The Seasonality of Conflict*

Jenny Guardado† and Steven Pennings‡

This Draft: April 2019

Abstract

This paper exploits the seasonality of agricultural labor markets to estimate the effect of changes in the returns to working on conflict intensity. Using a dynamic model of labor supply, we first show theoretically that exogenous, anticipated, and transitory changes in labor demand due to harvest are better able to capture the effects of changes in the opportunity cost of conflict relative to other shocks commonly analyzed in the literature. This is because harvest shocks hold constant other dynamic drivers of conflict which can bias empirical estimates and obscure the strength of the opportunity cost mechanism. Building on this insight, the empirical identification strategy exploits exogenous sub-national variation in the timing and intensity of harvest driven by local climatic conditions. Using data from several conflict settings – Afghanistan, Iraq, and Pakistan – our results show that the onset of harvest usually leads to a statistically significant reduction in the share of monthly insurgent attacks, generally those more labor intensive.

*We are grateful for comments from Scott Ashworth, Eli Berman, Ethan Bueno de Mesquita, James Fearon, Anthony Fowler, Noel Maurer, Matias Iaryczower, John Londregan, and participants of the 2018 Washington Area Political Economy Seminar; 2018 NYU Alumni Conference; 2017 NEUDC Conference; 2017 Cesifo Venice Summer Institute, the 2017 Princeton Political Economy Seminar; the 2015 Third Formal & Comparative Conference (Becker-Friedman Institute); World Bank MENA Seminar Series; Harris School of Public Policy Political Economy Lunch; the 2015 HiCN (Households in Conflict Network) conference; the Georgetown Political Economy & Development Seminars; and the 2016 Warwick-Princeton Political Economy Workshop. We thank financial support from Ethan Bueno de Mesquita and the Office of Naval Research; and are grateful to Paula Ganga, Jeong Whan Park, Marissa Barragan and Saisha Mediratta for their research assistance.

†Assistant Professor. Georgetown University. jennyguardado@gmail.com. Project developed while visiting the Harris School of Public Policy University of Chicago (2014-2015).

‡Research Economist. World Bank Research Department spennings@worldbank.org.

1 Introduction

Understanding why civil conflict takes place is of utmost policy importance for the developing world given its toll on human lives, human capital, and broader development prospects. The current view among international institutions such as the World Bank, academics, and even public opinion[1] is that economic factors such as poverty and unemployment are among the main drivers of conflict. Indeed, a number of theoretical (Becker 1968; Grossman 1991; Dal Bo and Dal Bo 2011) and empirical studies establish a connection between the returns to working and the intensity of conflict – implying that better wages or job prospects increase the opportunity cost of fighting versus working. Typically, these studies show that negative income shocks driven by rainfall (Miguel et. al. 2004) or commodity prices (Dube and Vargas 2013; Guardado 2016; Hodler and Raschky 2014, among others) are associated with an increase in the likelihood and intensity of civil confllict. Despite this evidence, other studies question both the strength and interpretation of the relationship between economic factors and conflict (Blattman and Bazzi 2014; Berman et. al. 2011b) and whether economic considerations are an important driver of participation in conflict altogether (Berman et. al. 2011a).

In this paper, we make two arguments: first, we show that these conflicting empirical findings on the opportunity cost mechanism are likely driven by the *type* of income shocks commonly analyzed in the literature. We demonstrate that when income shocks are highly persistent it leads to empirical results which systematically underestimate the strength of the opportunity cost mechanism. This is the case of income shocks driven by commodity prices — which tend to be highly persistent. Indeed, simulation data from different theoretical models shows that regressions estimates of the opportunity cost mechanism are systematically upward biased and could range from the negative to the positive depending on the degree of persistence. This range of estimates is consistent with the mixed empirical results in the literature and the ambiguity over the impact of income shocks documented in landmark models of conflict (Fearon 2008). These findings also suggest that the opportunity cost effect captured by commodity prices is likely to be even stronger (or more negative) than shown in current studies (e.g. Dube and Vargas 2013; Blattman and Bazzi 2014; Guardado 2018; Hodler and Raschky 2014, etc.).

[1] See WDR 2011.

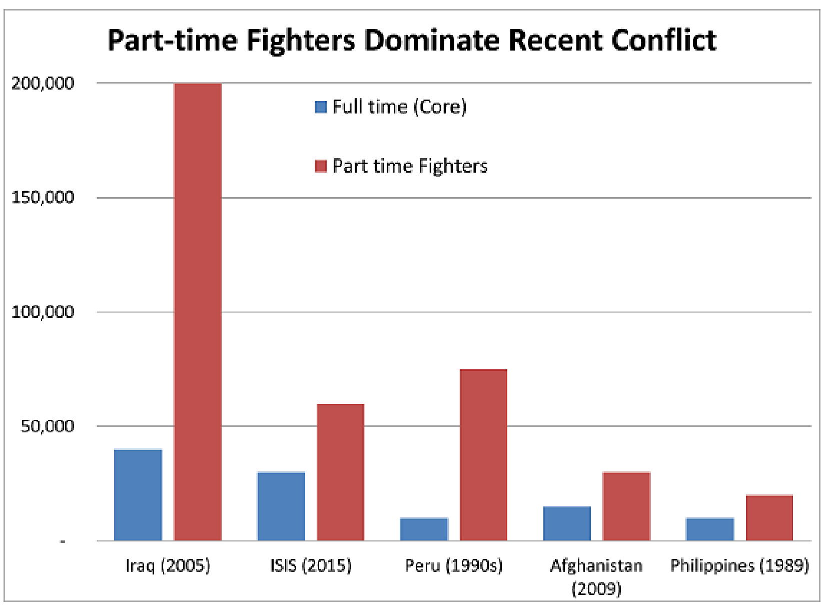
In response to these estimation concerns our second contribution is to propose a different way to empirically gauge the strength of the opportunity cost mechanism: by exploiting seasonal changes in labor demand driven by the timing and intensity of harvest. Due to the temporary and anticipated nature of harvest, we are able to hold constant important non-wage determinants of conflict such as the value of winning (Fearon 2008, Chassang and Padro-i-Miquel 2009) or the marginal utility of consumption, which normally upward biases empirical results. Estimates using simulated data show that the "true" opportunity cost of conflict can be uncovered almost exactly by regressing time allocated to violence on seasonal variation in wages.

Empirically, we focus our attention on the effect of seasonal labor demand shocks in Iraq (2004-2009), Pakistan (1988-2010), and Afghanistan (2004-2010), driven by the wheat harvest calendar (the main legal agricultural crop). Given the labor-intensive nature of agricultural activities, and the fact that many of these crops are harvested annually, they induce a large, transitory and anticipated change in the local demand for labor. Since the timing and intensity of harvest is determined by local climatic conditions (which we measure using pre-conflict data), we can rule out reverse causality running from conflict to opportunity costs. Because monthly time-series for local wages are normally lacking, we focus on the reduced-form relationship between the size of the area harvested and the number of attacks in a location.

Estimates across different conflict settings (Iraq, Pakistan, and Afghanistan) show that at times of greater labor demand due to harvest, the intensity of conflict is lower compared to non-harvest times in districts with a smaller area harvested. Our main findings show that an additional one hundred square kilometers of wheat production at harvest reduces the average number of monthly attacks by around 1% in Pakistan, 5% in Iraq, and 15% in Afghanistan. In addition, using household surveys and monthly weather information, we are able to rule out alternative explanations based on temperature, precipitation, state-driven violence, religious calendars, seasonal migration or job switching. Instead, consistent with our interpretation we show that during harvesting months agricultural workers tend to have differentially higher employment rates relative to other rural workers. Overall, these results indicate that in different conflict settings the opportunity costs of fighting — the foregone returns from working — may play a key role in determining the intensity of conflict.

Additional qualitative evidence suggests that such a trade-off between working and fighting is particularly applicable to "part-time" fighters – individuals who shift between conflict and legal work — depending on changing economic opportunities. In fact, part-time fighters are a common feature of the industrial organization of modern insurgencies.[2] For example, it is well known that some of members of the Vietcong guerrilla worked as farmers during the day but fought US forces at night. Conflict in the Philippines also explicitly relied on part-time fighters when entire battalions from the Moro Islamic Liberation Front (MILF) employed part-time soldiers on a monthly rotational basis to aid full-time combatants (Cline 2000). Similarly, in Afghanistan, Taliban forces have been known to organize in village cells each containing around ten to fifty part-time fighters (Afsar et. al. 2008). This was also the case for Iraq during the US intervention[3], as well as of highly ideological guerrillas such as Shining Path in Peru in the 1980s (McClintock 1998). The reason for such a division of labor is both financial – cheaper to maintain individuals who are ideologically committed but do not participate full-time — as well as tactical — full-time fighters tend to be more skilled and should be protected from unnecessary risks that would undermine the insurgent effort. Figure 1 shows the estimated number of full and part-time fighters for a number of modern insurgencies.

Figure 1



[2] The presence of part-time fighters already poses international law conundrums as to whether these fighters are protected by the Geneva conventions or not (Jensen 2005).

[3] Source: http://www.globalsecurity.org/military/ops/iraq_insurgency.htm

As noted, part-time fighters greatly outnumber those considered “full-time” or completely devoted to the insurgent effort. In fact, security-based NGOs have recognized the vulnerability of these part-time fighters to economic conditions and have launched initiatives to target part-time fighters for “reintegration” (New Strategic Security Initiative 2010, Afghanistan). Even historically, during the American Civil War (1861-1865) desertions from the Confederate Army increased in the months of June and July, the harvesting times for tobacco – an important Southern crop at the time (Giuffre 1997). In addition, during the Russian Civil War (1917-1922) desertion rates in the Red and White armies – largely formed by peasants – were notoriously high during the summer harvest (Figes 1996 cited by Dal bo and Dal bo 2011: 657). This is consistent with the ubiquitous presence of opportunity costs effects across conflict settings.

Contribution. The paper contributes to the literature in several ways. First, the paper shows that labor availability shapes the violent activities of insurgent groups, even those that are highly ideological such as the Taliban. Given these insurgencies heavily rely on part-time fighters — who shift between conflict and legal work — their labor availability is influenced by these changing economic opportunities. The robustness of these results across different settings and datasets is important given the conflicting results in the literature.

Relatedly, the paper contributes to two on-going debates in the literature: first, it provides provides a rationale for why we might observe mixed results on the strength and importance of the opportunity cost mechanism in different contexts: these may actually be driven by the high persistence of the shocks analyzed. Although some papers find mixed evidence in favor of the opportunity cost mechanisms, these might be systematically underestimating its importance, with important policy implications.

At the same time, the paper provides an alternative explanation for *why* development programs in conflict areas have not only failed to reduce conflict but often lead to unintended consequences such as actually increasing conflict. For instance, recent studies highlight how common it is for insurgent groups to appropriate aid which in turn leads to greater armed conflict (Nunn and Qian 2014; Crost et. al. 2014).[4]

Finally, methodologically, the paper provides a novel source of exogenous variation in the demand for labor to study the mechanisms affecting conflict. Because harvest increases the

[4] Other recent examples of aid-theft cited by Nunn and Qian (2014) are Afghanistan, Ethiopia, Sierra Leone, among others.

static opportunity costs of fighting, while keeping the dynamic benefits of fighting constant, it reduces potential omitted variable bias due to consumption patterns or the perceived returns to victory (Fearon 2008; Chassang and Padro-i-Miquel 2009). Studies concerned about the impact persistent shocks may have on these estimates could rely on this source of variation to estimate their results. As such, the paper makes a broader methodological point about how the use of certain income shocks may lead to systematic biases making it difficult to capture the mechanism of interest and lead to seemingly contradictory findings.

In terms of policy, care should be taken in interpreting our results for the opportunity cost mechanism as evidence in favor of employment programs or permanent forms of development aid. While there may be other reasons why these policies should be in place, their persistence across periods may lead to unintended consequences. For example, a permanent wage or employment subsidy may mean that households are wealthy enough to devote time to fight causes they care about. Or, they may encourage people to fight to capture the rents from these schemes as mentioned above. One possibility is to create policies that are both temporary and anticipated that could neutralize their dynamic impact on conflict.

