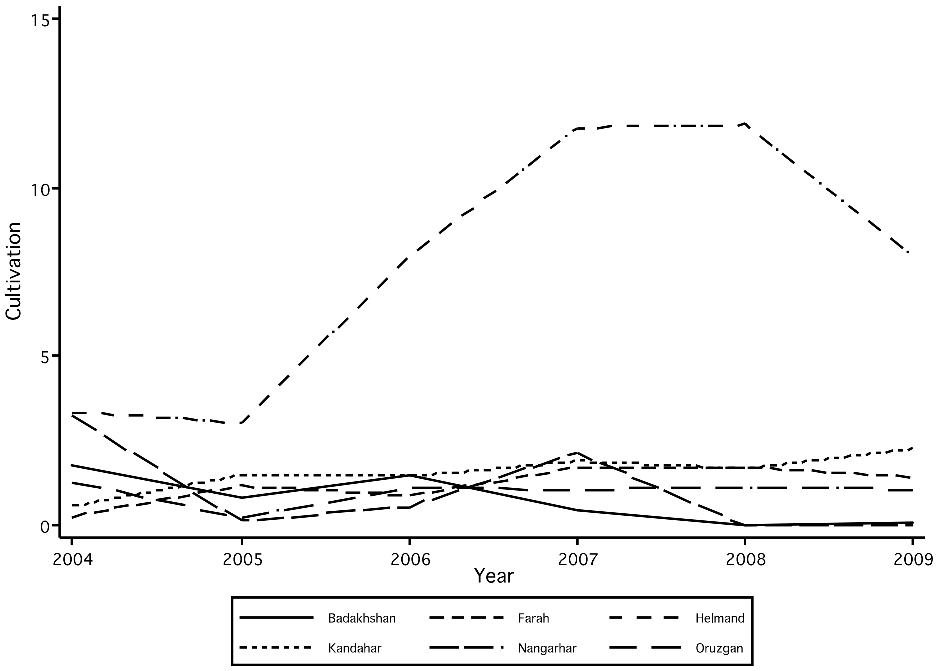


Figure 3. Provincial distribution of opium cultivation (percentage). Author's calculation based on records from the UNODC Statistics and Survey Section

