The Seasonality of Conflict*

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Abstract

We exploit the seasonality of agricultural labor markets to estimate the effect of changes in the opportunity cost of armed conflict. Based on a dynamic model, we argue that exogenous, anticipated, and transitory changes in labor demand due to harvesting are able to capture the intra-temporal substitution between labor and conflict because they hold constant the marginal utility of consumption and the present value of future victory. Indeed, regressions on model-generated data show that the estimated effect of seasonal labor shocks on violence are closer to the true opportunity cost effect than those exploiting persistent shocks to labor demand (e.g. commodity prices, rainfall shocks with lasting consequences) which will tend to be upward biased. Empirically, we exploit exogenous sub-national variation in the timing of harvest due to local climatic conditions to examine its effect on the intensity of violent conflict. Using data from two different conflict settings – Iraq and Pakistan – our results show that the onset of harvesting usually leads to a statistically significant reduction in the number of monthly insurgent attacks.

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1 Introduction

During the American Civil War (1861-1865) desertions from the Confederate Army sky-rocketed in the months of June and July, the harvesting times for tobacco – an important Southern crop at the time (Giuffre 1997). Similarly, 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). More recently, anecdotal accounts of on-going insurgencies in Iraq, the Philippines, and Afghanistan have noted that a high share of insurgents often participate on a seasonal or part-time basis.[1]

Such anecdotes suggest that the opportunity cost of fighting – the foregone returns from working – are a key consideration among individuals choosing between fighting or working. Indeed, a number of scholars draw a theoretical (Becker 1968; Grossman 1991; Dal Bo and Dal Bo 2011) and empirical connection (Miguel et. al. 2004; Dube and Vargas 2013; Guardado 2015; Hodler and Raschky 2014, among others) between the returns to working and the intensity of conflict thus implying that better wages or job prospects reduces the relative attractiveness of fighting. Despite these findings, questions remain as to whether economic considerations are an important motivation for conflict (Berman et. al. 2011a); whether the empirical relationship between price shocks and conflict is consistent with opportunity costs (Fearon and Laitin 2003); or whether the exogenous shocks examined (e.g. rainfall) are a good instrument for income (Sarsons 2011), among others. In this paper we make a theoretical and empirical case for why economic opportunity considerations play a role in on-going conflict settings.

Theoretically, we examine how seasonal changes in labor demand (motivated by the timing of harvest) influences the time allocated to working versus fighting. Because seasonal changes in labor demand are anticipated, it holds constant important determinants of conflict such as the value of winning (Fearon 2008, Chassang and Padro-i-Miquel 2009), the marginal utility of consumption, the value of sharing information for counterinsurgency efforts (Berman et. al. 2011a), among others. As a result, we show that the "true" opportunity cost of conflict can be uncovered almost exactly by a regression of time allocated to violence on seasonal variation in wages. Yet, because these factors, (marginal utility of consumption or the value of wining, etc.) are commonly omitted in standard regressions using highly persistent shocks (e.g. commodity prices or rainfall shocks with lasting consequences)[2] it results in estimates of the opportunity cost effect which are biased upwards ("too small"). That is, extant estimates showing a negative relationship between commodity price shocks

[1] For Iraq, GlobalSecurity.org estimates that around 40,000 insurgents are full-time or core, while approximately 200,000 participate on a part-time basis (http://www.globalsecurity.org/military/ops/iraq_insurgency.htm). In the case of the Phillipines, Ferrer and Cabangdang (2012: 263) – both from the Philippine army – highlight how many local residents in Mindanao also act as part-time fighters for the Islamic insurgency. In Afghanistan, a number of reintegration initiatives are targeted to "foot-soldiers" or seasonal participants who might be participating in exchange for money (http://newstrategicsecurityinitiative.org/).

[2] We thank Scott Ashworth for this observation.

and conflict (Dube and Vargas 2013; Guardado 2015) are likely to be a *lower bound* of the true effect of these income shocks on conflict. Finally, because we model the most common motivations for conflict in the literature – either driven by monetary expectations upon victory ("greed") or driven by intrinsic motivations ("grievance") – we believe it has a wide applicability across different contexts and conflict episodes.

Empirically, we estimate the effect of seasonal labor demand in two different contexts: the Iraqi civil conflict (2004-2011) and the Pakistani sectarian conflict (1988-2010). We focus on changes in labor demand induced by the timing of harvest of the main agricultural crop in both cases: wheat. Given the labor-intensive nature of agricultural activities, and the fact that these crops are harvested annually, they are likely to induce a large, transitory and anticipated change in local demand for labor. Since seasonality or the *timing* of harvest is determined by local climatic conditions and crop types it is unlikely to be influenced by on-going conflict dynamics thus alleviating potential endogeneity concerns. While ideally we would like to instrument local wages with the timing of harvest, the time-series for local wages are often unavailable in a number of conflict (and non-conflict settings) therefore we focus on the reduced form relationship between the number of attacks in a location and the size of the area harvested.

Our empirical results from these two different conflict settings[3] (Iraq, Pakistan) show that at times of greater labor demand (harvest), violent attacks are usually lower compared to regions in the same country that are not in harvest. Our main estimates suggest that in a cell or district with the average crop intensity, the onset of harvest reduces the number of attacks from 4-5% in Pakistan (BFRS dataset) to 30%-40% in Iraq (WITS dataset) relative to the average for that cell or district. However, results do also vary depending on data source: in particular estimated effects are smaller and less precisely estimated using the University of Maryland's Global Terrorism Dataset (GTD), suggesting the way attacks are coded might be important. Additional results focusing on the *type* of attack (as opposed to overall levels) show that the reduction in violence is mostly uniform across all types. Finally, using household surveys and monthly weather information for Iraq 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 that harvest affects local labor markets and conflict, we find that during harvesting months agricultural workers tend to have differentially higher employment rates than other rural workers.

Relation to the literature. The empirical findings suggest that labor market constraints are an important consideration in a number of different armed conflicts and contexts. To the extent that armed groups rely on part-timers to plan and execute attacks, and these individuals exhibit a higher demand of their time during harvesting, we expect this constraint to bind and

[3]On-going data-collection for Colombia and the Philippines will further assess the scope of these fiindings.

affect the "production" of violence. While our finding contrasts with studies highlighting the role of "grievances" as a mobile for insurgent participation (Wood 2003), it leaves ample room for other mechanisms to play a role within the same conflict-year.

Second, our paper is able to rationalize the results of recent studies which find little evidence for opportunity cost mechanisms: these may actually be driven by the high persistence of the shocks analyzed. For instance, Berman et. al. (2011b) document that in some conflict regions, higher unemployment appears to correlate with *less* violence. The authors argue that this might be explained by reductions in the cost of buying counter-insurgency information at times of high unemployment— but in our context the marginal utility of consumption is kept constant across seasons, and so is the incentive to provide information. Similarly, Blattman and Bazzi (2014) find a negative but weak relationship between commodity prices and conflict intensity, yet, given commodity prices are highly persistent, these estimates may actually constitute a *lower bound* of the true opportunity cost effect. Our results call for a deeper investigation into which types of shocks better allow us to identify the presence of opportunity cost mechanisms.

Third, the paper provides a novel source of exogenous variation in the demand for labor and cautions against the indiscriminate use of certain *persistent* income shocks (e.g. commodity prices or severe damage due to rainfall or lack thereof) as an instrument. While these shocks are indeed exogenous to conflict dynamics, they can also have distorting effects on an individual's consumption pattern or on the perceived returns to victory (Fearon 2008; Chassang and Padro-i-Miquel 2009) thus biasing the estimated effect. Similarly, because our resullts are not based on instrumenting income with rainfall, it reduces the concern that we are capturing the direct effect of rainfall on violence. For instance, during rainy seasons it is hard to coordinate and execute armed attacks.

Finally, 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. 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 capture the rents from these schemes. Indeed, 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] Similarly, permanent changes in productivity due to development aid (e.g. improving grain production) may also have a small effect in reducing violence, as first mentioned in Fearon (2008). 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 capture the rents from these schemes. For instance, a once-off capital

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

transfer may go a long way to improve economic livelihoods potentially reducing certain types of violence (Blattman and Ralston 2015).

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 two simple models of conflict. The two models are inspired by the main motivations for violence in the literature: (i) rebellion for a cause ("grievance") or (ii) rebellion for money ("greed"). In Section 2.2 we also provide a sketch of a model assessing the value of providing information about insurgents, which has a similar mechanism to the "grievance" model. 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 both cases we find that a regression of violence on seasonal variation on wages is able to uncover the "true" relationship almost exactly, and is much more accurate than regressions using variation in wages driven by persistent shocks which will tend to be upward biased.

The reason why estimates using variation in wages driven by persistent shocks are biased is that "everything else" is not constant. In fact, persistent shocks which cause a change in wages also lead to a change in the (i) level of consumption (wealth effects) and (ii) the reward for fighting. For instance, in the "grievance" model, the wealthier agent finds that additional consumption adds less to his utility, and so he reallocates time to violence instead. In the information-based model, the wealthier household is also less willing to provide information to counterinsurgency forces. In the "greed" model, the greater the potential spoils of victory, the greater the time allocated to violence (Fearon 2008; Chassang and Padro-i-Miquel 2009). Both of these effects are exacerbated with the persistence of the shock. Unfortunately, commonly used commodity prices in the literature are highly persistent: the quarterly persistence of oil and coffee prices is around 0.96.[5] Because seasonal

[5] 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 at the quarterly level. In contrast, $\rho = 0.04$ for Iraq rain cells 11 km x 11 km, 2000-2010, quarterly. $rain(mm)_{i,t} = \rho rain(mm)_{i,t-1} + \gamma t + \mu_i + \theta_{qrt}$, yet, for most regions in the world it may have little effect on

changes in wages are both temporary and anticipated, there is little change in either consumption or the spoils of victory, which means that our estimates are closer to the "true" opportunity cost of violence.