2 Theoretical Framework

A large empirical literature typically uses changes in commodity prices as an instrument for income to assess its effect on conflict. We study an *alternative* driver of the opportunity cost of fighting: the variation in labor demand due to the timing of harvest. In this section we compare our estimates of the opportunity cost of conflict to those in the literature to examine whether any one measure is better at uncovering the "true" effect.

Specifically, we compare estimates of opportunity cost parameters from persistent shocks versus seasonal shocks to labor supply in some simple models of conflict inspired by the main motivations for violence in the literature. For each model, we provide a precise definition of the "true opportunity cost" of violence – mainly, the elasticity of time spent on conflict activities with respect to wages keeping everything else constant – and compare it to estimates from a regression of violence on wages using model-generated data driven by persistent (e.g. commodity prices) versus seasonal variation in wages. In our main model (Section 2.1), rebels engage in violence in order to capture a resource which has some monetary value (a "greed" model). In Section 2.2, we sketch a model where rebels engage in violence for a cause (a "grievance" model), but leave the details of the dynamic model to the appendix. The intuition of the "greed" model is also easily extended to a situation where households provide counterinsurgency information in exchange for payment (Section 2.3).

It turns out that standard regressions with *persistent (non-seasonal) unanticipated shocks* lead to upward biased estimates of the opportunity cost of violence, because other factors determining violence also covary with wages. These other factors are model specific: in our main "greed" model, beneficial economic shocks that increase wages also increase value of spoils of wars, which (by itself) tends to increase the time allocated to violence (Fearon 2008; Chassang and Padro-i-Miquel 2009). In the grievance model, higher wages also make the agent wealthier, which reduces the marginal utility of consumption, increasing the relative value of an extra unit of time allocated to violence.[5] An increase in persistence exacerbates this bias. Because commonly used commodity prices in the literature are highly persistent they will tend to *underestimate* the role of opportunity costs mechanisms in conflict, which helps to rationalize the wide variety of estimates in the literature.[6]

In contrast, seasonal shocks are both temporary and anticipated, which means that other factors determining violence tend to be held constant, even though opportunity costs change. This creates an almost-ideal environment in which even simple regressions without controls can isolate the true effects of changes in the opportunity costs of violence. The reason other factors are held constant is because they are forward-looking variables. For example, the value of an asset captured by rebel armies in a "greed" model depends on the present discounted value of future cash flows generated by the asset (e.g. oil). Anticipated changes in earnings do not affect asset prices. In the grievance model, consumption doesn't respond to anticipated or temporary shocks, keeping the marginal utility of consumption constant. For these results, shocks only need to be temporary or anticipated — but seasonal shocks are both.

[5]In the counterinsurgency information model, higher consumption from persistent shocks lowers the marginal utility of consumption which reduces their willingness to provide tips, potentially increasing insurgent violence.

[6]We thank Scott Ashworth for this observation. The quarterly persistence of oil and coffee prices is around 0.96. Specifically, this is a regression $lpriceR_t = \rho lpriceR_{t-1} + \Xi t$ over 1960Q1-2015Q2 for average oil prices ($\rho = 0.97$), Arabica Coffee ($\rho = 0.95$) and Robusta Coffee ($\rho = 0.97$) taken from World Bank Pink Sheet., with nominal prices deflated by the US CPI (data from FRED). Results do vary over sub-samples, but commodity prices are still highly persistent. For example over 1988-2005, $\rho = 0.9 - 0.94$ for these same shocks. Rainfall shocks are unsurprisingly not very persistent, though often have limited effect on agricultural output due to presence of irrigation.

2.1 Greed Model

One of the most popular motivations for conflict in the literature is a contest for resources (Haavelmo 1954; Hirshleifer 1988, 1989; Garfinkel 1990; Skarpedas 1992; Garfinkel and Skaperdas 2007). In this section, we present the one side of a "contest" model, where rebels are fighting for control of economic profits and the probability that they win is increasing in their effort devoted to fighting. For tractability we keep constant the strength of counterinsurgency forces. In our model, effort is the time that seasonal fighters devote to conflict, which they could otherwise devote to working at wage W. The seasonal fighter balances the extra income they could get working against the greater chance they will win if they spend that time fighting. If economic profits are constant, then an increase in wages makes working relatively more attractive and fighting less attractive. However, as pointed out by Fearon (2008) and Chassang and Padro-i-Miquel (2009), the same shocks (e.g. productivity shocks or commodity price shocks) can increase both the costs (foregone wages) and benefits (profits) of fighting, and so have no net effect on violence. In a dynamic setting, the costs of fighting are incurred today, whereas the benefits of winning are potentially in the future, such that negative *temporary* shocks increase violence more than *persistent* shocks (Chassang and Padro-i-Miquel 2009). As such, seasonal labor demand allows for a clean identification of the true opportunity cost of violence, because seasonal variation in wages are temporary and predictable, meaning that the potential spoils of winning are constant in high versus low labor demand seasons.

Related literature Our model relates to Fearon (2008), Chassang and Padro-i-Miquel (2009) and Dal bo and Dal bo (2011). In Fearon's (2008) baseline model, there are no dynamics, and the rebels choose the optimal size of their forces, given the marginal cost of recruitment and the government's response function. Conflict is unavoidable and a larger force increases the probability of winning, which then allows the winner to tax at a given rate.[7] Chassang and Padro-i-Miquel (2009) present a bargaining model where two players decide to $\{attack, not\, attack\}$ rather than choosing the intensity of conflict, conditional on a fixed labor cost of fighting, and an offensive advantage. If the rebels win, they gain the resources of the other side and in the dynamic version, winning is decisive forever. Dal bo and Dal bo (2011) presents a two-industry, two-factor static trade model with an appropriation sector to show how sector-specific prices affect conflict. Our model includes ingredients

[7] In later models, Fearon (2008) add a detection probability, different abilities of rebels and governments to tax, and changes the contest function to a "capture" function.

from all of these models. Like in Fearon (2008), conflict varies at the intensive rather than extensive margin. Like Chassang and Padro-i-Miquel (2009), the gains from winning are dynamic whereas the costs are static, meaning that temporary but not permanent productivity shocks affect violence (winning is also decisive). Like Dal bo and Dal bo (2011), our appropriation/fighting technology is strictly concave in labor (reflecting congestion effects); our production function is non-linear in labor such that real wages depend on the allocation of labor; and we abstract from the government's response to violence.

2.1.1 Static Model

The household has one unit of time and decides at the start of the period how to split it between working or fighting. If the rebels win the fight, the agent earns the economic profits from production, Π. These profits can be thought of as the returns to a fixed factor like land, capital or a natural resource. If the rebels lose, the part-time fighter gains nothing. Whether the rebels win or lose, the agent still collects labor income from working $(1-V)W$. The probability that the rebel win is increasing but concave in the time allocated to violence V:

$$p = \psi V^{1-\gamma} \tag{1}$$

$0 < \gamma < 1$ governs the effectiveness of the fighting technology, which means that the $p'(v) = \psi(1-\gamma)V^{-\gamma}$ is decreasing in V.[8] A nice feature of this function is that the first hour of time devoted to conflict is infinitely productive (i.e. $lim_{v \to 0} p'(v) = \infty$), which captures the stylized fact that many countries have a low-level insurgency with very little chance of overthrowing the government (Fearon 2008).

The household's problem is:

$$max_V pU(c_{win}) + (1-p)U(c_{loses})$$

such that

$$c_{win} = W(1-V) + \Pi$$

$$c_{lose} = W(1-V)$$

[8]The strength of the counterinsurgency is governed by ψ. Restricting $0 < \gamma < 1$ also keeps the objective function concave.

Output is produced using only labor $(1-V)$, and labor is paid its marginal product W. As labor markets are competitive, the household takes the wages and profits as given. A is total factor productivity, which is the key exogenous variable in the model. If household produced a cash crop for export, and consumed only imported goods, then $A = p_Y/p_C$ could capture the terms of trade used when output, wages and profits (Equations 2-4) are written in terms of the consumption good.

$$Y = A(1-V)^{\alpha} \tag{2}$$

$$W = \alpha A(1-V)^{\alpha-1} \tag{3}$$

$$\Pi = Y - W(1-V) = (1-\alpha)A(1-V)^{\alpha} \tag{4}$$

To separate the mechanism from the one in a the grievance model (below and in the appendix), we make three assumptions (i) $U(C) = C$ (linear utility, risk neutral agents), (ii) No saving or borrowing, (iii) Violence is NOT in the utility function.

Substituting for p and $U(C)$, the HH's problem becomes:

$$max_V W(1-V) + \underbrace{\psi V^{1-\gamma}}_{Prob Win} \Pi$$

The FOC is:

$$V = \left[\psi(1-\gamma)\frac{\Pi}{W}\right]^{\frac{1}{\gamma}} \tag{5}$$

Taking logs, we can get an equation to take to the data (actual or simulated):

$$lnV = \frac{1}{\gamma}ln\psi(1-\gamma) + \frac{1}{\gamma}ln\Pi - \frac{1}{\gamma}lnW \tag{6}$$

Definition. The opportunity cost of violence is the elasticity of violence with respect to wages, keeping everything else constant, $\dfrac{\partial lnV}{\partial lnW} = -\dfrac{1}{\gamma}$.

In order to estimate $-\gamma^{-1}$ from a regression of violence on wages in Equation 6 requires controlling for $ln\Pi$. If instead researchers ran a univariate specification, $ln\Pi$ would be subsumed into the error term. As lnW and $ln\Pi$ tend to be positively correlated (see below), this will bias *upwards* the coefficient on wages.

To see this, suppose that changes in wages are driven by changes in productivity A (or alternatively, the terms of trade). By substituting in lnW and $ln\Pi$, Equation 5 becomes Equation 7. One can see that an increase in productivity (A) increases Π and W proportionately, and so in Equation 7 *A cancels out exactly and violence is constant* (i.e. A does not appear in Equation 7). This mean that if one ran a regression of lnV on lnW, one would get a coefficient of zero, rather than $-\gamma^{-1}$. This is Fearon's (2008) result that economic development increases both the opportunity cost of violence as well as the spoils of war, leaving the level of violence unchanged.

$$V = \left[\psi(1-\gamma)\frac{(1-\alpha)(1-V)^{\alpha}}{\alpha(1-V)^{\alpha-1}}\right]^{\frac{1}{\gamma}} \tag{7}$$

2.1.2 Dynamic Model

Seasonal variation in productivity provides a context where the opportunity cost of violence changes, but the value of the prize of fighting is approximately constant. This effectively removes the omitted variable bias described above, allowing an unbiased estimation of the "true opportunity cost" parameter $-\gamma^{-1}$ *even if we can't observe* Π. The opportunity cost of fighting varies with seasonal changes in productivity because it is incurred contemporaneously. In contrast, in a dynamic setting the bulk of the "prize of winning" are future rents from resources captured, which will be almost constant across "seasons" because changes in productivity are temporary and anticipated. In contrast, persistent shocks like commodity prices raise both the prize and cost of fighting, leading to upwards biased estimates of the opportunity cost of fighting.

More formally, let $V_L(A)$ be the value (discounted lifetime expected utility) of a part time rebel fighter not in power deciding how much time to devote to fighting versus working. The state of the economy is A (total factor productivity) and whether the rebels are in power (L for lose summarizes their past defeats). If the rebels win, they will gain profits today Π and the value of being in power next period V_W. This value depends on next period's productivity A' (next period is denoted with $'$). Like Chassang and Padro-i-Miquel (2009), we make the simplifying assumption that if rebels win they stay in power forever.[9] If the rebels lose, tomorrow the part-time rebel faces the same problem, and so have the same value $V_L(A')$. The probability of winning, as in the static model, is $p = \psi V^{1-\gamma}$. β is the quarterly discount

[9] An alternative version includes an exogenous loss of rebel control with probability $1-\delta$. For low values of $1-\delta$, the model produced similar results (for high values it sometimes did not solve). But this makes the model much more complicated.

rate. The household has linear utility in consumption, cannot save/borrow, and does not intrinsically value violence. $W(1-V)$ is the income received from working (regardless of whether the rebels win or lose).

$$V_L(A) = max_V W(1-V) + \underbrace{\psi V^{1-\gamma}}_{Prob\,Win} \left(\Pi + \beta E\left[V_W(A')\right]\right) + (\underbrace{1-\psi V^{1-\gamma}}_{Prob\,Lose})\beta E\left[V_L(A'')\right]$$

If the rebels win, then there is no gain from fighting anymore, and so seasonal fighters spend all their time working ($V=0$). As before, they earn labor income $W(1-V)=\alpha Y$ and also control profits $\Pi=(1-\alpha)Y$, yielding total income Y. However, we also allow for rebel controlled production to be less productive by a factor $0<\lambda\leq 1$ such that $Y=\lambda A(1-V)^{\alpha}=\lambda A$. As such, the value of a part-time fighter when they are in power is:

$$V_W(A) = \lambda A + \beta E V_W(A')$$

The exogenous process for productivity is given by Equation 8 if there are persistent productivity or commodity price shocks, or Equation 9 when there is seasonal variation in productivity.