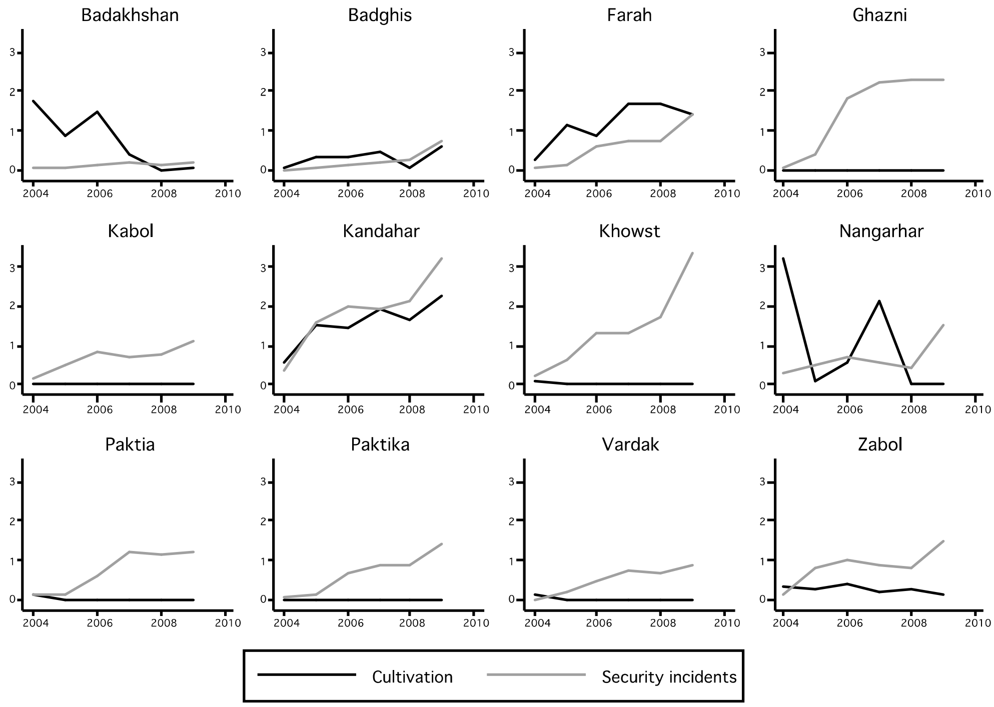


Figure 4. Security incidents and opium cultivation (in percentage of the total). Source: Author's calculation based on records from the Worldwide Incidents Tracking System, US National Counterterrorism Center, and from the UNODC Statistics and Survey Section

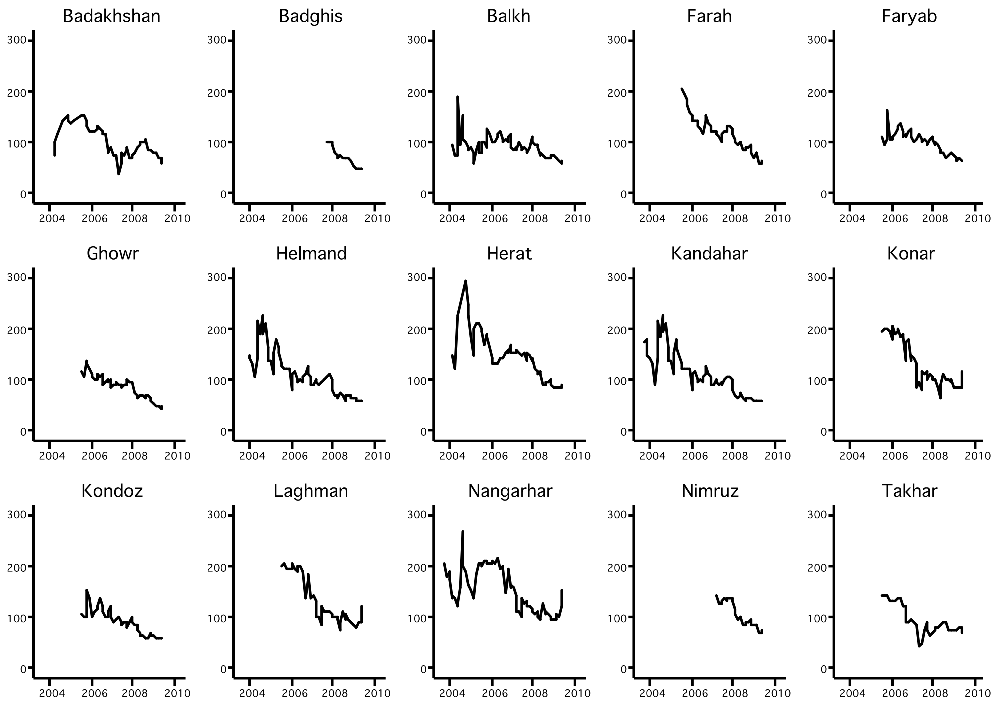


Figure 5. Monthly prices of dry opium at farm-gate level. Source: UNODC Global Illicit Crop Monitoring Program, Statistics and Survey Section

Table 1. 1st and 2nd generation panel unit root test for security incidents and opium prices.

	Maddala and Wu (1999)		Pesaran (2007)	
	SPECIFICATION WITHOUT TREND			
No. of lags	Security incidents	Opium Prices	Security incidents	Opium Prices
0	0.000	0.005	0.000	0.000
1	0.000	0.555	0.000	0.002
2	0.005	0.797	0.000	0.239
3	0.140	0.889	0.000	0.846
4	0.492	0.996	0.000	0.968
5	0.801	0.997	0.009	0.963
6	0.970	0.998	0.492	0.998
	SPECIFICATION WITH TREND			
0	0.000	0.000	0.000	0.002
1	0.000	0.000	0.000	0.029
2	0.000	0.000	0.000	0.592
3	0.012	0.000	0.000	0.968
4	0.326	0.016	0.007	0.995
5	0.702	0.048	0.140	0.883
6	0.979	0.226	0.955	0.991

Null hypothesis for Maddala and Wu (MW) and Pesaran (CIPS) tests: series is I(1). MW test assumes cross-section independence. CIPS test assumes cross-section dependence.