2.1 Model 1: Rebellion for a "Cause" (Grievance model)

In this model, we assume that rebels engage in violence for some "cause" in which they place intrinsic value: examples include ethnic or religious hatred, retaliation for past grievances, or nationalism (Horowitz 1985). That is, rebel violence is in the utility function. To make the mechanism completely clear, 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.[6] 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. We first consider a static model, and then a dynamic model which introduces seasonality and persistent shocks.

2.1.1 Static Model

Consider the problem of a household who has an endowment of one unit of time, and has choose how much time he wants to spend fighting V, and how much time $(1 - V)$ he wants to work at an exogenous wage W . More formally:

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

$$C = W(1 - V) \tag{2}$$

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

$$U_V = U_C W \tag{3}$$

Equation 3 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* reduce U_C (the marginal value of extra income in terms of utility, $U_{CC} < 0$), such that U_V falls

agricultural output.

[6] 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.

and violence increases (the "income effect"). Which effect dominates depends on the parameters of the model. In order to get further, we need to assume a functional form; so we choose a standard constant relative risk aversion formulation ($\sigma, \gamma > 0$):

$$U(C,V) = \frac{1}{1-\sigma}C^{1-\sigma} + \frac{\psi}{1-\gamma}V^{1-\gamma} \tag{4}$$

The FOC now becomes

$$\psi V^{-\gamma} = C^{-\sigma}W \tag{5}$$

Taking log of Equation6, the "true" model of violence is.

$$lnV = -\frac{1}{\gamma}ln\psi + \frac{\sigma}{\gamma}lnC - \frac{1}{\gamma}lnW \tag{6}$$

Definition. The effect of the opportunity cost of violence is the elasticity of violence with respect to wages, keeping everything else constant, or $-\gamma^{-1}$.

$$\frac{\partial lnV}{\partial lnW} = -\frac{1}{\gamma}$$

The problem with estimating empirical analogues of Equation 6 is that consumption is usually not observed (or is poorly measured) so 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 $cov(lnC, lnW) = \sigma_{CW} > 0$ (as people consume their higher incomes). As such, the estimated effect of the opportunity cost of violence will be upward biased as in Equation7.[7] Another way to see this bias is presented in the Appendix.

$$E\hat{\beta}_1 = -\frac{1}{\gamma} + \frac{\sigma}{\gamma}\frac{\sigma_{WC}}{\sigma_W^2} > -\frac{1}{\gamma} \tag{7}$$

The bias outlined above is driven by the fact that increases in wages also increase consumption. As seasonal variation in wages are anticipated, in a dynamic model consumption these will be constant, allowing a regression of violence on wages to uncover the true opportunity cost parameter $-1/\gamma$. In contrast, changes in commodity prices (which are unanticipated and persistent) move consumption in the same direction as wages, leading to the biases discussed above.

[7]Here we are assuming that we draw lnW from some distribution, solve the model to yield lnV and then run a regression of lnV on lnW.

2.1.2 Dynamic model: Set-up

In the dynamic model, we assume that the household can accumulate assets $A > 0$ or debt $A < 0$ at the risk free interest rate $1 + r$. [8] While frictionless financial markets are a simplification, there is plenty of evidence in developed (Hsieh et al 2003) and developing (Paxson 1992) countries that people save a large share of anticipated temporary income.[9] The problem of the household is:

$$max_{\{C_{t+i},V_{t+i},A_{t+i}\}_{i=0}^{\infty}} E_t \sum_{i=0}^{\infty} \beta^i \left[\frac{1}{1-\sigma} C_{t+i}^{1-\sigma} + \frac{\psi}{1-\gamma} V_{t+i}^{1-\gamma} \right] \quad such\ that$$

$$A_{t+i} = (1+r)A_{t-1+i} + W_{t+i}(1 - V_{t+i}) - C_{t+i} \tag{8}$$

Log linearizing the first order conditions and budget constraint yields an intertemporal Euler Equation 9, the same intra-temporal violence-labor FOC as before (Equation 10), and the log-linearized inter-temporal budget constraint Equation 11. As before, $\hat{x}$ indicate percentage deviation from steady state, except for assets $\hat{a}_t$, which are expressed as percentage of steady state consumption.[10]

$$\hat{c}_t \approx E_t \hat{c}_{t+1} \tag{9}$$

$$\hat{v} = \frac{\sigma}{\gamma}\hat{c} - \frac{1}{\gamma}\hat{w} \tag{10}$$

$$\hat{a}_t = (1+r)\hat{a}_{t-1} + \hat{w}_t - \frac{\bar{W}\bar{V}}{\bar{C}}\hat{v}_t - c_t \tag{11}$$

Now, let's assume that there are two processes driving wages: first this could be driven by persistent commodity price shocks as in the literature (Equation 12), or it could follow an anticipated seasonal pattern of high and low wages, as in the empirical part of this paper (Equation 13). For simplicity, we assume that wages are at the steady state level in the "low" (non harvest) season ($lnW_L = ln\bar{W}$), and they increase by a factor of $\chi > 0$ in the high (harvest) season.

$$\hat{w}_t = \rho\hat{w}_{t-1} + \hat{e}_t \tag{12}$$

or

[8] We also assume that household discount factor $\beta = \frac{1}{1+r}$ so that the household doesn't want borrow or save in steady state.

[9] Given the harvest is only once or twice or year, if agricultural household did not save a substantial fraction of their income during this period, they would starve to death during the off season.

[10] This allows assets to be zero in steady state. In simulation we typically assume that $a_{t-1} = 0$. Before log-linearizating, the Euler Equation 9 is $C_t^{-\sigma} = E_t \left[C_{t+1}^{-\sigma}(1+r)\beta \right]$ (recall $\beta = (1+r)^{-1}$), and the other two equations are 8 and 5.

$$\hat{w}_L = 0 \quad for\, t+1,\, t+3, ... \tag{13}$$
$$\hat{w_H} = \chi > 0\, for\, t, t+2, t+4, ...$$

Persistent Shocks. When lnW follows a persistent AR(1) process — such as when wages are driven by commodity price shocks (and $\hat{a}_{t-1} = \hat{w}_{t-1} = 0$) — consumption *jumps* on revelation of the size of the shock at $t = 0$ but then stays constant along the adjustment path. Constant consumption is due to the Euler Equation 9, with the size of the movement in consumption being as in Equation 14.

$$\hat{c}_0 = \frac{1-\beta}{1-\rho\beta}\left[\frac{\gamma\bar{C}+\bar{W}\bar{V}}{\gamma\bar{C}+\sigma\bar{W}\bar{V}}\right]\hat{w}_0 \tag{14}$$

In period zero (immediately following the shock), the level of violence is given by Equation 15. One can see that when $\sigma = 0$ (linear utility, no wealth effects), the second term disappears (as in the static model), and a simple regression yields the "true" coefficient. Yet, in a dynamic setting, the size of this term also depends on the persistence of the shock. With $\sigma = 1$ (log preferences) $\hat{v}_0 = -\frac{1}{\gamma}\beta\hat{w}_0$ for a transitory shock ($\rho = 0$), which is very close to the "true" opportunity cost parameter because $\beta \approx 1$. However, as $\rho \to 1$, violence will be constant, as in the static model.[11]

$$\hat{v}_0 = -\frac{1}{\gamma}\hat{w}_0 - \frac{\sigma}{\gamma}\hat{c}_0 = -\frac{1}{\gamma}\left[1-\sigma\frac{1-\beta}{1-\rho\beta}\left[\frac{\gamma\bar{C}+\bar{W}\bar{V}}{\gamma\bar{C}+\sigma\bar{W}\bar{V}}\right]\right]\hat{w}_0 \tag{15}$$

Seasonal Shocks. Unlike persistent unanticipated shocks, seasonal variation in labor demand due to harvests is *anticipated.* This means that changes in labor demand do not affect consumption, which is set based on the present value of income according to the permanent income hypothesis. For a χ% increase in wages during harvest, the solution of the model when wages are seasonal is in Equation 16.[12] One can see that a regression of log violence on the difference in violence between harvest and non-harvest periods is able to uncover the true opportunity cost parameter $-\gamma^{-1}$.

[11] Note that along the adjustment path following a persistent shock, $\Delta\hat{v}_t = -(1/\eta)\Delta\hat{w}_t$ as consumption is constant. However, this is not of any practical value since the model is constantly being hit by new shocks and it is hard to identify the response to a new shock or an old shock.