For **persistent shocks**:

$$lnA' = \rho lnA + e \tag{8}$$

Or, for **seasonal shocks**:

$$\begin{aligned} lnA_L &= ln\bar{A} \qquad for\, t+1,\, t+3, ... \\ lnA_H &= ln\bar{A} + \chi\, for\, t, t+2, t+4, ... \end{aligned} \tag{9}$$

The first order condition is:

$$W = (1-\gamma)\psi V^{-\gamma}\left[\Pi + \beta\left[EV_W(A') - EV_L(A')\right]\right] \tag{10}$$

On the left hand side is the gain from devoting an extra hour to working: wages. On the right hand side is the gain from an extra unit of violence: the change in the probability of winning $p'(V)=(1-\gamma)\psi V^{1-\gamma}$ times the prize of winning: profits today Π, and the discounted difference in future utility from being in power $V_W(A')$ relative to not being in power $V_L(A')$.

Model solution and simulation Log-linearizing the model around the non-stochastic steady state (where $A' = A = \bar{A}$), the losing value function, FOC, and winning value function become Equations 11, 12 and 13 respectively.[10] Here a lower case variable with a hat ($\hat{x}$) represents the percentage deviation from steady state (which are denoted in capitals X). If one could control for the prize of winning ($\Pi\hat{\Pi} + \beta(\bar{V}_W E\hat{v}'_W - \bar{V}_L E\hat{v}'_L)$), one could run a regression of violence ($\hat{v}$) on wages ($\hat{w}$) which Equation 12 suggests one would estimate the true opportunity cost parameter $-\gamma^{-1}$. But as the value of the prize of winning is typically unobserved and is correlated with wages, we use the model to calculate the degree of omitted variable bias for different types of shocks.

$$\bar{V}_L\hat{v}_L = \hat{w}\bar{W}(1-\bar{V}) - \hat{v}\bar{W}\bar{V} + (1-\gamma)\hat{v}\psi V^{1-\gamma}\left[\bar{\Pi} + \beta\bar{V_W}\right] + \psi V^{1-\gamma}\left[\bar{\Pi}\hat{\pi} + \beta\bar{V_W}E\hat{v}'_W\right] + \beta\bar{V}_L E\hat{v}'_L \quad (11)$$

$$\hat{v} = -\frac{1}{\gamma}\hat{w} + \frac{1}{\gamma}\frac{\Pi\hat{\Pi} + \beta(\bar{V}_W E\hat{v}'_W - \bar{V}_L E\hat{v}'_L)}{\Pi + \beta(\bar{V}_W - \bar{V}_L)} \quad (12)$$

$$\hat{v}_W = \frac{\bar{A}}{\bar{V_W}}\hat{a} + \beta E\hat{v}'_W \quad (13)$$

where the marginal product of labor and the value of profits are:

$$\hat{w} = \hat{a} + (1-\alpha)\frac{V}{1-V}\hat{v} \quad (14)$$

$$\hat{\pi} = \hat{a} - \alpha\frac{V}{1-V}\hat{v} \quad (15)$$

The model is not analytically tractable, so instead we simulate data when productivity is driven by persistent shocks (like commodity price shocks) or anticipated temporary seasonal variation in productivity, and estimate a regression of simulated violence on simulated wages. We calibrate $-\gamma = -\frac{1}{3}$ to match the estimated elasticity of violence with respect to wages found in Colombia (-1.5).[11] Specifically, we use an *indirect inference approach* and choose γ so

[10] This is a first order Taylor series approximation of the model's FOCs and value functions. The "log" part refers to the fact that we perform the Taylor's series approximation with respect to $logX_t$ rather than X_t (i.e. rewrite $X_t = e^{logX_t}$)).

[11] Yearly log wages are instrumented by coffee prices x coffee suitability. Estimated at the municipal level with fixed effects. We drop zero violence municipalities. Data are from Dube and Vargas (2013), though this is our own regression, not the ones that the authors estimate (the authors use wages as a *dependent variable).*

that our estimated coefficient on simulated data with shock persistence $\rho_{coffee} = 0.96$ (similar to the quarterly persistence of coffee prices) matches -1.5, which is what we empirically find with the available data.[12] As before, with a persistent shock of $\rho = 0.96$, the bias due to omitting variation in the value of the prize of winning is substantial: the estimated coefficient of -1.5 is around *half* of the true value of $-3 = -\gamma^{-1}$ (Figure 2 LHS, blue line). The bias is small for very transient shocks, but rises sharply as shocks become persistent. In fact, as shocks become perfectly persistent, the estimated elasticity of violence with respect to wages becomes *positive*. In contrast, a regression of violence on seasonal variation in wages almost exactly uncovers the true opportunity cost parameter (-2.98 (green line) versus a true value of -3 (red line)). Examples of simulated paths of violence, wages and the prize of fighting are shown on the RHS of Figure 2: in the persistent shocks simulation (top panel), the prize of fighting rises slowly in the middle of the simulation and then falls.[13] In the bottom panel, the prize of winning is almost completely unaffected by seasonal movements in productivity, which is what allows us to uncover the true opportunity cost parameter with a simple regression of violence on wages.

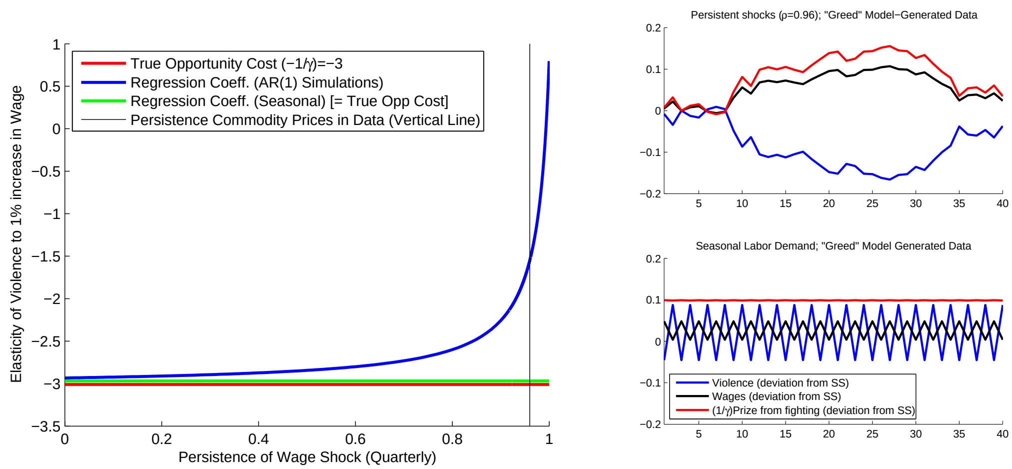


Figure 2: **Greed Model: Panel A:** estimated coefficient (LHS) and **Panel B:** simulated data (RHS)

[12] Other parameters: $\alpha = 0.5$ is calibrated to the all-countries, all-years average of the labor share from PWT8 (full value 0.5459). $\lambda = 3/4$ and $\psi = 0.015$ are chosen to keep the steady state share of violence low (at around 7%), while matching the elasticity of violence to wages in the data with $\rho = 0.96$. $\beta = 0.99$ implies an annual real interest rate of around 4%. Steady state values of $\bar{A} = 1$ and $\bar{V} = 0.07$. As discussed above, $\gamma = 1/3$ implies a true opportunity cost of -3

[13] The prize of the fighting moves slowly because it is forward looking: in steady state profits today are only around 2% over the value of winning $(\bar{\Pi}/(\bar{\Pi} + \beta(\bar{V}_W - \bar{V}_L))$.

2.2 Grievance model

In this model, we assume that rebels engage in violence for some "grievance" in which they place intrinsic value: examples include ethnic or religious hatred, retaliation, or nationalism (Horowitz 1985). That is, rebel violence is in the utility function. To make the mechanism completely clear — and to differentiate it from the "greed model" — we assume that there are no monetary benefits from violence, and to keep the model tractable we do not model the government's response. A key assumption is that households get diminishing marginal utility from allocating additional time to violence ($U_V > 0$; $U_{VV} < 0$), which means that an increase in "opportunity cost" will lead to a reduction in time allocated to violence, other things equal.[14] We sketch a static model here, and reserve the dynamic model — which introduces seasonality and persistent shocks — for the appendix.

Static Model

As before, consider the problem of a household who has an endowment of one unit of time to divide between fighting V and working $(1-V)$ at an exogenous wage W. More formally:

$$max_{V,C} U(C,V) \quad such\ that \quad C = W(1-V) \tag{16}$$

Assuming an interior solution, the household's first order condition is:

$$U_V = U_C W \tag{17}$$

Equation 17 says that the marginal utility from spending an extra hour fighting (LHS), must be equal to the hourly wage weighted multiplied by the contribution of consumption to utility (RHS). An increase in wages by itself means U_V must increase, which implies lower violence as $U_{VV} < 0$ (the "substitution effect" or opportunity cost channel). However, an increase in wages will *also* usually increase consumption and reduce U_C (the marginal value of extra income in terms of utility, $U_{CC} < 0$), such that U_V falls and violence increases (the "income effect"). Which effect dominates depends on the parameters of the model,

[14] We also assume that violence and consumption are separable, that is $U_{CV} = U_{VC} = 0$. This last assumption means that the marginal utility of fighting does not depend on how rich one is. Concavity also allows us to assume $lim_{V \to 0} U_V = \infty$, which corroborates the prevalence of low-level insurgencies described in Fearon (2008) —- even if the cause is not so convincing.

but so long as income effects are positive, violence will move by less than the opportunity cost/substitution effect suggests.

Assuming a standard constant relative risk aversion utility function , $U(C,V) = C^{1-\sigma}/(1-\sigma) + \psi V^{1-\gamma}/(1-\gamma)$ with $\sigma \geq 0$, $0 < \gamma < 1$ substituting and taking logs, we get a similar expression for violence as Equation 6 in the Greed model. As before, the opportunity cost is the elasticity of violence with respect to wages, keeping everything else constant, or $\partial lnV/\partial lnW = -\gamma^{-1}$.

$$lnV = -\frac{1}{\gamma}ln\psi + \frac{\sigma}{\gamma}lnC - \frac{1}{\gamma}lnW \tag{18}$$

Despite the different motivation for violence, the grievance model has a very similar omitted variable problem as the greed model above. The analogue of the unobserved value of the prize (Π) is consumption C (which determines the marginal utility of consumption) in Equation 18 and is usually not observed (or is poorly measured). As such researchers might be forced to estimate some variety of $lnV = \beta_0 + \beta_1 lnW + e_t$, where $e_t = \frac{\sigma}{\gamma}lnC$. However, typically $cov(lnC, lnW) = \sigma_{CW} > 0$ — people on higher wages have higher consumption and a lower marginal utility of consumption — and so the estimated magnitude of the opportunity cost of violence will be upward biased (towards zero).[15] In the special case that utility is linear ($\sigma = 0$), all income effects are removed and a simple uni-variate regression of violence on wages uncovers the true opportunity cost $-1/\gamma$, regardless of movements in consumption.