Table 2. CD test for cross-section dependence.

	p-value	ρ
Security incidents	0.000	0.350
Opium prices	0.000	0.696

Null hypothesis: of cross-section independence.

Table 3. Testing for spatial autocorrelation of security incidents and opium price.

	Moran’s I		Geary’s C	
	I	p-values	C	p-value
Security incidents	-0.06	0.086	1.032	0.669
Opium price	0.06	0.074	1.013	0.798

p-values refer to two tails test under the null hypothesis of global spatial independence. Sample comprises 15 provinces for which we have data for both security incidents and opium price. Weights matrix is binary.

Table 4. Security incidents (I_{it}) and opium price (P_{it})

	MEAN GROUP	BDS	BDG	BAL	FRA	FYB	GHO	HEL	HER	KAN	KNR	KDZ	LAG	NAN	NIM	TAK
Security incident equation																
I_{it-1}	**0.02**	-0.14	-0.26*	-0.05	0.08	0.17	0.09	0.27**	0.23*	-0.10	0.09	0.24	-0.28**	-0.07	0.24	-0.12
	(0.05)	(0.14)	(0.15)	(0.12)	(0.15)	(0.15)	(0.13)	(0.12)	(0.13)	(0.09)	(0.16)	(0.15)	(0.13)	(0.11)	(0.17)	(0.15)
I_{it-2}	**-0.05**	-0.00	-0.76***	-0.00	-0.01	0.04	-0.26	0.21*	0.12	-0.07	0.15	-0.16	-0.18	-0.02	0.29	-0.09
	(0.06)	(0.14)	(0.22)	(0.11)	(0.15)	(0.15)	(0.16)	(0.12)	(0.13)	(0.11)	(0.17)	(0.17)	(0.13)	(0.11)	(0.24)	(0.14)
P_{it-1}	**-0.02*** **	-0.02*	-0.07	-0.00	-0.03	-0.01	-0.03	-0.02	-0.01	-0.03	0.01	-0.01	-0.01	-0.00	-0.11*	-0.03**
	(0.00)	(0.01)	(0.07)	(0.01)	(0.04)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.06)	(0.02)
P_{it-2}	**0.01*** **	0.02*	0.01	-0.00	0.01	-0.00	0.02	0.01	-0.00	0.01	-0.00	0.01	0.04***	0.00	0.01	0.03**
	(0.00)	(0.01)	(0.05)	(0.01)	(0.04)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.01)	(0.05)	(0.02)
I_{CCE}	**0.97*** **	0.03	0.93***	0.65***	0.98***	0.15	0.53***	1.28***	0.98***	3.38***	0.46	1.22***	0.96***	1.66***	0.98***	0.42***
	(0.20)	(0.09)	(0.19)	(0.16)	(0.32)	(0.11)	(0.12)	(0.37)	(0.25)	(0.40)	(0.34)	(0.27)	(0.22)	(0.26)	(0.25)	(0.16)
P_{CCE}	**0.01**	-0.01	0.02	0.01	0.01	-0.00	0.00	0.03	-0.01	0.05*	-0.05	-0.02	-0.03	0.03**	0.24***	-0.00
	(0.01)	(0.01)	(0.08)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.03)	(0.05)	(0.02)	(0.03)	(0.01)	(0.08)	(0.01)
cons	**-0.51**	1.53*	2.90	-0.17	0.43	1.86	-0.44	-1.55	2.49	-1.20	5.91	-0.48	-1.01	-4.70**	-12.92**	-0.34
	(1.08)	(0.91)	(4.42)	(1.58)	(2.66)	(1.29)	(1.07)	(3.05)	(2.37)	(3.26)	(4.00)	(2.14)	(2.08)	(1.87)	(6.00)	(1.27)
Opium price equation																
I_{it-1}	**-0.54*** **	0.82	-0.86**	-0.66	-0.80*	-2.29	-1.61	-1.01**	0.35	-0.87**	-1.44*	-0.41	0.61	1.97**	-1.52***	-0.41
	(0.28)	(1.82)	(0.34)	(1.45)	(0.48)	(1.84)	(1.02)	(0.44)	(1.13)	(0.34)	(0.84)	(0.67)	(1.15)	(0.87)	(0.57)	(1.37)
I_{it-2}	**-0.37***	1.85	-0.01	-0.51	-0.78	-0.85	-0.50	-0.79*	-1.70	-0.46	-0.62	-0.29	0.02	-0.44	-0.88	0.33
	(0.20)	(1.87)	(0.49)	(1.37)	(0.49)	(1.79)	(1.25)	(0.44)	(1.11)	(0.40)	(0.87)	(0.76)	(1.19)	(0.91)	(0.78)	(1.29)
P_{it-1}	**0.44*** **	0.85***	0.38**	0.10	0.64***	0.20	0.37**	0.36***	0.29*	0.35***	0.35**	0.48***	0.40**	0.53***	0.47**	0.89***
	(0.05)	(0.14)	(0.16)	(0.11)	(0.15)	(0.13)	(0.15)	(0.09)	(0.17)	(0.09)	(0.14)	(0.11)	(0.16)	(0.10)	(0.19)	(0.15)
P_{it-2}	**-0.06***	-0.00	-0.26**	0.14	-0.14	-0.02	0.01	-0.16*	0.12	-0.17**	0.04	-0.28***	0.06	-0.01	-0.03	-0.17
	(0.03)	(0.14)	(0.11)	(0.11)	(0.12)	(0.12)	(0.12)	(0.09)	(0.14)	(0.08)	(0.13)	(0.10)	(0.14)	(0.09)	(0.16)	(0.15)
I_{CCE}	**0.71***	-0.93	-0.68	0.87	-0.96	-0.50	-1.20	0.72	-2.91	0.68	4.66***	1.04	2.89	4.67**	0.39	1.96
	(0.55)	(1.16)	(0.42)	(1.92)	(1.06)	(1.36)	(0.91)	(1.39)	(2.11)	(1.52)	(1.75)	(1.21)	(2.00)	(2.14)	(0.83)	(1.48)
P_{CCE}	**0.65**	0.07	1.16***	0.35***	0.42***	0.56***	0.45***	0.80***	0.49***	0.84***	1.00***	0.72***	0.98***	0.79***	0.87***	0.29**
	(8.08)	(0.10)	(0.18)	(0.10)	(0.11)	(0.10)	(0.09)	(0.09)	(0.14)	(0.10)	(0.27)	(0.09)	(0.28)	(0.11)	(0.25)	(0.13)
cons	**-3.40**	7.01	-30.72***	26.99	22.01**	27.85*	10.64	3.08	41.86**	-1.44	-36.99*	-7.17	-46.53**	-41.64***	-12.55	-13.50
	(7.01)	(12.04)	(9.91)	(19.03)	(8.79)	(15.81)	(8.26)	(11.30)	(20.30)	(12.33)	(20.61)	(9.58)	(18.96)	(15.15)	(19.82)	(11.67)
N	15	50	19	62	45	45	45	65	56	67	45	45	45	67	26	45