[12] Here consumption is $c = \frac{\bar{W}\bar{V}+\eta\bar{C}}{\sigma\bar{W}\bar{V}+\eta\bar{C}}\frac{\chi}{(1+\beta)}$

$$
\begin{aligned}
lnV_H - lnV_L &= (lnV_H - ln\bar{V}) - (lnV_L - ln\bar{V}) \qquad (16)\\
&= \hat{v}_H - \hat{v}_L \\
&= \frac{\sigma}{\gamma}c - \frac{1}{\gamma}(\hat{w_L} + \chi) - \left[\frac{\sigma}{\gamma}c - \frac{1}{\gamma}\hat{w_L}\right] \\
&= -\frac{1}{\gamma}\chi
\end{aligned}
$$

Numerical Simulations

To illustrate the advantage of using seasonality in labor demand, we calibrate the dynamic model and generate simulated data for both persistent shocks and seasonal labor demand, and estimate the regression of log violence on log wages. We calibrate $\gamma = -\frac{1}{3}$ to match the estimated elasticity of violence with respect to wages found in Colombia (-1.5).[13] Specifically, we use an *indirect inference approach* and choose γ so that our estimated coefficient on simulated data with shock persistence $\rho = 0.96$ (similar to the quarterly persistence of coffee prices) matches -1.5, which is what we empirically find with the available data. Examples of simulated data and the parameters are shown in Figure 1[14] and Table 4 in the Appendix.[15] The other important parameter in the model is $\sigma = 2$, which is a common value in macroeconomic models.

With a "true" opportunity cost of -3 (red line of Figure 1), the estimated coefficient from a regression of violence on seasonal variation in wages is identical to the true opportunity cost $-\gamma^{-1} = -3$ (green line).[16] In contrast, when the persistence of wage shocks is high, the estimated elasticity of violence with respect to wage shocks is biased upwards (i.e. less negative). Specifically, the estimated coefficient from the regression (in blue) and the analytical expression in Equation 15 from the first quarter (black)[17] both increasingly depart from the "true" opportunity cost as the shock comes more persistent. For $\rho = 0.96$ (as in the data for commodity prices), the bias is substantial; in fact the estimated elasticity with persistent shocks (-1.5) is around *half* of the true

[13] 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).*

[14] The simulations are implemented using the log linearized model Equations 9-13. For the persistent shocks model, a sequence of shocks $\{\hat{e}\}$ are drawn from a normal distribution with SD=0.01 (i.e. the path of $\hat{w}$ is stochastic). For seasonal violence, the data are generated as the impulse response to a *single* "seasonality" shock, where $\hat{w}_t = \hat{w}_{t-2} + \hat{e}_t$, where the size of the shock $\chi = 0.05$. Simulations conducted using Dynare.

[15] $\beta = 0.99$ implies a risk free rate of 4%, and ψ doesn't affect the model all that much.

[16] Persistence (ρ) on the x-axis refers to the AR(1) shock, so naturally the estimated coefficient on seasonal violence will be unaffected by changes in ρ.

[17] We would not expect the regression coefficient to be identical to that in Equation 15, as it only reflects the response in the first quarter after a shock. If the new shock is much smaller than old shocks, then the relationship between wages and violence will be dominated by adjustment to old shocks, rather than new shocks.

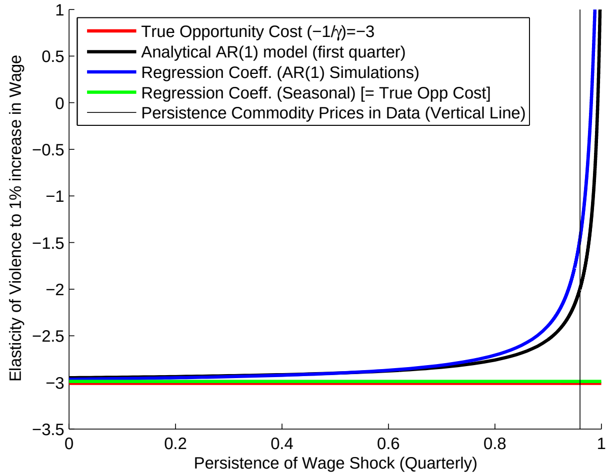


Figure 1: Rebel for a Cause Model: A. estimated coefficient (LHS)

elasticity of -3 (which implies $\gamma = -1/3$). Therefore, the "gain" from estimating the opportunity cost parameter from seasonality in wages is the "gap" between the blue and green lines. Relative to temporary shocks, the gain is small. But as commodity price shocks are highly persistent, the gain is sizable in most practical applications.

2.2 Extension: 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 tip-offs. 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 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, given the similarity to the mechanism in the "violence for a cause" model.

Consider a modification of the static set up in Equation 1 above to incorporate information provided to counter-insurgency forces I. The household doesn't like to provide information, so $U_I < 0$, and hates each additional unit of "snitching" even more, such that $U_{II} < 0$ (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:

$$max_{V,C}U(C, V, I) \quad such\ that \tag{17}$$

$$C = W(1 - V) + sI \tag{18}$$

The FOC wrt to time allocated to violence is unchanged from Equation 3 above, whereas the FOC wrt I implies:

$$-U_I = U_C s \tag{19}$$

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's (2011b), which could actually *increase* 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 unbiased estimate of the effect of the opportunity cost of violence.

2.3 Model 2: Rebellion for "Money" (Greed model)

The most popular motivation 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). 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.[18] 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 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.

2.3.1 Static Model

As in the previous 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:

$$p = \psi V^{1-\gamma} \tag{20}$$

[18] 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" functon.

$0 < \gamma < 1$ governs the effectiveness fighting technology, which means that the $p'(v) = \psi(1-\gamma)V^{-\gamma}$ is decreasing in V.[19] 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

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

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

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 21-23) are written in terms of the consumption good.

$$Y = A(1-V)^{\alpha} \tag{21}$$

$$W = \alpha A(1-V)^{\alpha-1} \tag{22}$$

$$\Pi = Y - W(1-V) = (1-\alpha)A(1-V)^{\alpha} \tag{23}$$

To separate the mechanism from the one above, we make three assumptions:

- $U(C) = C$ (linear utility, risk neutral agents)
- No Saving or Borrowing
- Violence is NOT in the utility function.

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

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

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

The FOC is:

$$V = \left[\psi(1-\gamma)\frac{\Pi}{W}\right]^{\frac{1}{\gamma}} \tag{24}$$

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

$$lnV = \frac{1}{\gamma}ln\psi(1-\gamma) + \frac{1}{\gamma}ln\Pi - \frac{1}{\gamma}lnW \tag{25}$$

The true opportunity cost unchanged from Definition 1 in Equation 25 is $\frac{\partial lnV}{\partial lnW} = -\frac{1}{\gamma}$, but this requires controlling for $ln\Pi$ in the regression. If instead researchers ran a univariate specification, $ln\Pi$ would be subsumed into the error term. As lnW and $ln\Pi$ are positively correlated (see below), this will bias *upwards* the coefficient on wages.

Now, 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 24 becomes Equation 26. One can see that A increases Π and W proportionately, and so in Equation 26 A cancels and violence is constant. 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.

$$V = \left[\psi(1-\gamma)\frac{(1-\alpha)(1-V)^{\alpha}}{\alpha(1-V)^{\alpha-1}}\right]^{\frac{1}{\gamma}} \tag{26}$$

2.3.2 Dynamic Model

Seasonal variation in productivity provides a context where the opportunity cost of violence changes, but 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 $-\gamma^{-1}$. 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.[20] 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 rate. The household has linear utility in consumption, cannot save, 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 $\Pi = (1-\alpha)Y$. We 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 27 if there are persistent productivity or commodity price shocks, or Equation 28 when there is seasonal variation in productivity. For **persistent shocks**:

$$lnA' = \rho lnA + e \tag{27}$$

Or, for **seasonal shocks**:

$$\begin{aligned} lnA_L &= ln\bar{A} \qquad for\, t+1\, t+3, ... \\ lnA_H &= ln\bar{A} + \chi\, for\, t, t+2, t+4, ... \end{aligned} \tag{28}$$

The first order condition is:

[20]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.

$$W = (1-\gamma)\psi V^{-\gamma}\left[\Pi + \beta\left[EV_W(A') - EV_L(A')\right]\right] \tag{29}$$

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 30, 31 and 32 respectively. If one could run a regression of violence $\hat{v}$ on wages ($\hat{w}$) and controlling for the prize of winning ($\Pi\hat{\Pi} + \beta(\bar{V}_W E\hat{v}_{Wt+1} - \bar{V}_L E\hat{v}_{Lt+1})$), Equation 31 suggests one would estimate the true opportunity cost parameter $-\gamma^{-1}$.[21]

$$\bar{V}_L\hat{v}_{L,t} = \hat{w}_t\bar{W}(1-\bar{V}) - \hat{v}\bar{W}\bar{V} + (1-\gamma)\hat{v}\psi V^{1-\gamma}\left[\bar{\Pi} + \beta\bar{V_W}\right] + \psi V^{1-\gamma}\left[\bar{\Pi}\hat{\pi}_t + \beta\bar{V_W}E\hat{v}_{W,t+1}\right] + \beta\bar{V}_L E\hat{v}_{L,t+1} \tag{30}$$

$$\hat{v} = -\frac{1}{\gamma}\hat{w}_t + \frac{1}{\gamma}\frac{\Pi\hat{\Pi} + \beta(\bar{V}_W\hat{v}_{Wt+1} - \bar{V}_L\hat{v}_{Lt+1})}{\Pi + \beta(\bar{V}_W - \bar{V}_L)} \tag{31}$$

$$\hat{v}_{W,t} = \frac{\bar{A}}{\bar{V_W}}\hat{a}_t + \beta\hat{v}_{W,t+1} \tag{32}$$

Wages and profits become:

$$\hat{w} = \hat{a} + (1-\alpha)\frac{V}{1-V}\hat{v} \tag{33}$$

$$\hat{\pi} = \hat{a} - \alpha\frac{V}{1-V}\hat{v} \tag{34}$$

The model is not analytically tractable, so instead we simulate data when productivity is driven by persistent shocks (like commodity price shocks) or anticipated seasonal variation in productivity, and estimate a regression of simulated violence on simulated wages. As in the previous model, we calibrate the parameters so that the estimated opportunity cost parameter when wages are driven by persistent shocks (with $\rho = 0.96$) is -1.5, as estimated in the data for Colombia (parameters in the appendix).[22] As before, with a persistent shock of $\rho = 0.96$, the bias due to omitting variation

[21] Unfortunately, the prize of winning is typically unobserved, and when productivity shocks are persistent the prize of winning is co-linear with wages.

