Fertile Ground for Conflict

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Abstract. We investigate how variations in soil productivity affect civil conflicts. We first present a model with heterogeneous land in which variations in input prices (fertilizers) affect appropriable rents and the opportunity costs of fighting. The theory predicts that spikes in input prices increase the likelihood of conflicts through their effect on income and inequality, and that this effect is magnified when soil fertility is naturally more heterogenous. We test these predictions using data on conflict events covering all Sub-Saharan African countries at a spatial resolution of 0.5 $\times$ 0.5 degree latitude and longitude over the 1997-2013 period. We combine information on soil characteristics and worldwide variations in fertilizer prices to identify local exogenous changes in input costs. As predicted, variations in soil productivity triggered by variations in fertilizer prices are positively associated with conflicts, especially in cells where land endowments are more heterogeneous. In addition, we find that the distribution of land fertility both within and across ethnic groups affects violence, and that the effect of between-group heterogeneity in soil quality is magnified in densely populated areas. Overall, our findings imply that inequality in access to fertile areas – an issue largely neglected in the literature dealing with the roots of Sub-Saharan African civil wars – constitutes a serious threat to peace at the local-level.

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1 Introduction

Are African conflicts rooted in fertile soils? Over the last decades, unequal access to productive areas has often been mentioned as a key contributing factor to some of the deadliest wars on the continent. In Rwanda for instance, increasing pressure over land stemming from rapid population growth and soil depletion has most likely been one of the triggers of conflicts and genocide (André and Platteau, 1998). Disputes over arable land have also historically played their part in conflicts in Darfur (Faris, 2009).[1] In many countries however, the apparent "ethnic" dimension of these tensions has obscured the fact that they originated from rising land inequality and lack of access to fertile soils.[2] As a result, researchers have investigated the impact of ethnic divisions at great length, largely overlooking similar investigations about the role of soil fertility (Peters, 2004).

This paper studies theoretically and empirically how variations in soil productivity influence the occurrence of violence. We are interested both in the effect of changes in soil productivity over time and in the role of its distribution across space. We proceed in two steps. First, we present a dynamic theory of conflict over agricultural land in which two groups are endowed with units of land that differ in terms of natural fertility. At each period, soil productivity varies due to changes in fertilizer prices. We use this model to derive predictions that relate conflict likelihood to fertilizer prices variations and to the distribution of land quality across groups. These predictions are tested in the second part of the paper using detailed data on conflict events, soil characteristics and local fertilizer prices.

In our model, an increase in the price of fertilizer reduces agricultural rents for both groups and has two opposite effects on conflict probability: it at once lowers the value of what can be appropriated through violence and decreases the opportunity cost of fighting. However, due to heterogeneous land quality, the opportunity cost effect dominates: naturally fertile soils are less dependent upon fertilizer use, which implies that the rents generated from these lands are less sensitive to changes in fertilizer prices. As a consequence, when fertilizer prices rise, the group endowed with the less fertile soil (the land-poor group) has a greater incentive to fight: the decrease in rents from their own land (i.e. opportunity cost of fighting) is greater than the decrease in the potential gains that stand to be obtained from land-rich. In other words, spikes in fertilizer prices increase the risk of conflict through their effect on the level of rents and on the dispersion of rents across groups (i.e. rent inequality). We also show that the positive link between fertilizer price variations and conflict is magnified when natural soil quality is more heterogeneous.

In sum, our model generates two testable predictions: a) variations in fertilizer prices are positively associated with the likelihood of conflict, b) this association is stronger when natural soil fertility is more heterogeneous. We test these predictions using a dataset in which the units of analysis are cells of 0.5 × 0.5 degree latitude and longitude (approx. 55km × 55km at the equator) covering all of Sub-Saharan Africa (SSA) from 1997 to 2013. Testing our theory requires data on (i) conflict events, (ii) soil fertility, and (iii) local variations in fertilizer prices.[3] First,

[1] The violent conflicts between Mauritania and Senegal and between Mali and Burkina Faso (the "wars between brethren") also originated from land disputes between pastoralists and herders (Van den Brink *et al.*, 1995).

[2] Ethnic diversity has been shown to be linked to land characteristics such as soil quality (Michalopoulos, 2012).