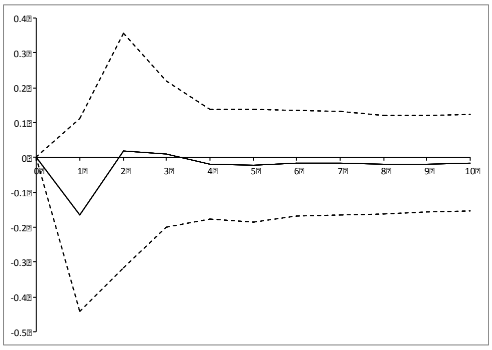
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

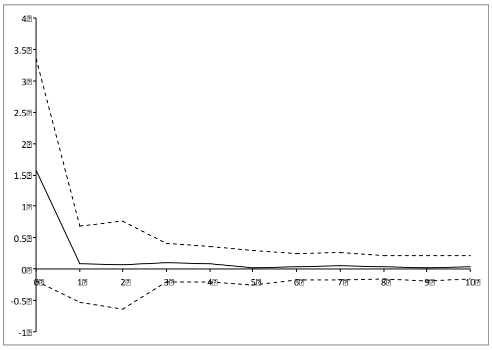
Table 5. Security incidents (I_{it}) and opium price (P_{it}). VAR in first-difference.