[22] Other parameters are λ, ψ and α. $\alpha = 0.5$ calibrated to the all-countries, all-years average of the labor share from PWT8 (full value 0.5459). λ and ψ are chosen to keep the steady state share of violence low (at around 7%),

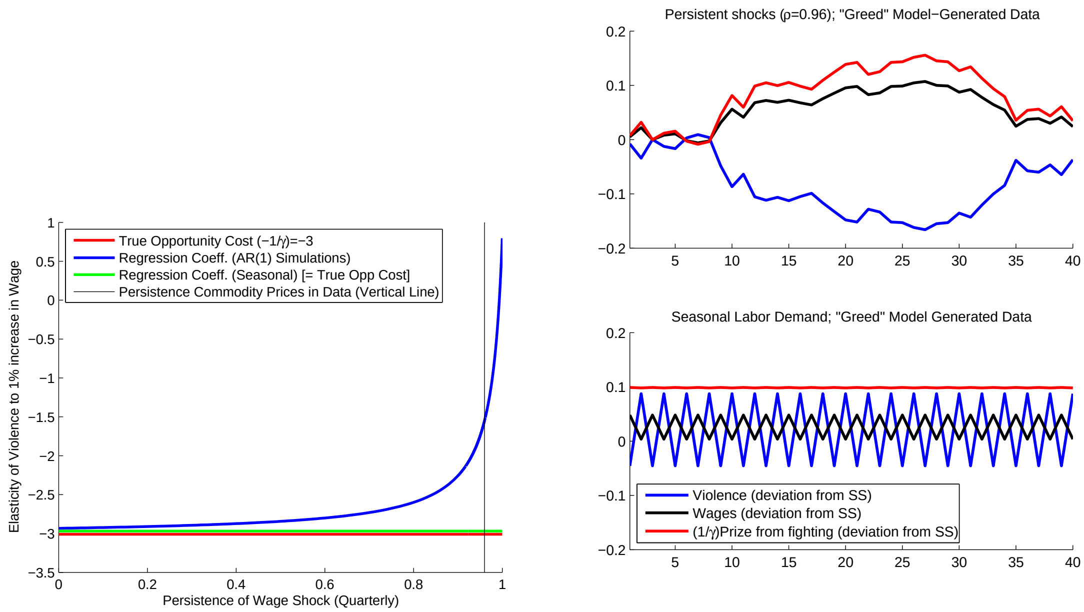


Figure 2: Rebel for Money Model: A. estimated coefficient (LHS) and B. simulated data (RHS)

in 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 price 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.[23] 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.

while matching the elasticity of violence to wages in the data with $\rho = 0.96$.

[23] 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 $(\bar{\Pi}/(\bar{\Pi} + \beta(\bar{V}_W - \bar{V}_L))$.

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 ideally one would 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 time-series for local wages, hence we estimate 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. Additional evidence showing that harvest brings about changes in local labor markets also supports 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 sought the most disaggregated data on violent incidents to match the fine-grained spatial variation of harvesting calendars across the country. Because we exploit monthly by-cell or 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 cell-by-month or district-by-month level (for example, precipitation or temperature).

Violence. Our main dependent variable is the number of attacks per cell[24] per month or the number of attacks per district per month. For each case we attempt to examine as many different datasets on violence as possible, 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). For *Iraq* we use the World Incident Tracking System (WITS) and the Global Terrorism Dataset (GTD). We also examine results using SIGACTS v.3. provided by Berman et. al. (2011a), which is based on coalition reports but is sensitive to the specification used and discussed further in the Appendix. In the case of *Pakistan*, we use the BFRS dataset on political violence which is available at the district-level as well as the GTD data which is precisely geo-located.

Harvesting Calendars. The timing of harvest for each cell or district is constructed from the FAO Global Agro Ecological Zones v3.0[25] (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 immediately after a given cell ends its growing cycle. Because this will

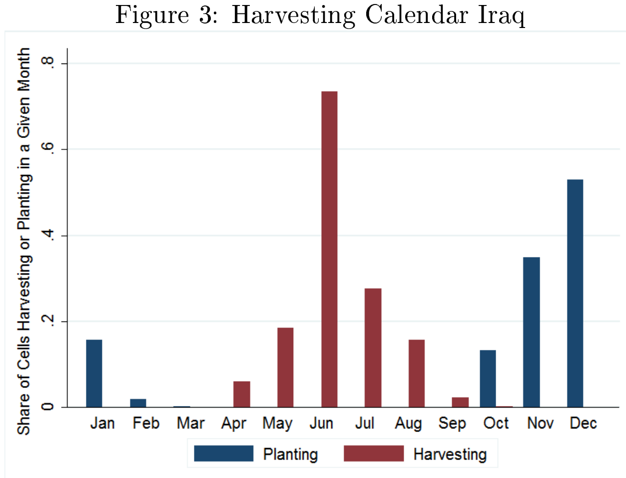
[24] A cell is the equivalent of around 121 square kilometers, which is 47 sq miles or 2/3 the area of the District of Columbia

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

measure imprecisely those areas whose cycle ends early in the month, we also conduct robustness checks which simply examine the month in which growing ends. For each crop we also capture whether the crop cultivated uses high, medium or low inputs which captures whether the crop is mainly for subsistence or commercial agriculture. Because our indicator captures the onset of harvesting for any type, one given cell 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 prior to 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. Robustness checks for planting also include shifting the calendar by one month to examine whether results are robust. As an example, Figure 3 below shows the harvesting calendars for Iraq. Since the harvesting date varies across cells within the year, it provides within country variation in the month in which wheat is cultivated thus allowing for identification of its effect. For Iraq, around half the wheat is cultivated in June, yet, some areas also harvest as late as September and others as early as April.

Figure 3: Harvesting Calendar Iraq



Crop Production. Crop production is measured in hundreds of square kilometers and is calculated by the FAO using statistics from the year 2000 following the outline of the study "Agriculture Towards 2010/30". 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 (start day in days) combined by how long it needs to grow according to where it is cultivated (length cycle) and weighted by how much wheat is cultivated in the cell.

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

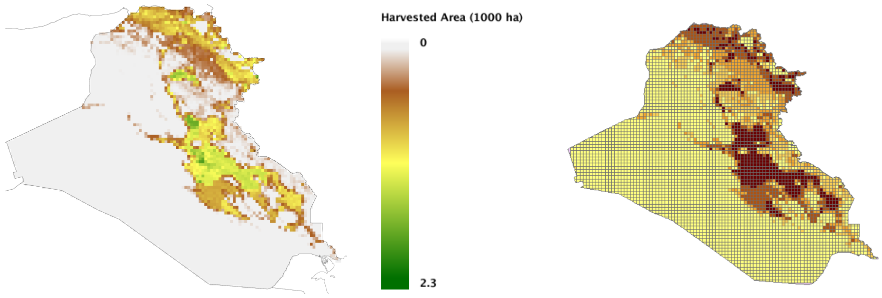


Figure 5: Left: Start Day Medium Input Wheat Irrigated. Right: Gridded Start Day

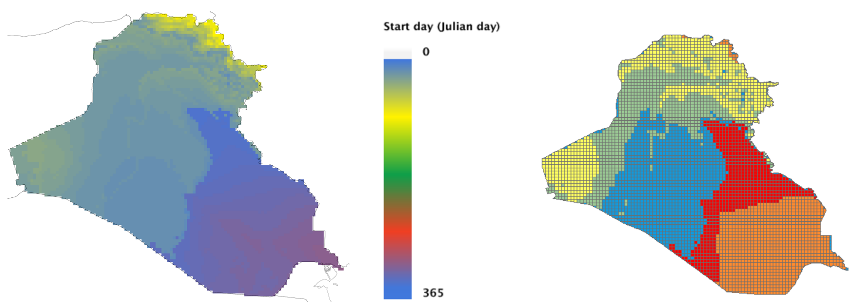
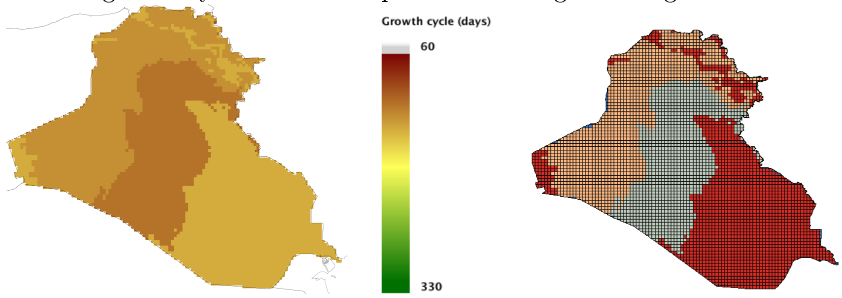