Seasonal vs persistent shocks and the permanent income hypothesis (PIH)

In the dynamic model in the appendix, consumption is determined by the *permanent income hypothesis* — agents smooth their consumption over time and only consume out of their permanent income.[16] This means that anticipated or temporary shocks to income/wages will be smoothed by savings/borrowing and will have almost no effect on consumption. As seasonal shocks are both anticipated and temporary, $\frac{\sigma}{\gamma}lnC$ in Equation 18 will be kept constant, yielding an unbiased estimate of the opportunity cost mechanism from a regression of violence on seasonal wage shocks — even if lnC is unobserved.

In contrast, highly persistent increases in wages will lead to a large increase in permanent income, which will increase consumption. With log preferences ($\sigma \to 1$), a permanent shock

[15] That is, $E\hat{\beta}_1 - [-1/\gamma] = \frac{\sigma}{\gamma}\frac{\sigma_{WC}}{\sigma_W^2} > 0$

[16] That is log-linearized Euler equation implies $\hat{c}_t \approx E_t\hat{c}_{t+1}$.

will raise consumption in proportion to wages, which will mean permanent labor demand shocks *have no effect on* violence, leading to a estimated opportunity cost of zero if the researcher can not control for consumption.[17]

In the appendix, we generate simulated data in the grievance model with seasonal and persistent commodity shocks, and run a univariate regression of simulated violence on simulated wages. As in the dynamic greed model above, regressions on seasonal shocks are able to uncover the true opportunity cost, but regression on data driven by commodity prices shocks are substantially upward biased because commodity prices are highly persistent.

2.3 Counter-insurgency and the value of information

Berman et al (2011a) argue that information is a key component of any counterinsurgency strategy: if government forces do not receive information on where the rebels are hiding (for example), then counterinsurgency efforts will be ineffective. In other words, military effort and information are *complements*. In order to gain information, government forces often pay locals for tips. Berman et al (2011b) argue that this provides a reason why they find a *negative* relation between unemployment and violence: when unemployment is high, it is cheaper for government forces to buy information from the local population, which then reduces insurgent violence. The fact that the local population does not provide information freely suggests that there is some sort of utility cost to providing it (e.g. they don't like "snitching", or it is dangerous). Hence, the willingness of the household to provide information depends on its marginal utility of consumption, which could fall with positive persistent shocks, but is kept constant by seasonal shocks. We briefly sketch the argument below, as it is almost identical to the mechanism in the grievance model above.

Consider a modification of the static set up in Equation 16 above to incorporate information provided to counter-insurgency forces I. The household doesn't like to provide information, so $U_I < 0$, and dislikes each additional unit of "snitching" even more, such that

[17] The larger is σ, the stronger are income effects and the larger the bias for permanent wage shocks. For permanent shocks, one can take a log-linear approximation of of FOC and budget constraint to yield: $\hat{v} = \dfrac{(\sigma - 1)}{\gamma + \sigma \bar{V}/(1 - \bar{V})} \hat{w}$. If $0 < \sigma < 1$, the substitution effect dominates the income effect: the coefficient on wages is still negative, but is biased upwards. However if $\sigma > 1$ — such as $\sigma = 2$ for numerical simulations in the appendix — a permanent increase in wages reduces the marginal utility of consumption sufficiently that an increase in wages actually *increases* violence. However, commodity price shocks are highly persistent but not permanent, and as such simulations suggest that an increase in wages due to a persistent commodity price shock still reduces violence, though by half as much as the true opportunity cost mechanism would suggest.

$U_{II} < 0$ (we continue to assume that utility is separable in information, consumption and time allocated to violence). The household gets a payment s for each "snitch", which we assume is constant. The household's problem is then:

$$max_{V,I} U(C, V, I) \quad such\ that \quad C = W(1 - V) + sI \tag{19}$$

The FOC wrt to time allocated to violence is unchanged from Equation 17 above, whereas the FOC wrt I implies:

$$-U_I = U_C s \tag{20}$$

One can see that if there is an increase in consumption from a persistent shock (such as a persistent commodity price shock), then U_C will fall (because $U_{CC} < 0$). As s is constant $-U_I$ also must fall. Note that $-U_I > 0$ and $-U_{II} > 0$, so the only way for $-U_I$ to fall is for the household to provide less information: richer households have less need to become an informant as in Berman et al (2011b), which could actually *increase* aggregate violence. But because seasonal shocks are temporary and anticipated they will not lead to a change in consumption, and so U_C will be constant, and information provision will be unaffected. As before, this allows seasonal variation in wages to produce an cleaner estimate of the opportunity cost of mechanism.

3 Data and Empirical Methodology

The results described above lead to the following empirical implication: the onset of harvest has a negative impact on conflict intensity by increasing the returns to working (e.g. wages) relative to fighting. To bring this implication to the data one would ideally instrument the variation in monthly wages driven by harvest and examine its effect on conflict. In practice, conflict-ridden areas (and even non-conflict ones) often lack comprehensive monthly time-series for local wages. Hence we focus on estimating the reduced-form effect of violence on harvest onset. The idea is that a negative coefficient would be consistent with the idea that increases in local labor demand reduces the attractiveness of fighting. We also provide additional evidence showing that harvest brings about changes in local labor markets to support the idea that the effect is driven through this mechanism.

3.1 Data

The data for our conflict episodes relies on a number of different sources. For every conflict episode we use geocoded data on violent incidents to match the spatial variation of harvesting calendars across the country. Because we exploit monthly-by-district changes in labor markets and include a number fixed effects indicators, the only factors that could confound the effect observed are those which vary at the district-by-month level (for example, precipitation or temperature).

Violence. Our main dependent variable is the log the total number of monthly (m) attacks per district (i). For robustness, we look at different conflict settings and datasets on violence, as a way to avoid assigning disproportionate weight to a single data collection procedure given the well-known difficulties in recording violence. We use both very precisely geolocated datasets (e.g. latitude, longitude) as well as those in which the level of aggregation is that of small administrative units (e.g. districts or municipalities). However, we generally rely on the district level results as a way to reduce measurement error. For *Iraq* we use the SIGACTs dataset based on reports by Coalition forces used in Berman, Shapiro and Felter (2011) as well as the one disclosed by Wikileaks which provides the raw reports, not pre-processed. For Iraq we also use the Iraq Body Count dataset (IBC) which tracks civilian deaths due to conflict. We complement this data with information from the newspaper-based World Incident Tracking System (WITS) of terrorism events. In the case of *Pakistan*, we use the BFRS dataset on political violence which is available at the district-level and collected from reports by local newspapers (as opposed to only those in English) as well as the GTD data which is precisely geolocated but solely focuses on instance of terrorism. In the case of *Afghanistan*, we rely on conflict data provided by WITS between 2004 and 2010 aggregated at the level of the district as reports of significant activity (SIGACTs) by ISAF troops for the same period.

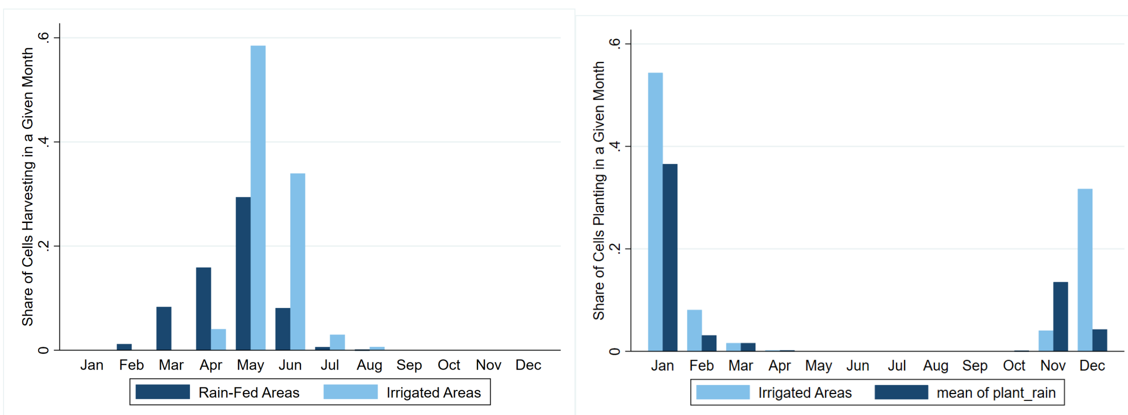
Harvesting Calendars. For the case of Afghanistan, Pakistan and Iraq, the timing of harvest is provided by the FAO Global Agro Ecological Zones v3.0[18] (GAEZ v.3.0) which provides high resolution maps for the start and length of the growing cycle for a number of crops. Our harvesting indicator takes the value of 1 in the month the growing cycle ends. For each crop we also capture whether it utilizes high, medium or low inputs which indicates whether the crop is rain-fed or irrigated, the latter will help us improve the precision of the estimates as the importance of labor during harvest depends on whether cultivation is

[18] Available at: http://www.gaez.iiasa.ac.at/

rain-fed or irrigated. Because our indicator captures the onset of harvesting for any type, districts could have more than one harvesting month if it cultivates more than one type of crop and these differ in their harvesting date.

In the case of planting, we follow the same approach and create an indicator for the month of the start of the growing season under the logic that this is the time in which land is prepared and sowed before seeds can grow. As an example, Figure 3 below shows the harvesting calendars for Iraq. Since the harvesting month varies across districts within the year, it provides within country variation for the month in which wheat is cultivated thus allowing for identification of its effect. For Iraq, most wheat is harvested in May-June, yet, some areas also harvest as early as March and as late as August, depending on whether it is rain-fed or irrigated.

Figure 3: Harvesting and Planting Calendar Iraq



Crop Intensity. Crop intensity is measured in hundreds of square kilometers and is calculated by the FAO as the historical average of the period 1960-1990, which clearly precedes our period under study. We interact the harvesting and planting indicator with the historical intensity of crop production to avoid giving greater weight to areas with little to no crop production.

To illustrate, Figures 4 through 6 show the raw images provided by GAEZ v.3.0 and those once linked to a 0.1 by 0.1 decimal degrees grid for the Iraqi case (approximately 11kms by 11kms cells). Figure 4 shows the intensity of wheat production; Figure 5 shows the start day cycle for medium input crops and Figure 6 shows the length of the cycle. The weighted harvesting calendar is thus determined by when wheat is planted combined by how long it needs to grow interacted with how much wheat is cultivated. This fine-grained information is then aggregated at the district-level to calculate the intensity with which a given district is “in harvest”.

Figure 4: Left: Wheat Production. Right: Production Grid

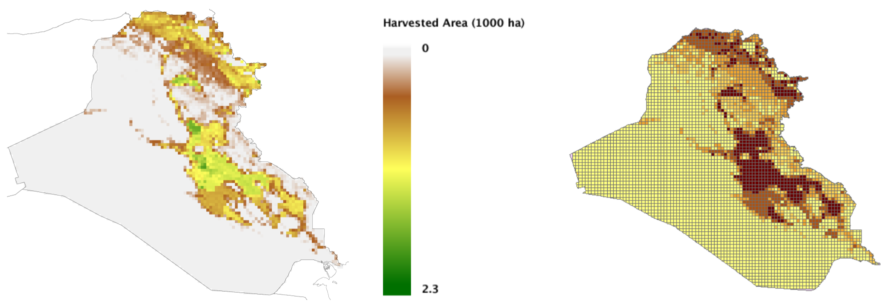


Figure 5: Left: Start Day Medium Inputs Wheat Irrigated. Right: Start Day Cycle

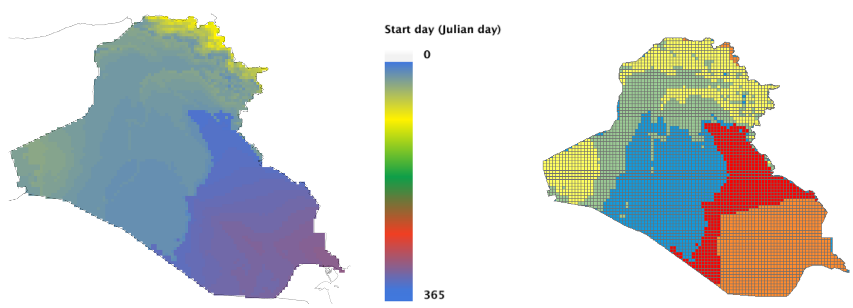
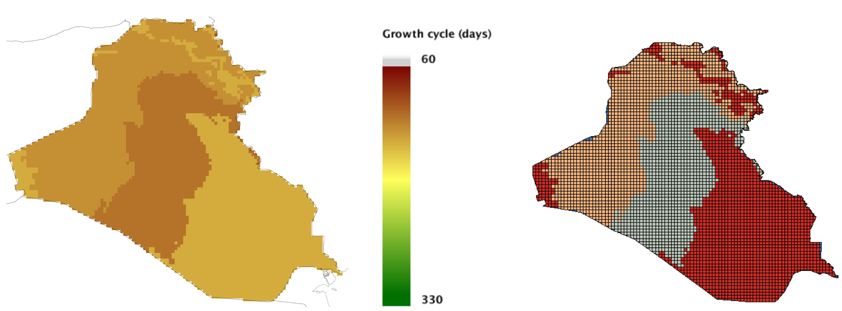


Figure 6: Left: Length of Cycle Medium Inputs Wheat Irrigated. Right: Length of Cycle Grid



Additional controls. Additional control variables at the cell or district level always include those of precipitation and temperature. Although the timing of harvesting is unlikely to be influenced by crop production, it is possible that monthly factors determining harvest may also affect the intensity of violence thus confounding our results. Therefore, we collected data on monthly-district measures of precipitation (in millimeters) and temperature (degrees Celsius) for Iraq, Afghanistan, and Pakistan provided by Willmott and Matsuura (2001).