[3] Instead of fertilizer prices, one could have also used weather shocks to study (heterogeneous) changes in soil fertility across time and space. Weather shocks may however affect the likelihood of conflict through other channels than agricultural productivity, such as migration, infrastructure quality or competition over water – channels that

we combine original geo-localized datasets on soil characteristics with information on conflict occurrence. The Armed Conflict Location Events Data (ACLED) provides detailed information on the date, location and type of conflict events, and can be used to identify subsets of events that are more likely to be land-related. For each cell, we complement this conflict data with measures of the natural fertility of soils, defined as their inherent nutrient content. These measures come from the Harmonized World Soil Database and are available at a highly disaggregated level; this allows us to calculate our measure of land inequality, as the variance of natural soil fertility within each cell.

The final variable we construct is the local price of fertilizers. Direct information on time-varying prices at a spatially disaggregated level is not readily available. Furthermore, even if we were able to observe such prices, they would be endogenous to conflict. We circumvent this issue by computing a proxy for local fertilizer prices. The measure we build is informed by the fact that fertilizers are comprised of three main nutrients (nitrogen, phosphate and potassium) and that the ideal composition of fertilizers varies across crops. More precisely, for each cell we identify the main crop(s) produced – using the FAO's Global Agro-Ecological Zones (GAEZ) – and the required balance of nutrients for each of these crops. We then use data on the world prices of each nutrient to construct a cell-specific, time-varying indicator of fertilizer price. Because our identification strategy makes use of within-cell variations in fertilizer prices and conflicts over time, we are able to control for cell-fixed effects and unobserved common time shocks. Moreover, since we use the world prices of nutrients to compute local fertilizer prices, reverse causality from conflict to fertilizer prices is unlikely to drive our results. Using external data for a subset of countries and years, however, we show that such prices for specific nutrients are indeed transmitted to local fertilizer prices. We also provide indirect evidence that the mix of nutrients used by farmers in SSA is indeed correlated with the recommended mix for their particular crop.

We find empirical support for the predictions of the model. First, an increase in fertilizer price makes local conflicts more likely to occur. Second, spikes in fertilizer prices are found to trigger more conflict in cells where soil fertility is naturally heterogeneous, i.e. in cells characterized by areas of both nutrient-rich as well as nutrient-poor soil. Quantitatively, the effect of variations in fertilizer prices is 50% higher in cells where soil fertility is one standard deviation more heterogeneous than the sample mean. These results hold across various measures of conflicts, soil fertility and nutrient mixes, and are robust to the use of alternative estimators and inference methods. Dropping the years during which commodities prices spiked (2008-2009) has little effect on our estimates. They also remain stable when we control for other co-determinants of violence that might be correlated with soil characteristics or with fertilizer price variations (e.g. time-invariant or slow-moving characteristics such as geography, institutions, social cleavages, or time-varying determinants such as weather conditions, or the prices of produced or consumed commodities). Interestingly, we find quantitatively stronger results when we restrict our sample to events that are more likely to reflect conflict over land. On the other hand, no significant effect is detected in countries where fertilizer use is close to zero.

We also provide suggestive evidence that our results indeed originate from the mechanisms at play in our model. Using data at the household-plot level from the World Bank Living Standard

cannot be easily controlled for. See Sarsons (2015) for a discussion of the impact of rainfall on conflict through other channels than income.

Measurement Study (LSMS), we document in particular that farmers whose plots are located on nutrient-rich lands tend to use less fertilizer, and that the value of their land is less negatively impacted by fertilizer prices. We also find that several indicators of violence at the individual level significantly correlate with fertilizer prices. Importantly, we provide strong evidence that fertilizer prices fluctuations significantly affect agricultural output in our sample of countries, using a combination of yields measures at the regional, cell and household-plot levels. This is key given the widespread belief that African farmers use little fertilizers compared to their Asian or Latin-American counterparts (Morris *et al.*, 2007).[4] Combining our estimates of the elasticity of yields to fertilizer prices with our baseline results on conflict, we show that the elasticity of conflict to changes in agricultural productivity falls within the range found in the literature on economic shocks and conflict (e.g. Miguel *et al.*, 2004).

As mentioned earlier, several dramatic conflict episodes, such as the war and genocide in Rwanda, were caused by a confluence of factors, namely population growth, scarcity of fertile land, and inherent ethnic tensions. In the final part of the paper, we find support for this account on a much larger scale. More precisely, combining our data on soil fertility with geocoded information on the contours of ethnic homelands, we split our cell-specific measure of soil fertility heterogeneity into two components: one component arising from heterogeneity in soil quality *between* ethnic groups, and the another component arising from differences in soil quality *within* ethnic groups. We find that both within- and between-group land inequality amplify the impact of fertilizer price variations on conflict. Inequality in soil quality between ethnic group tends however to matter quantitatively more, especially in densely populated areas.