Figure 6: Left: Length of Cycle Medium Input Wheat Irrigated. Right: Gridded Length Cycle



Additional controls. Additional control variables at the cell or district level 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-cell or monthly-district measures of precipitation (in milimeters) and temperature (degrees celsius) for Iraq (2003-2010) and Pakistan (1988 to 2010) coded 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, and 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.[26]

3.2 Estimation

Let c index each 0.1 by 0.1 decimal degree cell in the country (approximately 11 kms by 11 kms or 121 square kilometers), i index districts, m months and year t . Our outcome of interest $Attacks_{cimt}$, is the number and type of attacks in a given cell, district, calendar month and year. This is equivalent to looking at the monthly number of attacks per 121 square kilometers. Our key independent variable $Harv_{cim} \times Prod_{ci}$ is the number of hundred square kilometer of wheat in harvest in cell c, district i , month m and year t . In all specifications we also include the effect of the planting season on violence. At the cell level we estimate:

$$Attacks_{cimt} = \alpha_{it} + \gamma_m + \beta(Harv_{cim} \times Prod_{ci}) + \mathbf{x}_{cimt} + e_{cimt} \tag{35}$$

At the district level, we estimate a similar specification (without the c subscripts):

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

$$Attacks_{imt} = \alpha_{it} + \gamma_m + \beta(Harv_{im} \times Prod_i) + \mathbf{x}_{imt} + e_{imt} \tag{36}$$

Where α_{it} is a district by year fixed effect, and γ_m is a month fixed effect (e.g June); $\mathbf{x}_{cimt}$ is a vector of monthly cell or district characteristics such as monthly temperature in degrees Celsius and precipitation in millimeters. The parameter of interest is β which captures the effect of harvesting on conflict intensity and types of attacks.

Standard errors are clustered in two ways. First, we cluster at the governorate-year level which allows for correlation across districts within the same governorate, while still having a large number of clusters (Panel A of Tables 1, 9 and 3).[27] Second, we cluster at the district level, which accounts for serial correlation in the error terms for that spatial unit (Panel B in those same tables).[28] Finally, for comparability with the BFRS dataset, which is available at the district level, we aggregate cell-based estimates to the district level (Panel C of Tables 1, 9 and 3), with standard errors clustered at the district level.

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. Specifically, we exploit the roll-out of harvest and compare cells in harvest with other cells in the same district and month that are not.[29] Since the timing of harvest is given by a combination of geographic and climate factors, it is unlikely to be manipulated by conflict dynamics.[30] 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.

While reverse causality is not 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 exert an upward bias in our results. That is, the true coefficients would be actually larger (e.g. more negative) than the our estimated coefficient. Similar concerns arise with the amount of precipitation, since intense rainfall

[27] Bertrand et al (2004) argue that in diff-in-diff studies, serial correlation does not lead to incorrect inference if the policy variable (harvest in our case) is not serially correlated.

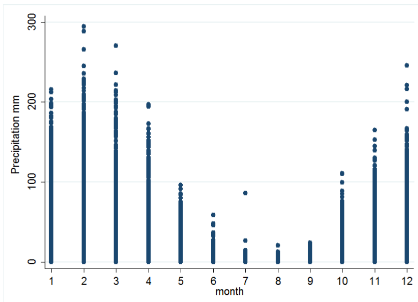
[28] In order to prevent results that are sensitive to particular observations, in all cell-based regressions we drop outliers defined as those above the 99th percentile (conditional on a positive number of attacks).

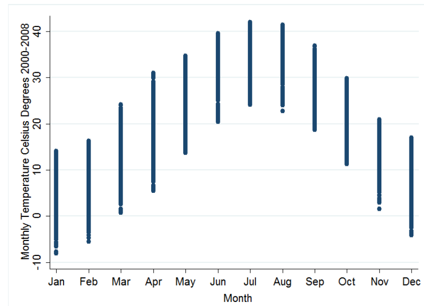
[29] Alternatively, how violence changes in districts in harvest relative to the change in districts not in harvest.

[30] Moreover, since we are looking at months, these constitute a relative large "window". That is, while is it possible that conflict may shift grain collection for some weeks, it is unlikely to do so for a whole month since it would be pointless from the production standpoint: either crops will not be ripe or would be losing moisture as time passes.

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 ocurring such that, if anything, coefficients would also be upward biased.

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





4 Empirical Results

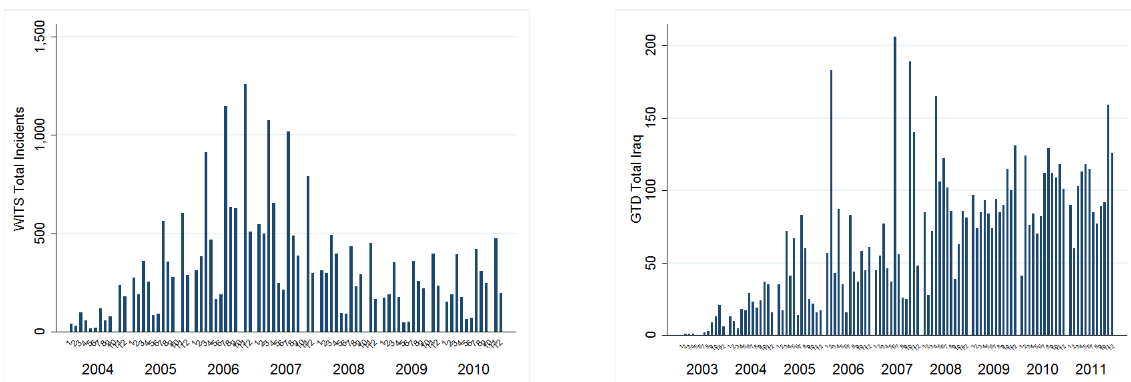
Our results show that across different conflicts seasonal labor markets play a key role in determining within-year variation in the intensity of violence. Given the differences in data sources and coding methods we present each case separately while holding constant the main specification.

The Iraqi Conflict

Between 2004-2011 Iraq was grippled by a civil conflict along sectarian lines as well as Sunni insurgencies in numerous parts of the country. The intensity of the conflict, coupled with the long 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. Figure 8 and 9 below shows the spatial and time distribution of conflict incidents across cells of approximately 0.1 by 0.1 degrees (or approximately 11 kms by 11 kms) recorded by two different datasets: WITS (left) and GTD (center). As noticed in the bottom panel, these differ both in the overall frequency of the attacks recorded and their distribution over time.

Figure 8: Left: WITS. Right: GTD.

Figure 9: Left: WITS. Right: GTD.



WITS Dataset (Iraq). Our analysis starts by examining the patterns of insurgent activity using geo-coded incidents captured by the Worldwide Incidents Tracking System (WITS) which is based on media accounts of terrorist events.[31] 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).[32] In addition to tracking the number of terrorist events, the dataset also provides

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

[32] "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)

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. We use these different categorizations to examine whether harvest induces insurgent groups to switch to certain tactics at the expense of others (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. IED's) (Bueno de Mesquita et. al. 2015). We also report results where we pool across all attack types.

Table 1 Panel A & B shows the estimates from Equation 35 using as dependent variable the monthly number of terrorist incidents across cells (aprox. 121 square kms) between 2004 and 2010. Columns (1) through (3) in Panel A show how the onset of harvest leads to a reduction in total levels of violence, and a reduction in both asymmetric and labor-intensive attacks. In terms of magnitude, the coefficient of -0.94 in column (1) suggests that an increase of one hundred square kilometers of wheat production at harvest leads to a reduction of approximately 0.94 less total attacks per month. Considering the average production of wheat at the cell-level is 0.019 hundred square kilometers (1.9 square kms), the coefficient implies a reduction of 0.018 attacks, or around 37% of average number of total attacks per month per cell (0.049). Similar effects are shown in column (2), where a reduction of 0.5 asymmetric attacks per hundred square kilometers of wheat cultivated at harvest also represents around a 40% reduction in the average number of asymmetric attacks, while column (3) shows the reduction in labor intensive attacks by 0.45 per hundred sq km in harvest, or about 36% of mean labor intensive attacks. Consistent with these findings, column (4) shows that the number of victims declines by 1.3 for each additional hundred square kilometers of cultivated wheat at harvest or 38% evaluated at the mean number of victims per month. These results are significant at the 1% level. In Panel B, we cluster standard errors at the district level (rather than gov$\times$ yr) in order to take account of serial correlation. Although this level of clustering doubles the standard errors, coefficient estimates are still significant at the 5% level. In Panel C, we aggregate cell-level data up to the district level (also with district level clustering). The estimates are significant at the 5% level, and coefficients sizes (and % of mean attacks) are only slightly smaller than those in Panels A and B. Additional results in the appendix show that the results are mostly driven by the reduction in armed attacks, IEDs and bombings during harvest (Table 5). Table 6 and 7 show these findings are similar when restricting the sample to wheat producing areas or areas which experience conflict during the sample, respectively.[33]

[33] Additional results in the Table 8 in the appendix shows that harvest seems unrelated to the mix of labor versus asymmetric attacks once we condition on violence.