To examine the effect of harvesting on local labor markets we also examine household surveys which ask for monthly patterns of employment and time use, which are designed to be representative of the rural sector. While the survey asks for monthly employment patterns, unfortunately it does not do the same for wages. In the case of Iraq, we use the Living Standards and Measurement Study collected by the World Bank in 2006-2007.[19]

3.2 Estimation

Our outcome of interest $Log(Attacks_{imt})$, is the log of the total number of attacks in a district i, calendar month m and year t relative to the total in that district and year. Our key independent variables are the timing of harvest for rain-fed and irrigated areas, namely, $RHarv_{im} \times RProd_i$ and $IHarv_{im} \times IProd_i$, where $RProd_i$ and $IProd_i$ are the number of hundred square kilometer of wheat in harvest in district i , month m and year t, depending on whether rain-fed (R) or irrigated (I), respectively. In all specifications we also include the effect of the planting season on conflict. Hence we estimate:

$$Log(Attacks_{imt}) = \alpha_{it} + \gamma_m + \beta_1(RHarv_{im} \times RProd_i) + \beta_2(IHarv_{im} \times IProd_i) + \mathbf{x}_{imt} + e_{imt} \tag{21}$$

Where α_{it} is a district by year fixed effect to account for district and year specific factors affecting conflict, and γ_m is a month fixed effect (e.g June); $\mathbf{x}_{imt}$ is a vector of monthly district characteristics such as monthly temperature in degrees Celsius and precipitation in millimeters. The parameters of interest are β_1 and β_2 which captures the effect of harvesting on conflict intensity. Standard errors are clustered at the district level, which accounts for serial correlation in the error terms for that spatial unit.

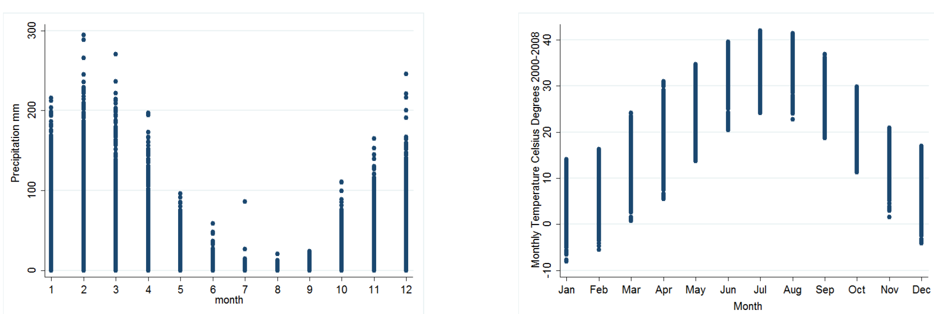
[19] Available at: http://econ.worldbank.org/

3.3 Threats to Identification

Our identification strategy exploits the fact that seasonality or the *timing* of harvest is clearly exogenous to the intensity of armed conflict. That is, we exploit the roll-out of harvest and compare how violence changes in districts in harvest relative to months without it. Since the timing of harvest is given by a combination of geographic and climate factors, it is unlikely to be manipulated by conflict dynamics. Certainly conflict may affect crop production itself, yet, this would only run against finding any relationship between the harvesting month and the intensity of armed conflict within a district.[20]

While reverse causality is not necessarily a concern, a more important challenge comes from omitted variable bias or time-varying determinants of harvest (e.g. precipitation, or temperature) which may correlate with conflict. For example, in the Iraqi case Figure 7 below shows how the onset of harvesting (roughly from May to July) is indeed accompanied by an increase in temperature and a decrease in precipitation. If temperature were to have a positive effect on conflict, as a number of studies suggest (Burke et. al.2009; Hsiang et. al. 2013), this would only exert an upward bias in our results. That is, the true coefficients would be actually larger (e.g. more negative) than our estimated coefficients. Similar concerns arise with the amount of precipitation, since intense rainfall may constitute a physical impediment to conducting attacks. However, as shown in the LHS of Figure 7, precipitation is actually lower at times in which most of the harvesting is occurring such that, if anything, coefficients run against the hypothesized effect.

Figure 7: Monthly Precipitation (left) and Temperature (right)Patterns in Iraq



[20] For instance, conflict may shift grain collection for some weeks, yet, it is unlikely to do so for a whole month (which is our the size of our indicator "window") as it would be pointless from the producer standpoint: either crops will not be ripe or they would rot as time passes.

4 Empirical Results

In this section we show how seasonal labor markets play a key role in determining within-year variation in the intensity of violence across different conflict settings. Given the differences in data sources and coding methods we present each case separately while holding constant the main specification, unless otherwise specified.

4.1 The Iraqi Conflict

Between 2004-2011 Iraq was gripped by a civil conflict along sectarian lines as well as against Coalition Forces present in the country (until 2009). The intensity of the conflict, coupled with the strong reliance on agriculture as an economic activity and the cultivation of wheat as the main subsistence crop, makes it an ideal setting to explore the importance of seasonal labor markets for violence intensity.

SIGACTS (2004-2009) and Iraq Body Count (2000-2014). Our analysis starts by examining the patterns of insurgent activity using incidents of "significant activity" recorded by Coalition Forces in Iraq from 2004-2009. The collection and coding of this data is described in Berman, Shapiro and Felter (2011) and covers a period of intense US involvement in the country. The key variables we analyze are the (1) raw measure of significant criminal activity; (2) a second version in which criminal (as opposed to insurgent) activities are excluded; (3) instances of direct fire against Coalition Forces, considered more labor intensive; and (4) the presence of Improved Explosive Devices (IED) which are in theory less labor intensive. Two limitations of this dataset is that it only captures attacks involving or in the presence of Coalition forces; and, second, that its quality could vary across reporting units (Berman, Shapiro, and Felter 2011: 790). Moreover, because this dataset this might systematically undercount instances of violence, we complement this dataset with district-level measures of violence leading to civilian casualties as collected by the Iraqi Body Count dataset (IBC). This dataset is maintained by a non-profit organization which quantifies the number of civilian casualties based on multiple sources (from the media and administrative sources) and distinguishes between the types of attack such as airstrikes, artillery fire, bomb devices, gunfire, among others.

We use these different categorizations of violent attacks to examine whether harvest leads insurgent groups to favor certain tactics at the expense of others when labor availability is low (Bueno de Mesquita 2013). Specifically, we distinguish between *labor intensive* attacks, or those that require greater manpower to be carried out (e.g. armed attack or assault), and *asymmetric* attacks, those in which participants are not able to exchange fire and have generally lower manpower requirements (e.g. IEDs) (Bueno de Mesquita et. al. 2015). We also report results where we pool across all attack types.

Table 1 below shows that there is evidence of seasonality in the intensity of attacks around the harvest period. In the case of SIGACTS (columns 1-4), an increase of a hundred square kilometers of wheat production at harvest in rain-fed areas leads to a reduction in the number of "significant activity" episodes in around 5% in general as well as those involving IED's. For the case of irrigated areas, we find a negative sign, but not statistically significant. Consistent with the above, the Iraq Body Count dataset (columns 5-8), we find that the intensity of attacks leading to civilian casualties are much less frequent during harvest in rain-fed areas. This is particularly the case for labor intensive (direct fire and selective targets) as opposed to asymmetric ones (indirect fire and bombing). Specifically, column 5 shows that an increase of a hundred square kilometers of wheat cultivation in the district at harvest leads to a reduction of 1.3% less violent events. While this effect is smaller than that of SIGACTS, this is partly driven by the nature of the dataset which relies on media and administrative reports, as opposed to those of coalition forces, which reports less incidents on average likely due to the fact that the IBC covers a wider time period.

Table 1: Seasonal Labor and Violent Incidents in Iraq

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SIGACTS				Iraq Body Count			
	District-Level Analysis							
DV: Log of...	Total Attacks Raw	Total Attacks	Laborint	IED	Total	Laborint	IED	Victims
$RHarv_{im} \times RProd_i$	-0.048**	-0.057**	-0.028	-0.056**	-0.013**	-0.012*	-0.003	-0.014**
	(0.023)	(0.025)	(0.019)	(0.024)	(0.006)	(0.006)	(0.004)	(0.006)
$IHarv_{im} \times IProd_i$	-0.012	-0.009	-0.011	0.005	-0.011	-0.008	-0.001	-0.011
	(0.016)	(0.015)	(0.017)	(0.020)	(0.008)	(0.008)	(0.004)	(0.008)
Observations	6,344	6,344	6,344	6,344	18,720	18,720	18,720	18,720
Clusters	104	104	104	104	104	104	104	104
Mean DV	1.589	1.660	0.947	1.299	0.209	0.142	0.0690	0.208
Avg Effect %	-4.771	-5.737	-2.805	-5.562	-1.346	-1.178	-0.266	-1.445
DistXYear FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Temp & Precip	Y	Y	Y	Y	Y	Y	Y	Y

Clustered robust standard errors at the district level in parentheses. $Prod_i$ is measured in hundred sq kilometers. DV is in logs. All specifications include a control for planting X area harvested for rain-fed and irrigated areas. *** p<0.01, ** p<0.05, * p<0.1

Cross-validation: SIGACTS (wikileaks 2000-2014) and WITS Dataset (2000-2014). As a cross-check to our results we run the same specification but now using as dependent variable significant insurgent activity (SIGACTS) for a longer time-frame, as provided by wikileaks. The purpose of this exercise is to check whether the results are largely similar to those when using the Berman, Shapiro and Felter (2011) version for a sub-sample of the data in Table 1 and without pre-processing the data. Similarly, columns (5) to (8) of Table 2 below show the results using the Worldwide Incidents Tracking System (WITS) which is based on media accounts of terrorist events.[21] This dataset focuses on incidents that are both "international and significant" in nature and is used as a reference point for the State Department (Wigle 2010).[22] In addition to tracking the number of terrorist events, the dataset also provides broad categorizations of the *type* of terrorist attacks – whether it was an armed attack, an attack using improvised explosive device (IED), a suicide bomb, among others.