	MEAN GROUP	BDS	BDG	BAL	FRA	FYB	GHO	HEL	HER	KAN	KNR	KDZ	LAG	NAN	NIM	TAK
Security incident equation																
I_{it-1}	**-0.66*****	-0.68***	-0.84***	-0.68***	-0.51***	-0.57***	-0.61***	-0.55***	-0.53***	-0.83***	-0.58***	-0.60***	-0.73***	-0.67***	-0.68***	-0.82***
	(0.03)	(0.14)	(0.14)	(0.12)	(0.15)	(0.15)	(0.13)	(0.13)	(0.13)	(0.10)	(0.17)	(0.18)	(0.15)	(0.12)	(0.21)	(0.14)
I_{it-2}	**-0.36*****	-0.27*	-0.91***	-0.39***	-0.12	-0.33**	-0.45***	-0.22*	-0.32**	-0.49***	-0.06	-0.49***	-0.33**	-0.23*	-0.18	-0.62***
	(0.05)	(0.14)	(0.18)	(0.12)	(0.15)	(0.15)	(0.14)	(0.13)	(0.12)	(0.11)	(0.17)	(0.17)	(0.15)	(0.13)	(0.22)	(0.14)
P_{it-1}	**-0.01*****	-0.02	-0.06	-0.00	-0.01	-0.00	-0.02	-0.01	0.01	-0.04	0.01	-0.01	-0.02	-0.01	0.02	-0.05***
	(0.00)	(0.01)	(0.07)	(0.01)	(0.04)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)	(0.06)	(0.02)
P_{it-2}	**0.01**	0.02*	0.13**	-0.01	0.00	-0.00	0.02	0.01	0.00	-0.05*	-0.01	0.03	0.02	-0.01	-0.02	0.01
	(0.01)	(0.01)	(0.06)	(0.01)	(0.04)	(0.01)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.06)	(0.02)
I_{CCE}	**0.48*****	0.05	0.56**	0.41**	0.21	0.06	0.30***	0.61	0.42*	1.72***	0.20	0.71**	0.22	0.54*	1.07***	0.15
	(0.11)	(0.11)	(0.25)	(0.19)	(0.34)	(0.11)	(0.12)	(0.39)	(0.24)	(0.44)	(0.36)	(0.30)	(0.25)	(0.28)	(0.30)	(0.14)
P_{CCE}	**0.02*****	0.00	0.06	0.01	0.01	-0.00	0.01	0.03	0.00	0.06***	0.01	0.01	0.00	0.02	0.12***	-0.00
	(0.008)	(0.01)	(0.06)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.01)
cons	**-3.58*****	-0.39	-6.45	-2.85*	-1.69	-0.04	-1.47	-4.48	-1.16	-11.71***	-1.36	-2.81	-0.97	-3.40	-14.95***	0.03
	(1.12)	(1.08)	(5.76)	(1.61)	(3.27)	(1.13)	(1.13)	(3.42)	(2.19)	(3.98)	(3.51)	(2.61)	(2.47)	(2.55)	(5.14)	(1.33)
Opium price equation																
I_{it-1}	**-0.58*****	-0.38	0.25	-0.49	-0.82*	-1.83	-0.88	-0.67	-0.60	-0.48	-1.15	-0.49	-0.10	0.98	-1.45*	-0.69
	(0.17)	(1.55)	(0.51)	(1.36)	(0.44)	(1.97)	(0.88)	(0.66)	(0.87)	(0.45)	(0.90)	(0.94)	(1.04)	(0.95)	(0.80)	(1.24)
I_{it-2}	**-0.53*****	0.83	0.37	-0.70	-1.17***	-0.86	-0.58	-0.45	-1.61*	-0.15	-1.18	-0.27	-0.27	-0.74	-0.92	-0.26
	(0.16)	(1.57)	(0.64)	(1.41)	(0.44)	(1.98)	(0.95)	(0.65)	(0.87)	(0.49)	(0.93)	(0.91)	(1.05)	(0.97)	(0.84)	(1.26)
P_{it-1}	**-0.14****	-0.15	0.21	-0.71***	0.13	-0.51***	-0.08	-0.16	0.03	-0.16	-0.32**	-0.06	-0.36**	-0.17	0.22	0.04
	(0.06)	(0.15)	(0.23)	(0.12)	(0.13)	(0.14)	(0.13)	(0.12)	(0.13)	(0.12)	(0.15)	(0.13)	(0.15)	(0.12)	(0.23)	(0.15)
P_{it-2}	**-0.21*****	-0.21	-0.10	-0.28**	-0.34***	-0.38***	-0.06	-0.03	0.00	-0.09	-0.22	-0.41***	-0.31**	-0.25**	-0.31	-0.22
	(0.03)	(0.15)	(0.23)	(0.12)	(0.13)	(0.13)	(0.12)	(0.13)	(0.12)	(0.12)	(0.15)	(0.13)	(0.15)	(0.12)	(0.23)	(0.16)
I_{CCE}	**1.37*****	-1.11	-0.48	2.38	-1.28	2.19	0.01	2.45	0.93	2.84	0.63	2.08	1.52	6.74***	1.12	0.54
	(0.51)	(1.20)	(0.90)	(2.14)	(1.00)	(1.50)	(0.78)	(1.95)	(1.67)	(1.95)	(1.96)	(1.57)	(1.83)	(2.18)	(1.18)	(1.26)
P_{CCE}	**0.08****	-0.11	-0.24	0.23**	-0.10	0.24**	-0.01	0.19*	0.03	0.22**	-0.02	0.19**	0.01	0.41***	0.21	-0.02
	(0.04)	(0.08)	(0.21)	(0.11)	(0.07)	(0.10)	(0.05)	(0.10)	(0.09)	(0.11)	(0.13)	(0.09)	(0.12)	(0.12)	(0.18)	(0.08)
cons	**-16.02****	12.85	19.53	-35.72*	11.42	-34.57**	-0.78	-31.39*	-7.99	-36.09**	-3.31	-28.52**	-9.63	-69.88***	-24.97	-1.34
	(6.20)	(11.78)	(20.40)	(18.59)	(9.64)	(14.71)	(7.63)	(17.19)	(15.20)	(17.50)	(19.17)	(13.77)	(17.72)	(19.56)	(19.82)	(11.97)
N	15	47	18	61	44	44	44	64	54	66	44	44	44	66	25	44