Table 1: Seasonal Labor and Violent Incidents in Iraq: WITS Data

	(1)	(2)	(3)	(4)
	Panel A: GovXYear Clusters			
VARIABLES	Total	Asymm	Laborint	Victims
$Harv_{cim} \times Prod_{ci}$	-0.946***	-0.504***	-0.450***	-1.318***
	(0.204)	(0.120)	(0.098)	(0.291)
Mean DV	0.049	0.024	0.024	0.066
Observations	371,242	371,242	371,242	371,242
GovXYear Cluster	119	119	119	119
	Panel B: District Clusters			
$Harv_{cim} \times Prod_{ci}$	-0.946**	-0.504**	-0.450**	-1.318**
	(0.422)	(0.233)	(0.195)	(0.589)
Mean DV	0.049	0.024	0.024	0.066
Observations	371,242	371,242	371,242	371,242
District Cluster	101	101	101	101
	Panel C: Aggregating by District			
$Harv_{cim} \times Prod_{ci}$	-0.739**	-0.369*	-0.380**	-1.018**
	(0.355)	(0.204)	(0.174)	(0.489)
Mean DV	2.15	1.080	1.067	2.91
Observations	8,484	8,484	8,484	8,484
District Cluster	101	101	101	101
District X Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y
Planting	Y	Y	Y	Y

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells / district
is 0.019 / 0.86 hundred sq kilometers, respectively
*** p<0.01, ** p<0.05, * p<0.1

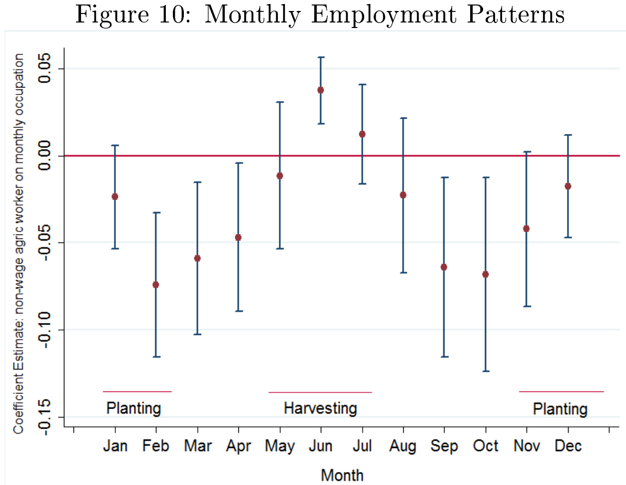
GTD Dataset (Iraq). As a cross-check to our results we run the same specification but now using as dependent variable instances of violence coded by the Global Terrorism Dataset (GTD). This dataset is maintained by the National Consortium for the Study of Terrorism and Responses to Terrorism (START) at the University of Maryland and is also based on media reports, includes relatively more detailed information on attack types, yet exhibits a much lower frequency of attacks overall. Table 9 in the Appendix shows that there is some evidence of lower seasonal attacks during harvest periods, but it is not robust across specifications. Specifically, in Panel A an increase of a hundred square kilometers of wheat cultivation per cell at harvest leads to a reduction of 0.09 attacks, driven almost entirely by asymmetric attacks. These results are significant at 10% level, and suggest a fall in the number of attacks by about 7-8%. The results in the rest of the table are not significant. A more detailed investigation of differences between the GTD and WITS results are an area for future research.[34]

Mechanism and Alternative Explanations

For these results to be consistent with the theoretical framework, it must be that the onset of harvest in a cell leads to tangible differences in labor market outcomes. To assess whether this is the case we use 2006 LSMS Iraqi household survey, to examine whether regional patterns of harvesting relate to employment and wage changes among agricultural workers. Ideally, we would like to match each respondent to a particular cell and follow it throughout the years. However, due to privacy concerns and budget constraints, 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 10 shows the difference in the probability of employment among agricultural workers (relative to non-agricultural workers) by month. As shown, these differences, controlling for a number of factors, closely follow the harvesting season in rural Iraq. This is consistent with the idea that harvesting affects conflict by influencing local labor markets.

Figure 10: Monthly Employment Patterns



Y-axis: coefficients from a regression of monthly employment ("Do you worked in this job in month..."?) on agricultural worker status. 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 survey cluster.

[34]Further robustness tests in the appendix show these results are similar when disaggregating among different conflict categories 10, while shows that the relative mix of tactics – conditioning on violence — appears to be unrelated to the onset of harvest (Table 11).

Job Switching and Migration. One concern with these findings is whether the wording of the question leaves open the possibility that individuals switched jobs within the year. However, 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. Thus unlikely to be switching across 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%.

Religious Calendar. In addition to showing how employment patterns vary with 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 (1988-2011) Ramadan always fell between August and October or August and January respectively, well after the harvesting season in each case. More importantly, these festivities are likely to be captured in specifications that include month of the year fixed effects. 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 12 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. These patterns are consistent with the idea that the reduction in violence is unlikely to be driven by increased religiosity among agricultural workers at harvest.

The Pakistani Conflict (1988-2010)

For the case of Pakistan we examine patterns of seasonal conflict using the BFRS Political Violence Dataset (Bueno de Mesquita et. al. 2015) which carefully categorizes every violent incident – regardless of whether terrorist in nature or not – into whether it is conventional (e.g. labor intensive) or asymmetric (e.g. relies less on labor) for Pakistan between 1988 and 2010. We also include the Global Terrorism Dataset (GTD) which provides precisely geolocated information on the number of attacks across the country for the same period.[35]

[35] More precisely, the authors 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

BFRS Dataset (Pakistan). Table 2 below presents the results with the same specification as before but using district-level attacks in Pakistan between 1988 and 2010. 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) which is mostly driven by the reduction in asymmetric attacks (column 3). In contrast, there is a negative, yet small and imprecise effect on the number of conventional attacks per district per month throughout the period. This is potentially driven by the fact that conventional attacks are about 10 times less prevalent than asymmetric attacks. Nonetheless, these coefficients suggest that an additional hundred square kilometers at harvest would lead to a reduction of 0.001 monthly district attacks. Since on average, districts cultivate about 4.51 hundred square kilometers of wheat and the average number of monthly attacks per district is 0.12, the coefficients imply an overall reduction of 4-5% in the number of attacks evaluated at means. Similar effects, if not larger, are observed for the planting season. Other results looking at the share of certain types of attacks yield no clear pattern of results (Table 13 in the appendix); in addition, state-initiated attacks are not more prevalent during harvesting months (not shown), thus are not driving the reduction in other forms of violence.

Table 2: Seasonal Labor and Violent Incidents in Pakistan: BFRS Data

VARIABLES	(1) Total	(2) Total Mil	(3) Mil Asym	(4) Mil Convt
$Harv_{cim} \times Prod_{ci}$	-0.001**	-0.001**	-0.001**	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)
$Plan_{cim} \times Prod_{ci}$	-0.002***	-0.002**	-0.001**	-0.000*
	(0.001)	(0.001)	(0.001)	(0.000)
Mean DV	0.12	0.11	0.10	0.01
Observations	35,022	35,022	35,022	35,022
Clusters	128	128	128	128
District X Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y

Robust Standard Errors Clustered at the District level in parentehsis.
$Prod_{ci}$ is measured in hundred sq kms.
The average level of wheat production per district in Pakistan is 4.5 hundred sq kms. *** p<0.01, ** p<0.05, * p<0.1

GTD Dataset (Pakistan). Additional evidence from the Global Terrorism Dataset (GTD) shows some evidence in favor some seasonality of conflict, though results are not as robust as using BFRS. Panel A of Table 3 shows that an increase of a hundred square kilometers of wheat at harvest reduces attacks involving bombs (asymmetric) by around 0.001. Considering that the average cell cultivates around 0.074 hundred square kilometers of wheat this implies a 7% reduction

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) of attacks evaluated at the average monthly number of total or asymmetric attacks. These results are consistent in sign but less precisely estimated when clustering the standard errors at the district-level (Panel B). When reducing potential measurement error via aggregation, the overall reduction in violence (column 1 Panel C) is consistent with the findings from Panel A.

Table 3: Seasonal Labor and Violent Incidents in Pakistan: GTD Data

	(1)	(2)	(3)
	Panel A: GovXYear Cluster		
VARIABLES	Total	Asym (Bomb)	Laborint (Attack)
$Harv_{cim} \times Prod_{ci}$	-0.001*	-0.001**	0.000
	(0.001)	(0.001)	(0.000)
Mean DV	0.001	0.001	0.0008
Observations	2,151,950	2,151,950	2,151,950
GovXYear Cluster	138	138	138
	Panel B: District Cluster		
$Harv_{cim} \times Prod_{ci}$	-0.001	-0.001	0.000
	(0.002)	(0.001)	(0.001)
Mean DV	0.001	0.001	0.0008
Observations	2,151,950	2,151,950	2,151,950
District Cluster	128	128	128
	Panel C: Aggregating by District		
$Harv_{cim} \times Prod_{ci}$	-0.002**	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Mean DV	0.1	0.07	0.05
Observations	35,328	35,328	35,328
District Cluster	128	128	128
District X FE	Y	Y	Y
Month FE	Y	Y	Y
Temp& Precip	Y	Y	Y

Ouliters, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred square kilometers.
The average level of wheat production per cell/district in Pakistan
is 0.074 /4.51 hundred sq kms. respectively. *** p<0.01, ** p<0.05, * p<0.1

Conclusion

This paper has examined how seasonal variation in labor demand has a negative effect on the intensity of violence. In both Iraq and Pakistan, the number of attacks is lower during harvest. Such a reduction in violent attacks ranges between 4-5% in Pakistan (BFRS data) to 30-40% in Iraq (WITS dataset) when evaluated at the average number of monthly attacks and the average amount of wheat cultivated by cell/district. The main results are robust to excluding regions that are not wheat 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. However, the way that attacks are coded seems important: although there is some evidence of seasonality using the Global Terrorism Dataset, 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. Similary, 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 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.