Table 2: Seasonal Labor and Violent Incidents in Iraq: Cross-Validation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SIGACTS-Wiki				WITS			
	District-Level Analysis							
DV: Log of...	Total Events	Direct Fire	Enemy Act	Explosive	Total	Asymm	Laborint	Victims
$RHarv_{im} \times RProd_i$	-0.020**	-0.012*	-0.019**	-0.008	-0.003	-0.004	0.003	-0.002
	(0.008)	(0.006)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
$IHarv_{im} \times IProd_i$	-0.026***	-0.008**	-0.020***	-0.008	-0.006	-0.002	-0.001	-0.009*
	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.007)	(0.004)	(0.005)
Observations	18,720	18,720	18,720	18,720	18,720	18,720	18,720	18,720
Clusters	104	104	104	104	104	104	104	104
Mean DV	0.359	0.127	0.324	0.173	0.223	0.151	0.141	0.253
Avg Effect %	-1.956	-1.152	-1.913	-0.849	-0.271	-0.417	0.286	-0.220
DistXYear FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Temp & Precip	Y	Y	Y	Y	Y	Y	Y	Y

Clustered robust standard errors at the district level in parentheses. $Prod_i$ is measured in hundred sq kilometers. DV is in logs. All specifications include a control for planting X area harvested for rain-fed and irrigated areas. *** p<0.01, ** p<0.05, * p<0.1

[21] Available at: http://www.nctc.gov/site/other/wits.html

[22] "International meant any acts that involved the citizens or territory of more than one country. (...) What constituted a significant act was even fuzzier and was legally left to the opinion of the Secretary of State,[5] although there were some prescribed rules promulgated by the State Department. For example, a significant attack meant an act of terrorism that either killed or seriously injured a person, or caused USD $10,000 in property damage." (Wigle 2010)

Table 2 shows the estimates from Equation 21 using as dependent variable the log of the total number of violent incidents in the district. Columns (1) through (4) show how the onset of harvest in *both* rain-fed and irrigated areas leads to a reduction in total levels of violence, as well as a reduction in labor-intensive attacks as exemplified by the "direct fire" and "enemy actions" variable. In contrast, the results for asymmetric or explosive attacks see no significant difference during harvest. In terms of magnitude, the coefficient of in column (1) suggests that an increase of one hundred square kilometers of wheat production at harvest leads to a reduction in the share of monthly attacks of approximately 2% and 2.5% percentage points for rain-fed and irrigated areas, respectively. Similar effects are shown in column (3), where the coefficient on enemy actions represents a reduction of around 2% for each additional hundred square kilometer at harvest. These results are similar to those of the IBC dataset which covers the same time period 2000-2014. In contrast, the results using the WITS dataset are consistently negative for harvesting periods, but small in magnitude and not statistically distinguishable from zero.

Robustness. Additional results in the online appendix[23] show that these findings are similar when restricting the sample to only wheat producing areas for the SIGACTS and IBC dataset (Table 2) and the SIGACTS-Wiki and WITS one. (Table 3) It is worth noting that the onset of planting is either associated with a reduction in attacks or with a very small coefficient, but estimates are often less precisely estimated. This lower effect is likely driven by the lower demand for labor posed by planting as opposed to harvesting. To further explore the results, Tables 3 and 4 show the results in a full dynamic specification, showing that in most cases the negative effect is driven by the contemporaneous change in harvesting status, particularly for the IBC evidence. Thus providing little evidence of anticipation effects by armed groups. If anything, the negative effect of harvest lingers in the following month after it takes place (particularly for the SIGACTS dataset which covers a shorter time frame), which could be due to how we are measuring harvest which could extend into the following month as well. More importantly, this lingering negative effect rules out that possibility that harvest in some way finances conflict or creates it – as we would expect the following month $(m + 1)$ to exhibit higher rates of conflict (and not lower). However, in the following section we discuss other potential drivers of conflict.

[23] Available at https://sites.google.com/site/jennyguardado/

Table 3: Seasonal Labor and Violent Incidents in Iraq: Dynamic Specification SIGACTS, IBC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		SIGACTS				Iraq Body Count		
			District-Level Analysis					
DV: Log of...	Total Attacks	Total Attacks Raw	Laborint	IED	Total	Laborint	IED	Victims
$RHarv_{im} \times RProd_i$	-0.036	-0.044*	-0.011	-0.055**	-0.014**	-0.013**	-0.006	-0.014**
	(0.024)	(0.026)	(0.018)	(0.027)	(0.006)	(0.006)	(0.004)	(0.006)
$RHarv_{im-1} \times RProd_i$	-0.021	-0.030	-0.026	-0.028	0.003	-0.003	0.003	0.006
	(0.023)	(0.022)	(0.017)	(0.017)	(0.005)	(0.005)	(0.004)	(0.006)
$RHarv_{im+1} \times RProd_i$	-0.089***	-0.090***	-0.063**	-0.047	-0.011	-0.011*	-0.005	-0.011
	(0.033)	(0.032)	(0.024)	(0.029)	(0.007)	(0.006)	(0.005)	(0.008)
$IHarv_{im} \times IProd_i$	-0.015	-0.013	-0.009	0.007	-0.015*	-0.012	-0.004	-0.015
	(0.019)	(0.016)	(0.019)	(0.024)	(0.008)	(0.008)	(0.005)	(0.009)
$IHarv_{im-1} \times IProd_i$	0.047	0.046*	0.056**	0.019	-0.006	-0.010	-0.010***	-0.003
	(0.029)	(0.026)	(0.022)	(0.027)	(0.005)	(0.006)	(0.004)	(0.006)
$IHarv_{im+1} \times IProd_i$	0.035*	0.028	0.031	0.043**	-0.010	-0.014*	-0.007	-0.012
	(0.019)	(0.019)	(0.022)	(0.017)	(0.008)	(0.008)	(0.005)	(0.010)
Observations	6,136	6,136	6,136	6,136	18,512	18,512	18,512	18,512
Clusters	104	104	104	104	104	104	104	104
Mean DV	1.614	1.687	0.967	1.320	0.211	0.144	0.0698	0.210
Avg Effect %	-3.591	-4.397	-1.140	-5.488	-1.379	-1.298	-0.555	-1.367
DistXYear FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Temp & Precip	Y	Y	Y	Y	Y	Y	Y	Y

Clustered robust standard errors at the district level in parentheses. $Prod_i$ is measured in hundred sq kilometers. DV is in logs. All specifications include a control for planting X area harvested for rain-fed and irrigated areas. *** p<0.01, ** p<0.05, * p<0.1

Table 4: Seasonal Labor and Violent Incidents in Iraq: Dynamic Specification WIKILEAKS, WITS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SIGACTS-Wiki				WITS			
	District-Level Analysis							
DV: Log of...	Total Events	Direct Fire	Enemy Act	Explosive	Total	Asymm	Laborint	Victims
$RHarv_{im} \times RProd_i$	-0.019**	-0.010*	-0.017*	-0.007	-0.003	-0.004	0.002	-0.004
	(0.009)	(0.006)	(0.009)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
$RHarv_{im-1} \times RProd_i$	-0.007	0.007	-0.006	0.004	-0.001	0.003	0.001	-0.001
	(0.006)	(0.006)	(0.007)	(0.005)	(0.006)	(0.007)	(0.006)	(0.007)
$RHarv_{im+1} \times RProd_i$	0.002	-0.006	-0.001	-0.003	0.000	0.001	0.002	-0.000
	(0.009)	(0.005)	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)	(0.008)
$IHarv_{im} \times IProd_i$	-0.024***	-0.008*	-0.018***	-0.008	-0.008	-0.003	-0.002	-0.011**
	(0.005)	(0.004)	(0.006)	(0.006)	(0.005)	(0.007)	(0.005)	(0.005)
$IHarv_{im-1} \times IProd_i$	0.003	0.005	0.007	0.004	-0.005	-0.003	-0.004	-0.008
	(0.005)	(0.004)	(0.006)	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)
$IHarv_{im+1} \times IProd_i$	0.006	0.004	0.006	0.002	-0.010	-0.008	-0.003	-0.006
	(0.007)	(0.005)	(0.006)	(0.004)	(0.009)	(0.010)	(0.006)	(0.008)
Observations	18,512	18,512	18,512	18,512	18,512	18,512	18,512	18,512
Clusters	104	104	104	104	104	104	104	104
Mean DV	0.363	0.128	0.327	0.175	0.226	0.153	0.142	0.256
Avg Effect	-1.915	-1.012	-1.693	-0.728	-0.309	-0.423	0.156	-0.428
DistXYear FE	Y	Y	Y	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y	Y	Y	Y
Temp & Precip	Y	Y	Y	Y	Y	Y	Y	Y

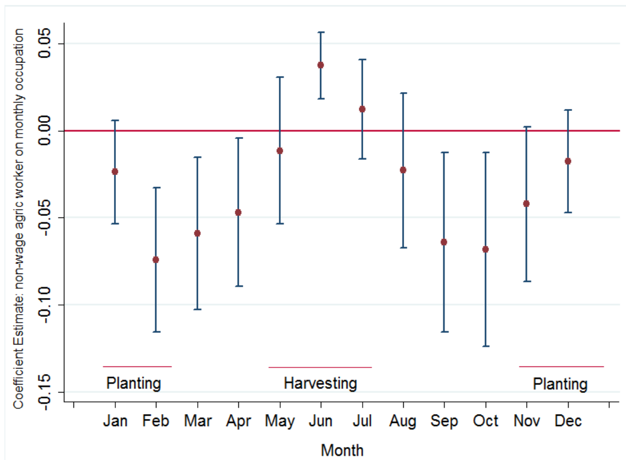
Clustered robust standard errors at the district level in parentheses. $Prod_i$ is measured in hundred sq kilometers. DV is in logs. All specifications include a control for planting X area harvested for rain-fed and irrigated areas. *** p<0.01, ** p<0.05, * p<0.1

Mechanisms and Alternative Explanations

For these results to be consistent with the theoretical framework, it must be that the onset of harvest leads to tangible differences in labor market outcomes. To assess whether this is the case we use the 2006 LSMS Iraqi household survey, to examine whether regional patterns of harvesting relate to employment among agricultural workers. Ideally, we would like to match each respondent to a particular district and follow it throughout the years. However, due to privacy concerns, the survey only provides a cross-sectional snapshot at the time of harvest of individual employment at the governorate level in Iraq (of which there are 18), therefore, this evidence should be taken as indicative of seasonal patterns of employment until more fine-grained information becomes available.

Figure 8 shows the difference in the probability of employment among rural agricultural workers (relative to non-agricultural ones) by month. As shown, these differences, controlling for a number of others factors, closely follows the harvesting calendar in rural Iraq. This is consistent with the idea that harvesting affects conflict by influencing local labor markets.

Figure 8: Monthly Employment Patterns



Y-axis: coefficients from a regression of monthly indicators on employment ("Did you work in this job in month..."?). Additional controls include: individual's age, level of education, gender, household size and language (Arab or not). We include governorate fixed effects and cluster the standard errors at the level of the survey cluster.

Job Switching and Migration. Although employment patterns mirror the harvesting calendar in Iraq, it is important to rule out the possibility that individuals switch jobs within the year. Of the 11,157 individuals surveyed living in rural areas only 521 individuals or 4.67% reported more than one occupation throughout the year and 0.23% reported the maximum of three occupations during the year. This shows it is unlikely they will switch occupations throughout the year. A related concern is whether individuals migrate to other areas for work, potentially explaining the observed patterns of conflict. However, among agricultural workers, the share of individuals reporting an absence from home for an extended period is only 3.67%.

Labor availability versus Harvest Income. A different concern with our measure is whether the time of harvest is instead proxying for the income received as opposed to actual labor availability. This is unlikely in the Iraqi context because most farmers sell their grain to the governmental Iraqi Grain Board who subsidizes wheat production. Once a year farmers take their harvest to one of the numerous silos across the country. This takes place once all harvest is collected due to logistics and transportation costs. Farmers then receive a receipt which has to be cashed in a bank.[24] The process ensures that the time of harvest is prior to receiving any income.

Religious Calendar. In addition to showing how employment patterns vary with the monthly harvesting season, it is important to rule out the presence of any religious significance or activities associated with harvest which may explain the decline in violent activities. Although Islamic religious festivities are common to all districts, its exact dates changes each year. However, for the period under study in Iraq (2004-2009) and Pakistan (1988-2010) Ramadan always fell between August and October or August and January respectively, well after the harvesting season in each case. Nonetheless, we make sure that harvesting does not carry a local religious significance that would explain the reduced violence and examine the 2008 Iraqi Time Use survey to examine whether the hours allocated to religious activities vary by month. Figure 3 in the Appendix shows the coefficients from a regression of hours spent on religious activities on whether the individual is an agricultural worker or not. For each month, there is no difference in religiosity among agricultural workers versus others. However, we do observe a slight *reduction* in religious activities in June, the month when about half of the districts experience harvest. This is consistent with the idea that the reduction in violence is unlikely to be driven by increased religiosity among agricultural workers.