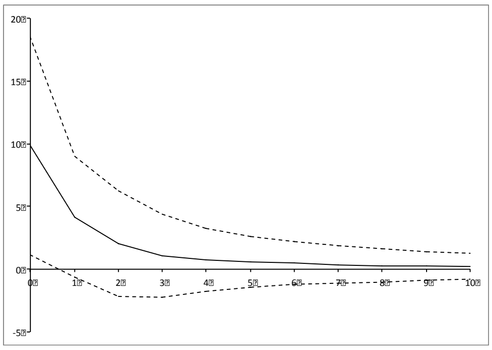
Standard errors in parentheses* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$



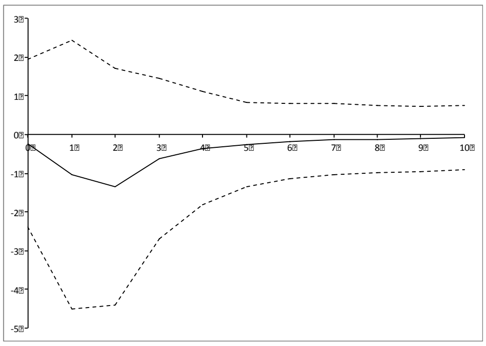
a) Security incidents response to opium prices shock



b) Security incidents response to incidents shock



c) Opium prices response to opium prices shock



d) Opium prices response to security incidents shock

Figure 6. Impulse response functions