References

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

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

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

[4] 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.

[5] 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)*

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

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

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

[9] 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.

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

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

[12] 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.

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

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

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

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

[17] 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.

[18] 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.

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

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

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

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

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

[24] 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.

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

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

[27] Guardado, J. 2015. "Land Tenure, Price Shocks and Insurgency: Evidence from Peru and Colombia". Mimeo.

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

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

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

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

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

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

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

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

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

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

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

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

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

[41] 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.

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

Theoretical Appendix

Model 1: Rebellion for a "Cause or Grievance"

Static Model

Another way to see the bias is solve explicitly for violence as a function of wages, after substituting out consumption. Taking a log-linear approximation[36] of Equation 5, and constraint 2, the expression for violence becomes Equation 37. Here $\hat{x} = lnX - ln\bar{X}$ represents the percentage deviation from "steady state", and $\bar{X}$ represents the value around which we are approximating (the non-stochastic steady state in a dynamic model).

$$\hat{v} = \frac{(1-\bar{V})(\sigma-1)}{\gamma(1-\bar{V})+\sigma\bar{V}}\hat{w} \tag{37}$$

From Equation 37, one can see that the relative strength of the income and substitution effects depends on the size of σ (risk aversion). For $\sigma = 0$ (linear utility), all income effects are removed and a simple uni-variate regression uncovers the true elasticity $-1/\gamma$. If $0 < \sigma < 1$, the substitution effect dominates the income effect: the coefficient on wages is still negative, but is biased upwards. For $\sigma = 1$ (*log* preferences), the income and substitution effects exactly cancel, so there is no effect of wages on violence. Finally, in the case where $\sigma > 1$: the marginal utility of consumption changes so much that an increase in wages actually *increases* consumption.

Table 4: Parameters for Model Simulations

Model	True Opp. cost ($-\gamma^{-1}$)	γ	ψ	σ	$\bar{W}$	$\bar{A}$	β	λ	α	$\bar{V}$	ρ_{LIT}	Estimated Elasticity
(1) Rebel for A Cause	-3	1/3	0.5	2	1	-	0.99	-	-	0.07	0.96	-1.5
(2) Rebel for Money	-3	1/3	0.015	-	-	1	0.99	3/4	0.5	0.07	0.96	-1.5

[36]The log-linear approximation is a first order Taylor series approximation of the model's FOCs and budget/resource constraints. 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 $X_t = e^{logX_t}$)).

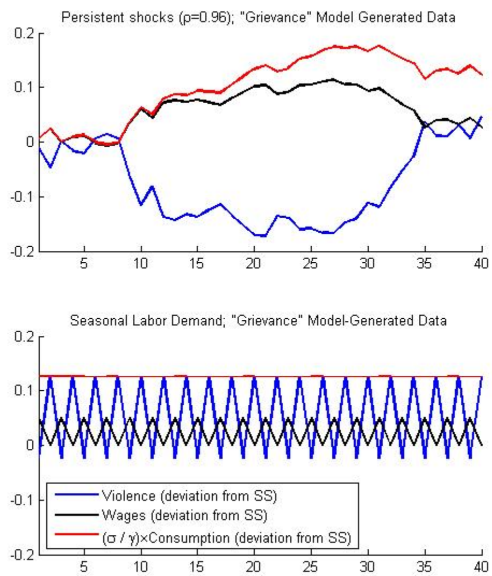


Figure 11: Rebel for a Cause Model: simulated data

Empirical Appendix

Iraq

Table 5: Seasonal Labor and Violence: Disaggregating Types (WITS)

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Armed Attack	Assault	IED	Suicide	Bombing
	Panel A: GovXYear Cluster				
$Harv_{cim} \times Prod_{ci}$	-0.450***	-0.009***	-0.453***	-0.051***	-0.459***
	(0.098)	(0.002)	(0.108)	(0.017)	(0.109)
Mean DV	0.024	0.0003	0.021	0.002	0.021
Observations	371,242	371,242	371,242	371,242	371,242
GovXYear Clusters	119	119	119	119	119
	Panel B: District Cluster				
$Harv_{cim} \times Prod_{ci}$	-0.450**	-0.009***	-0.453**	-0.051*	-0.459**
	(0.195)	(0.003)	(0.208)	(0.026)	(0.210)
Mean DV	0.024	0.0003	0.021	0.002	0.021
Observations	371,242	371,242	371,242	371,242	371,242
District Clusters	101	101	101	101	101
	Panel C: Aggregating by District				
$Harv_{cim} \times Prod_{ci}$	-0.739**	-0.380**	-0.006	-0.331*	-0.038
	(0.355)	(0.174)	(0.005)	(0.174)	(0.031)
Mean DV	1.067	0.015	0.95	0.12	0.96
Observations	8,484	8,484	8,484	8,484	8,484
District Clusters	101	101	101	101	101
District X Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Temp & Precip	Y	Y	Y	Y	Y
Planting	Y	Y	Y	Y	Y

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells / district
is 0.019 / 0.86 hundred sq kilometers, respectively
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Seasonal Labor and Violence: WITS Data and Dropping Cells with No Wheat Production

VARIABLES	(1) Total	(2) Asym	(3) Laborint	(4) Victimcoun
	Panel A: GovXYear Cluster			
$Harv_{cim} \times Prod_{ci}$	-1.025***	-0.531***	-0.497***	-1.432***
	(0.233)	(0.128)	(0.117)	(0.329)
Observations	141,586	141,586	141,586	141,586
Gov X Year	119	119	119	119
	Panel B: District Cluster			
$Harv_{cim} \times Prod_{ci}$	-1.025**	-0.531**	-0.497**	-1.432**
	(0.470)	(0.253)	(0.218)	(0.659)
Observations	141,586	141,586	141,586	141,586
District Clusters	100	100	100	100
	Panel C: Aggregating by District			
$Harv_{cim} \times Prod_{ci}$	-0.735**	-0.367*	-0.378**	-1.013**
	(0.355)	(0.204)	(0.175)	(0.489)
Observations	8,400	8,400	8,400	8,400
District Clusters	100	100	100	100
District by Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Planting	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells / district
is 0.019 / 0.86 hundred sq kilometers, respectively
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: Seasonal Labor and Violence: WITS Data and Only Cells Ever in Conflict

	(1)	(2)	(3)	(4)
VARIABLES	Total	Asym	Laborint	Victimcoun
Panel A: GovXYear Cluster				
$Harv_{cim} \times Prod_{ci}$	-4.273***	-2.219***	-1.965***	-6.046***
	(1.081)	(0.524)	(0.594)	(1.499)
Observations	23,482	23,482	23,482	23,482
GovXYear Clusters	119	119	119	119
Panel B: District Cluster				
$Harv_{cim} \times Prod_{ci}$	-4.273*	-2.219**	-1.965*	-6.046*
	(2.171)	(1.072)	(1.068)	(3.039)
Observations	23,482	23,482	23,482	23,482
District Clusters	79	79	79	79
Panel C: Aggregating by District				
$Harv_{cim} \times Prod_{ci}$	-0.751*	-0.374*	-0.386**	-1.035*
	(0.379)	(0.217)	(0.188)	(0.522)
Observations	8,148	8,148	8,148	8,148
District Clusters	97	97	97	97
District by Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Planting	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells / district
is 0.019 / 0.86 hundred sq kilometers, respectively
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Seasonal Labor and Violence: Share of Violence Types of Total in WITS Data

	(1)	(2)	(3)	(4)
Panel A: GovXYear Cluster				
VARIABLES	% IED	% Attack	% Suicide	% Assault
$Harv_{cim} \times Prod_{ci}$	-0.141	0.036	-0.143	-0.064
	(0.405)	(0.449)	(0.232)	(0.052)
Observations	3,661	3,661	3,661	3,661
GovXYear Clusters	114	114	114	114
Panel B: District Cluster				
VARIABLES	% IED	% Attack	% Suicide	% Assault
$Harv_{cim} \times Prod_{ci}$	-0.141	0.036	-0.143	-0.064
	(0.391)	(0.488)	(0.260)	(0.052)
Observations	3,661	3,661	3,661	3,661
District Clusters	79	79	79	79
Panel C: Aggregating by District				
VARIABLES	% IED	% Attack	% Suicide	% Assault
$Harv_{cim} \times Prod_{ci}$	-0.033**	0.012	-0.008	0.002
	(0.015)	(0.014)	(0.018)	(0.003)
Observations	2,176	2,176	2,176	2,176
District Clusters	79	79	79	79
District X Year FE	Y	Y	Y	
Month FE	Y	Y	Y	
Planting	Y	Y	Y	
Temp& Precip	Y	Y	Y	