In addition, in Tables 4 and 5 of the online Appendix we estimate our baseline specification using month of the year time effects (as opposed to only month with district by year fixed effects separate) to account for any common factor affecting all districts in the same month and year (e.g. religious festivals). Results are similar and more precisely estimated for all datasets, except for the IBC data– when compared to the baseline specification – thus reducing any concern that certain months may carry special significance affecting conflict intensity.

4.2 The Pakistani Conflict (2006-2010)

For the case of Pakistan we examine patterns of seasonal conflict using the BFRS Political Violence Dataset (Bueno de Mesquita et. al. 2015). This datasets categorize violents incident

[24] http://www.world-grain.com/Departments/Country-Focus/Iraq/Focus-on-Iraq.aspx?cck=1

into whether they are conventional (e.g. labor intensive) or asymmetric (e.g. less reliant on labor – IEDs, suicide bombs) for Pakistan between 2006-2010.[25] Given the constant presence of political violence by different militant groups in Pakistan, their high reliance on part-time forces, and the importance of agriculture (in particular wheat) as a source of employment, we would expect that seasonality play a role in conflict intensity. For instance, Figure 3 of the online appendix, shows how the peak of wheat harvesting in Pakistan occurs mostly in April-May, while planting occurs mostly in October-November. This stands in contrast to Iraq's calendar, where most of the harvesting occurs in May-June and the planting in December-January. It should also be noted that most of wheat cultivation takes place under irrigated conditions (from rivers) as opposed to rain-fed.

The period under study is centered in the renewed insurgent efforts by the Afghan Taliban in Pakistan starting in 2005 for the districts of Quetta, Peshawar, and Karachi; the newly formed Pakistani Taliban likely established around 2006; as well as the presence fo Al-Qaeda, and the insurgent activities of multiple sectarian groups. Table 5 below presents the results with the same specification as before but using district-level attacks in Pakistan from 2006-2010 in the BFRS dataset. The first row shows that the onset of harvest is associated with a reduction in the total number of attacks (column 1), and the total number of attacks by militants (column 2). However, for the case of asymmetric attacks by militans (column 3) and conventional ones (column 5), the effect is negative, but less precisely estimated. Finally, it appears as if the the state is more likely to initiate attacks around harvest (positive coefficient), but less precisely estimated. In terms of magnitude, an additional hundred square kilometers in harvest is associated with a reduction in 0.4 percentage points in conflict events, yet, the higher average intensity of wheat production in these areas (around 6.5 hundred square kilometers per district) imply an average reduction in event of around 2.5%.

[25] More precisely, the authors of the BFRS dataset distinguish between militant, conventional and asymmetric attacks as follows "Militant attacks are those attributed to organized armed groups that use violence in pursuit of pre-defined political goals in ways that are: (a) planned; and (b) use weapons and tactics attributed to sustained conventional or guerrilla warfare and not to spontaneous violence. Conventional attacks by militants include direct conventional attacks on military, police, paramilitary, and intelligence targets such that violence has the potential to be exchanged between the attackers and their targets. Asymmetric attacks include both terrorist attacks by militants, as well as militant attacks on military, police, paramilitary and intelligence targets that employ tactics that conventional forces do not, such as improvised explosive devices (IEDs)." (Bueno de Mesquita et. al. 2015: 17)

Table 5: Seasonal Labor and Violent Incidents in Pakistan: BFRS Dataset

	(1)	(2)	(3)	(4)	(5))
	BFRS Dataset				
	Panel A: Levels of Violence				
DV: Log of...	Total Attacks	By Militants	Asymmetric	Laborint	By State
$RHarv_{im} \times RProd_i$	-0.004	-0.003	0.000	-0.003	-0.002
	(0.013)	(0.009)	(0.009)	(0.002)	(0.002)
$IHarv_{im} \times IProd_i$	-0.004**	-0.002*	-0.002	-0.000	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	7,680	7,680	7,680	7,680	7,680
Clusters	128	128	128	128	128
Mean DV	0.400	0.211	0.184	0.05	0.066
Avg Effect	-0.397	-0.236	-0.193	-0.00	0.130
	Panel B: Monthly Share of Violence				
DV: Monthly % of...	Total Attacks	By Militants	Asymmetric	Laborint	By State
$RHarv_{im} \times RProd_i$	0.630	0.975	1.473	-1.356**	-2.355
	(0.842)	(1.179)	(1.242)	(0.592)	(1.447)
$IHarv_{im} \times IProd_i$	-0.271***	-0.334*	-0.274	-0.595**	0.060
	(0.081)	(0.184)	(0.201)	(0.234)	(0.336)
Observations	5,880	4,092	3,864	1,692	1,440
Clusters	115	98	97	58	60
Mean DV	8.333	8.333	8.333	8.333	8.333
Avg Effect	-3.252	-4.012	-3.285	-7.145	0.726
DistXYear FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Temp & Precip	Y	Y	Y	Y	Y

Clustered robust standard errors at the district level in parentheses. $Prod_i$ is measured in hundred sq kilometers. DV is in logs. All specifications include a control for planting X area harvested for rain-fed and irrigated areas. *** p<0.01, ** p<0.05, * p<0.1

One concern with these findings is that there might be heterogeneity across districts in the prevalence of political violence with violence concentrated in a few district-years, while the rest showing little to no violence. In fact, in the 2006-2010 period, 50% of the districts saw no conflict event, whereas only 5% or less saw more than 5 events. For this reason, Panel B implements a variant of the baseline specification focusing instead on the monthly share of conflict events of a certain type relative to the years' total. This means that we exclude from the analysis months that do not have any conflict event. Using this approach, estimates show that results are consistent with those observed in levels: an additional hundred square kilometer of wheat production at harvest leads to a reduction in conflict effects, particularly those labor intensive (coded as conventional tactics), visible in both rain-fed and irrigated areas. Altogether, the findings would suggest that in conflict affected district-years, the onset of harvest is associated with a lower prevalence of violent events.

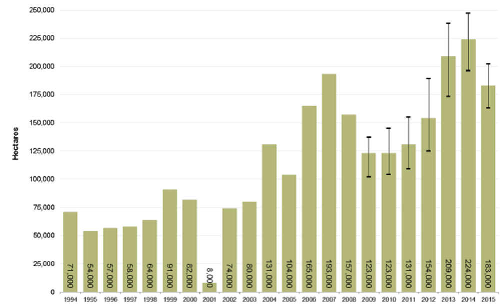
Cross-validation: GTD Dataset (2006-2011). Additional evidence from the GTD dataset shows some evidence in favor some seasonality of conflict, though results are even more imprecise than those using the BFRS data. Table 6 in the online appendix shows that while most coefficients have expected sign, they do not achieve conventional level of statistical significance, except when looking at the share of monthly attacks in Panel B – for the case of labor intensive attacks. Altogether, it appears the case of Pakistan may be sensitive to the dataset used – with the effects only visible in datasets coding all types of political violence (BFRS) and not just those focused on terrorism (GTD).

Robustness. Similar to the Iraqi case, results are robust to excluding all districts that do not produce wheat, as all of them do. In addition, Table 7 in the appendix shows how the results are robust to including a month-year fixed effect (as opposed to a district-year fixed effect with added month of the year fixed effect) which would account for a number of alternative explanations such as variation in the strength of the overall conflict, or levels of religiosity between months, or changes in the state engagement, etc. Finally, Table 8 in the online appendix shows how most of the effect estimated above are driven by the contemporaneous onset of harvest and not by its lags suggesting little anticipation effects. However, as in the case of Iraq, the negative impact of harvest on conflict spills into the following month ($m+1$) which could be simply driven by the way we code harvest.

4.3 Afghanistan (2004-2009)

After being overthrown by U.S. and U.K forces in 2001, the Taliban launched an insurgent movement to regain power. Since then the insurgency has waged asymmetric warfare against ISAF forces – the UN assistance force, later aided by NATO – as well as members of the Afghan military and the government. Most of the Taliban recruits came from poor madrassas, motivated by local grievances, and participated only on a part-time basis due to their work as farmers or laborers (Qazi, S. H. 2011: 10). Taliban cells were thus composed by around ten to fifty part-time fighters (Afsar, Samples, and Wood 2008: 65) who periodically gather to launch attacks but then return to their laboring activities. Given their reliance on part-time fighters, it is likely that their availability and the intensity of the attacks will be dictated by times of labor demand driven related to harvest.

Figure 1: Opium poppy cultivation in Afghanistan, 1994-2015 (Hectares)

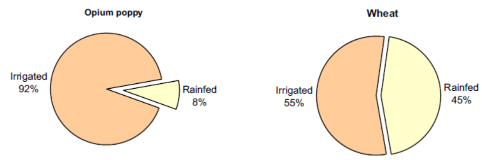


Sources: UNODC and MCN/UNODC opium surveys 1994-2015. The high-low lines represent the upper and lower bounds of the 95% confidence interval.

One difficulty with the Afghan case is the presence of a highly lucrative opium trade which has boomed with the Taliban presence. In fact, existing studies draw a connection between conflict and the incentives to cultivate opium (Lind et. al. 2014). While this connection is interesting in its own right and an area for future research, it is a confounding factor in our estimates, particularly because the conditions favoring wheat and opium production are very similar, thus acting as substitutes. Since the harvest calendars overlap it makes it hard to distinguish whether violence intensity is driven by wheat production or other dynamics associated with illegal markets. The distinction is crucial given the huge differentials in value created at harvest between wheat and poppy ("growing poppies is six times as profitable as growing wheat" UNODC 2010: 5) which may trigger appropriation incentives (or "rapacity mechanisms") dominating opportunity cost mechanisms as well as violence more generally, such as in the Colombian case with coca production (Angrist and Kugler 2008).

To account for this possibility, we limit the sample to those districts for which the median of hectares devoted to opium production in the years 2004-2010 is zero. This does not mean there was zero production, but that around 50% of the time they did not produce opium in this period - this characterizes around 62% of district-years observations in the sample. Moreover, to fully control for the potential effect of opium producion, we take advantage of the fact that most poppy is cultivated in irrigated areas, while wheat is cultivated in both irrigated and rain-fed areas. Hence focusing on the wheat calendar of rain-fed areas will better capture demand for labor due to wheat cultivation as opposed to poppy. By examining only in rain-fed wheat in non-opium provinces, we make sure that poppy cultivation is not present and unlikely to be biasing our estimates.

Figure 12. Proportions of crops cultivated on rain-fed and on irrigated land in 2004



Sources: UNODC, Opium Survey results and FAO/WFP, *Crop and Food Supply Assessment Mission to Afghanistan*, September 2004.

Results from Table 6 below show indeed that focusing only in areas unlikely to be cultivating poppy, the onset of harvest leads to a reduction in the intensity of more labor intensive attacks and those by the Taliban - as reported in Panel A using the WITS dataset. Coefficients in columns 3 and 4 imply sizeable effects: an additional hundred square kilometer at harvest reduces the in about 10 to 12% the monthly number of attacks and those by the Taliban, respectively. In contrast the coefficient for irrigated areas, more likely to be associated with poppy production, is positive but not statistically different from zero as well as those for all types of attacks and asymmetric ones (those involving explosives). In all, this dataset suggests that the timing of the wheat harvest significantly reduces the level of violent activities in a province.

Table 6: Seasonal Labor and Violent Incidents in Afghanistan: WITS, SIGACTS

	(1)	(2)	(3)	(4)
Provinces Below Median Opium Production				
		WITS Dataset		
DV: Log of Attacks...	Total	Asymmetric	Laborint	By Taliban
$RHarv_{im} \times RainProd_{ci}$	-0.098	-0.078	-0.106***	-0.124**
	(0.074)	(0.071)	(0.040)	(0.050)
$IHarv_{cim} \times IrrigProd_{ci}$	0.024	0.027	0.006	0.018
	(0.021)	(0.022)	(0.014)	(0.020)
Observations	20,076	20,076	20,076	20,076
Mean DV	0.088	0.082	0.043	0.047
Avg Effect	-9.770	-7.752	-10.59	-12.38
Clusters	239	239	239	239
		SIGACTS Dataset		
DV: Log of Attacks...	Total	Asymmetric	COIN	Enemy
$RHarv_{im} \times RainProd_{ci}$	-0.137	0.025	-0.089*	-0.152**
	(0.091)	(0.053)	(0.047)	(0.060)
$IHarv_{cim} \times IrrigProd_{ci}$	-0.025	0.018	0.004	0.008
	(0.021)	(0.020)	(0.015)	(0.021)
Observations	21,840	21,840	21,840	21,840
Clusters	260	260	260	260
Mean DV	0.297	0.106	0.0486	0.156
Avg Effect	-13.68	2.531	-8.910	-15.17
District X Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y

Clustered robust standard errors at the district level in parentheses. $Prod_{ci}$ is measured in hundred sq kilometers.*** p<0.01, ** p<0.05, * p<0.1

Cross-validation SIGACTS (2004-2009). To complement the above results, we also use information on "Significant Activity" reported by the International Security Assistant Force (ISAF) troops in Afghanistan. This dataset contains information on location, date, and type of insurgent activity. Similarly to the Iraqi case, it codes the total number of attacks, the presence of any conflict event, IED's, counter-insurgency operations, and attacks from "enemy" forces which in this case generally consisted of the Taliban. In line with the results Panel A, focusing on instances of Significant Activity shows that enemy attacks were much less likely in these periods. This reduction does not appear to the driven by counterinsurgency operations, as these are also lower during this period. In terms of magnitude, the effects are sizeable compared to those of Iraq and Pakistan, and it is likely driven by the high-reliance of Taliban forces on part-time fighters and the importance of agriculture for the Afghan economy.

Robustness. Additional analysis in the online appendix shows that the inclusion of month of the year fixed effects yield similar results to those of the baseline. More importantly, estimates from a full dynamic specification shows that most of the effect is driven by the contemporaneous onset of harvests with no anticipations effects (e.g. conflict increasing in the month before harvest). In fact, the effect of harvest seems to linger into the following month which rules out the possibility that harvest could be promoting future conflict by financing it; trying to make-up for the "lost" time; or that individuals fight over the proceeds from the harvest. Similarly, the fact that counter-insurgent operations are lower during harvest and its aftermath suggest that government and coalition forces are not trying to "protect" the harvest, for example.

5 Conclusion

This paper has examined how seasonal variation in labor demand has a negative effect on the intensity of violence. In Iraq, Pakistan, and Afghanistan, the number of attacks is lower during harvest. Specifically, an additional hundred square kilometer of wheat production at harvest reduces the number of monthly attacks in around 1% to 15% reduction depending on the specific case and dataset, with the largest estimates observed for the most agriculturally reliant country: Afghanistan. Results are robust to excluding regions that are not crop producers, a wide array of fixed effect variables, and do not appear to be driven by alternative explanations such as the weather, religious festivities, within-year variation in occupations, or seasonal migration. Consistent with our interpretation that harvest affects local labor markets and conflict, we find that during these months agricultural workers tend to have higher employment rates non-agricultural workers in Iraq. However, the way that attacks are coded seems important: although there is some evidence of seasonality using the BFRS and GTD dataset in Pakistan, estimated coefficients are usually smaller and/or less precisely estimated.

In terms of policy implications, care should be taken into interpreting our results for the opportunity cost mechanism as evidence in favor of employment programs or permanent forms of development aid. In theory, the problem is that those policy schemes may have unintended consequences if highly persistent. For example, a permanent wage or employment subsidy scheme may mean that households are wealthy enough to devote time to fighting for causes they care about, or are less likely to provide information to counter-insurgency forces. Or, they may encourage people to fight in order to capture the rents from these schemes. Similarly, permanent changes in productivity (due to foreign or development aid) may have a reduced effect of zero on violence, as first mentioned in Fearon (2008).

However, it might be possible to design more sophisticated policies which increase the opportunity cost of violence without increasing either consumption or the value of winning. For example, reducing food and energy subsidies (which are pervasive in regions prone to conflict) and using the money for an employment subsidy would have little effect on the marginal utility of consumption but would increase the incentive to work rather than fight. Funding employment schemes by local taxes would have a similar effect. Making employment subsidies conditional on a successful counterinsurgency means they would not affect the value of winning. These are just ideas: a thorough assessment would be an interesting area for future research. An online appendix is available at https://sites.google.com/site/jennyguardado/.

References

[1] Afsar, S., Samples, C., and Wood, T. (2008). The Taliban: an organizational analysis. Naval Postgraduate School Monterey CA. Department of National Security Affairs, Chicago IL.

[2] Arjona AM and Kalyvas SN (2008) Rebelling against rebellion: Comparing insurgent and counter-insurgent recruitment. Working paper. Yale, CT: Yale University.

[3] Bazzi, S., and Blattman, C. (2014). Economic shocks and conflict: Evidence from commodity prices. *American Economic Journal: Macroeconomics*, 6(4), 1-38.

[4] Becker, G. 1968. "Crime and Punishment: An Economic Approach." *Journal of Political Economy* 76(2):169-217.

[5] Berman, E, J N. Shapiro and J H. Felter. 2011a. "Can Hearts and Minds be Bought? The Economics of Counterinsurgency in Iraq." *Journal of Political Economy* 119:766-819.

[6] Berman, E, M Callen, J H. Felter and J N. Shapiro. 2011b. "Do Working Men Rebel? Insurgency and Unemployment in Afghanistan, Iraq, and the Philippines." *Journal of Conflict Resolution 55(4)*

[7] Blattman C and Miguel E (2010) Civil war. *Journal of Economic Literature* 48(1): 3–57.

[8] Blattman C and Ralston L (2015) Generating employment in poor and fragile states: Evidence from labor market and entrepreneurship programs. Mimeo.

[9] Bertrand M., E. Duflo and S. Mullianathan (2004) "Hoe much should we trust differences-in-differences estimates?" *The Quarterly Journal of Economics* 119 (1)

[10] Brückner, Markus, and Antonio Ciccone. "International Commodity Prices, Growth and the Outbreak of Civil War in Sub-Saharan Africa." *The Economic Journal* 120, no. 544 (2010): 519-534.

[11] Bueno de Mesquita, E. (2013). Rebel tactics. *Journal of Political Economy*, 121(2), 323-357.

[12] Bueno de Mesquita, et. al. (2014). Measuring political violence in Pakistan: Insights from the BFRS Dataset. *Conflict Management and Peace Science.*

[13] Burke, M. B., Miguel, E., Satyanath, S., Dykema, J. A., & Lobell, D. B. (2009). Warming increases the risk of civil war in Africa. Proceedings of the National Academy of Sciences, 106(49), 20670-20674.

[14] Ciccone, A. (2011). Economic shocks and civil conflict: A comment. *American Economic Journal: Applied Economics*, 3(4), 215-227.

[15] Chassang S and Padró i Miquel G (2009) Econmic shocks and civil war. *Quarterly Journal of Political Science* 4(3): 211–228.

[16] Collier P and Hoeffler A (2004) Greed and grievance in civil war. Oxford Economic Papers 56(4): 563–595.

[17] Crost, B., Felter, J., & Johnston, P. (2014). Aid under fire: Development projects and civil conflict. The American Economic Review, 104(6), 1833-1856.

[18] Dal Bo, Ernesto, and Dal Bo, Pedro. (2011). "Workers, warriors, and criminals: social conflict in general equilibrium."*Journal of the European Economic Association*, 9(4), 646-677.

[19] Dube, Oeindrila, and Juan F. Vargas. "Commodity price shocks and civil conflict: Evidence from Colombia." *The Review of Economic Studies* 80, no. 4 (2013): 1384-1421.

[20] Fearon J. (2005) Primary commodity exports and civil war. *Journal of Conflict Resolution* 49(4): 483–507.

[21] Fearon J. and Laitin D. (2003) Ethnicity, insurgency, and civil war. *American Political Science Review* 97(1): 75–90.

[22] Fearon, J. (2008). Economic development, insurgency, and civil war. Institutions and economic performance, 292, 328.

[23] Figes, Orlando (1996). A People's Tragedy: The Russian Revolution 1891–1924. Pimlico, London.

[24] Garfinkel, Michelle R. 1990. "Arming as a Strategic Investment in a Cooperative Equilibrium." American Economic Review, 80(1): 50–68.

[25] Garfinkel, Michelle R., and Stergios Skaperdas. 2007. "Economics of Conflict: An Overview." In Handbook of Defense Economics, Volume 2, Defense in a Globalized

World, ed. Todd Sandler, and Keith Hartley, 649–710. Amsterdam and Oxford: Elsevier, North-Holland.

[26] Giuffre, K. A. (1997). First in Flight: Desertion as Politics in the North Carolina Confederate Army. Social Science History, 245-263.

[27] Grossman, Herschel I. 1991. “A General Equilibrium Model of Insurrections.” *American Economic Review*, 81(4): 912–21.

[28] Guardado, J. 2015. “Land Tenure, Price Shocks and Insurgency: Evidence from Peru and Colombia”. Mimeo.

[29] Haavelmo, Trygve. 1954. *A Study in the Theory of Economic Evolution*. Amsterdam: North-Holland.

[30] Hirshleifer, Jack. 1988. “The Analytics of Continuing Conflict.” Synthese, 76(2): 201–33.

[31] Hirshleifer, Jack. 1989. “Conflict and Rent-Seeking Success Functions: Ratio vs. Difference Models of Relative Success.” *Public Choice*, 63(2): 101–12.

[32] Hodler, Roland, and Paul A. Raschky. "Economic shocks and civil conflict at the regional level." *Economics Letters* 124, no. 3 (2014): 530-533.

[33] Horowitz, Donald L. 1985. *Ethnic Groups in Conflict*. Berkeley and London: University of California Press.

[34] Hsiang, S. M., Burke, M., and Miguel, E. (2013). Quantifying the influence of climate on human conflict. *Science*, 341(6151), 1235367.

[35] Jensen, E. T. (2005). Combatant Status: It Is Time for Intermediate Levels of Recognition for Partial Compliance. Va. J. Int’l L., 46, 209.

[36] Lind, J. T., Moene, K. O., & Willumsen, F. (2014). Opium for the masses? Conflict-induced narcotics production in Afghanistan. Review of Economics and Statistics, 96(5), 949-966.

[37] McClintock, Cynthia. 1998. *Revolutionary Movements in Latin America: El Salvador’s FMLN and Peru’s Shining Path*. Washington, DC: United States Institute of Peace.

[38] Miguel, Edward, Shanker Satyanath and Ernest Sergenti. 2004. "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy* 112:725-753

[39] Nunn, N., & Qian, N. (2014). US food aid and civil conflict. *The American Economic Review*, 104(6), 1630-1666.

[40] Paxson, C. H. (1992). Using weather variability to estimate the response of savings to transitory income in Thailand. The American Economic Review, 15-33.

[41] Qazi, S. H. (2011). The neo-taliban, counterinsurgency & the american endgame in afghanistan. Institute for Social Policy and Understanding.

[42] Sarsons, Heather. "Rainfall and conflict." In Manuscript. http://www. econ. yale. edu/conference/neudc11/papers/paper_199. pdf. 2011.

[43] Skaperdas, Stergios. 1992. "Cooperation, Conflict, and Power in the Absence of Property Rights." American Economic Review, 82(4): 720–39.

[44] Watkin, K., & Norris, A. J. (2012). Non-international Armed Conflict in the Twenty-first Century. Government Printing Office.

[45] Wigle, J. (2010). Introducing the worldwide incidents tracking system (WITS). *Perspectives on Terrorism*, 4(1).

[46] Willmott, C. J. and K. Matsuura (2001) Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series (1950 - 1999), http://climate.geog.udel.edu/~climate/html_pages/README.ghcn_ts2.html.

[47] Wood, E. J. (2003). Insurgent collective action and civil war in El Salvador. Cambridge University Press.