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells / district
is 0.019 / 0.86 hundred sq kilometers, respectively
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Seasonal Labor and Violent Incidents in Iraq: GTD Data

VARIABLES	(1) Total Att	(2) Asymm	(3) Laborint
	Panel A: GovXYear Cluster		
$Harv_{cim} \times Prod_{ci}$	-0.096*	-0.084*	-0.031
	(0.052)	(0.047)	(0.020)
Mean DV	0.024	0.022	0.007
Observations	371,256	371,256	371,256
GovXYear Cluster	119	119	119
	Panel B: District Cluster		
$Harv_{cim} \times Prod_{ci}$	-0.096	-0.084	-0.031
	(0.119)	(0.106)	(0.040)
Mean DV	0.024	0.022	0.007
Observations	371,256	371,256	371,256
District Cluster	101	101	101
	Panel C: District Aggregate		
$Harv_{cim} \times Prod_{ci}$	0.042	0.045	0.002
	(0.032)	(0.034)	(0.018)
Mean DV	1.08	0.97	0.35
Observations	8,484	8,484	8,484
District Cluster	101	101	101
District X Year FE	Y	Y	Y
Month FE	Y	Y	Y
Temp& Precip	Y	Y	Y
Planting	Y	Y	Y

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells/district is 0.019/0.86 hundred sq kms, respectively.
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Seasonal Labor and Violent Incidents in Iraq: GTD Dataset - Disaggregating types of violence.

VARIABLES	(1) guerrilla	(2) suicide	(3) attack	(4) bomb	(5) total
Panel A: GovXYear Cluster					
$Harv_{cim} \times Prod_{ci}$	-0.010*	-0.005	-0.031	-0.080*	-0.096*
	(0.006)	(0.009)	(0.020)	(0.043)	(0.052)
Observations	371,256	371,256	371,256	371,256	371,256
GovXYear Cluster	119	119	119	119	119
Panel B: District Cluster					
$Harv_{cim} \times Prod_{ci}$	-0.010	-0.005	-0.031	-0.080	-0.096
	(0.008)	(0.015)	(0.040)	(0.092)	(0.119)
Observations	371,256	371,256	371,256	371,256	371,256
District Cluster	101	101	101	101	101
Panel C: Aggregating by District					
$Harv_{cim} \times Prod_{ci}$	-0.010	-0.005	-0.031	-0.080	-0.096
	(0.008)	(0.015)	(0.040)	(0.092)	(0.119)
Observations	8,484	8,484	8,484	8,484	8,484
District Clusters	101	101	101	101	101
District X Year FE	Y	Y	Y	Y	Y
Month FE	Y	Y	Y	Y	Y
Planting	Y	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y	Y

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells / district
is 0.019 / 0.86 hundred sq kilometers, respectively
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Seasonal Labor and Violent Incidents in Iraq: Share of Violence Types in GTD Data

	(1)	(2)	(3)	(4)
VARIABLES	% Guerrilla	% Suicide	% Bomb	% Attack
Panel A: GovXYear Cluster				
$Harv_{cim} \times Prod_{ci}$	0.010	0.376	0.313	-0.323
	(0.132)	(0.396)	(0.531)	(0.543)
Observations	1,799	1,799	1,799	1,799
GovXYear Cluster	100	100	100	100
Panel B: District Clusters				
$Harv_{cim} \times Prod_{ci}$	0.010	0.376	0.313	-0.323
	(0.154)	(0.369)	(0.603)	(0.585)
Observations	1,799	1,799	1,799	1,799
District Clusters	66	66	66	66
Panel C: Aggregating by District				
$Harv_{cim} \times Prod_{ci}$	-0.006	0.006	0.003	-0.007
	(0.010)	(0.017)	(0.024)	(0.024)
Observations	1,369	1,369	1,369	1,369
District Clusters	66	66	66	66
District X Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Planting	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y

Outliers, defined as above 99th pct, dropped.
$Prod_{ci}$ is measured in hundred sq kilometers.
The average level wheat production for Iraqi cells / district
is 0.019 / 0.86 hundred sq kilometers, respectively
*** p<0.01, ** p<0.05, * p<0.1

We show the results using measures of insurgent activity based on reports by Coalition Forces (SIGACTS)[37] aggregated at the district-month-level by Berman et. al. (2011a). Although this dataset appears to be more comprehensive than others, it has the limitation that it only records violent incidents witnessed by coalition forces thus undercounts instances in which they are not present. Therefore, if Coalition Forces are deployed in non-random ways across wheat producing areas during harvest, this will tend to over or under report actual instances of violence. Results in Table 12 shows that these findings are indicative of a reduction in the number of attacks during harvest period, but these should be interpreted with caution because they are somewhat sensitive to the specification used and scaling of the dependent variable.

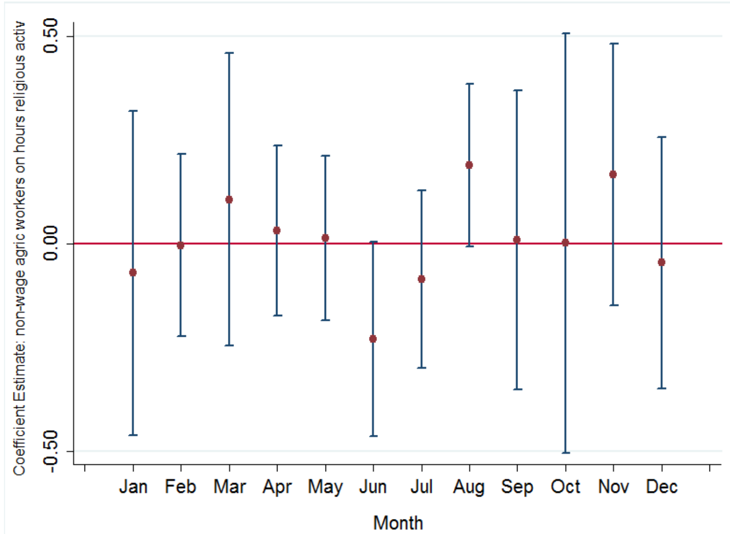
Table 12: Seasonal Labor and Violent Incidents in Iraq: SIGACTS Data

	(1)	(2)	(3)
VARIABLES	SIGACT	DirFire	IED + Suic
$Harv_{im} \times Prod_i$	-0.001*	-0.0004	-0.0004**
	(0.001)	(0.000)	(0.000)
$Plant_{im} \times Prod_i$	-0.001***	-0.0002*	-0.0005**
	(0.000)	(0.000)	(0.000)
Mean DV	2.78	1.18	1.45
Observations	5,985	5,985	5,985
Clusters	101	101	101
Month FE	Y	Y	Y
Year FE	Y	Y	Y
Temp& Precip	Y	Y	Y

Following Berman et.al. 2011a, we cluster standard errors at the district level and estimate the coefficients using first differences.
Incidents (DV) are normalized by number of cells per district.
Estimate equation is
*** p<0.01, ** p<0.05, * p<0.1

[37]This data has been used in a number of other papers. For instance, in Berman et. al. (2011a); Berman et. al. (2011b); Shapiro and Weidmann (2015).

Figure 12: Time Use Survey: Religious Activities per Month



Coefficients from a regression of hours spent on religious activities ("In a given day, how many hours do you spend on..."?) on agricultural worker status or not. 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 survey cluster.

Pakistan (1988-2010)

Figure 13: HARVESTING CALENDAR - PAKISTAN - DISTRICT LEVEL

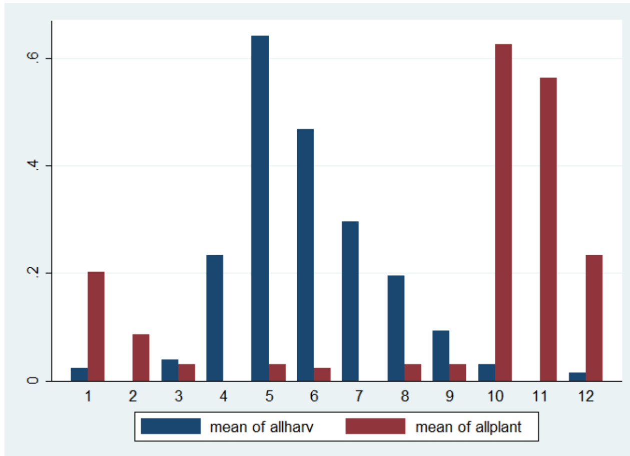


Table 13: Seasonal Labor and Violent Incidents in Pakistan: Share of Violence Types in BFRS Data

VARIABLES	(1) % Milit	(2) % Asym	(3) % Convent	(4) % State
$Harv_{cim} \times Prod_{ci}$	0.000	-0.000	0.000	0.001
	(0.001)	(0.003)	(0.003)	(0.002)
$Plan_{cim} \times Prod_{ci}$	0.001	0.002	-0.002	-0.002
	(0.001)	(0.004)	(0.004)	(0.001)
Observations	2,743	2,667	2,667	2,667
Clusters	95	95	95	95
District X Year FE	Y	Y	Y	Y
Month FE	Y	Y	Y	Y
Temp& Precip	Y	Y	Y	Y

Robust Standard errors Clustered at the District level.
*** p<0.01, ** p<0.05, * p<0.1