Related literature. Our paper relates to several strands of the literature. The recent decade has seen a surge of empirical studies examining the roots of civil wars - first at the country-level, and more recently using spatially disaggregated data. The role of natural resource extraction, ethnic divisions, and income variations have received particular interest.[6] Our paper contributes in particular to the literature on agricultural income shocks, which typically associates conflict with changes in commodity prices or demand (e.g. Dube and Vargas, 2013, Bazzi and Blattman, 2014, Berman and Couttenier, 2015, McGuirke and Burke, 2018), weather conditions (e.g. Miguel *et al.*, 2004, Hsiang *et al.*, 2013, Couttenier and Soubeyran, 2014, Iyigun *et al.*, 2017, Adhvaryu *et al.*, 2017, Harari and Ferrara, 2018), or long-run changes in agricultural productivity (Iyigun *et al.*, 2015). We complement these works by demonstrating that variations in the price of an agricultural production technology (fertilizer) affect the likelihood of conflict, and that local heterogeneity in agricultural productivity plays a key role in this dynamic.

We also contribute more specifically to the relatively scarce empirical literature on land conflicts. Hidalgo *et al.* (2010) study the determinants of land invasions in Brazil, and emphasize the role of unequal landholding and land tenure systems. Di Falco *et al.* (2017) find that tenure

[4]A recent World Bank report (Sheahan and Barrett, 2014) challenges this view using survey data for 6 SSA countries from the *Living Standards Measurement Study*. More than a third of the households are found to use inorganic fertilizers in this sample, and this share reaches 55% in Ethiopia and 77% in Malawi. Moreover, even low levels of fertilizer use do not necessarily imply that African farmers' income are insensitive to world market fertilizer prices variations. Available estimates of fertilizer demand price elasticity in Africa range from -0.82 to -1.08,[5] which suggests that the demand of fertilizer is inelastic but still sensitive to fertilizer price variations.

[6]On the role of natural resources, see, for example, Fearon and Laitin (2003), Ross (2004, 2006), Berman *et al.* (2017), and Sanchez de la Sierra (forth.), and on ethnic fractionalization and polarization, see, Montalvo and Reynal-Querol (2005), Esteban *et al.* (2012), and Michalopoulos and Papaioannou (2016), among many others.

security and climate affect the likelihood of observing land disputes in Ethiopia and Guardado (2018) finds that changes in crop prices trigger more violence in Peruvian districts where land ownership is primarily individual. Our paper differs from these studies in terms of geographic coverage (43 countries over a period of 17 years) as well as objectives. We focus on inequality in terms of natural soil fertility, and we identify periods during which this inequality rises using fertilizer price variations.

While we ultimately apply our theory to the case of agricultural production and fertilizer use, we begin by extending the conflict model developed by Chassang and Padró i Miquel (2009) to a situation in which rents are heterogeneous. Our paper therefore adds to existing models that deal with the relationship between inequality among different individuals/groups and violence. Esteban and Ray (2011b) consider a rent-seeking game between groups of different sizes and show that the equilibrium level of conflict depends on inequality, fractionalization and polarization (see also Esteban and Ray, 1999). Fearon (2007), on the other hand, considers a rent-seeking model in which a rebel group enters into conflict with the government in order to appropriate the national tax revenue. In this framework, greater income inequality among citizens increases the number of relatively poor people and decreases the marginal cost of recruitment for both rebels and the government, which, in turn, leads to an increase in the intensity of the conflict. Compared with these papers, we use a model that more closely aligns with bargaining models, in which both peace and conflict are potential outcomes, rather than a rent-seeking game in which conflict is inherent. More importantly, while they find that the level of conflict increases with inequality in static frameworks, we consider a dynamic model that demonstrates that the probability of conflict increases *when* inequality in soil fertility is high, while the relationship between average inequality and the likelihood of conflict is ambiguous. The underlying mechanism comes from our agricultural production model: fertilizer prices impact inequality and conflict because they affect less the (appropriable) revenue of the rich than the opportunity cost of the poor. This in turn is due to the fact that fertile soils use less fertilizers, which makes their rents less sensitive to such price variations – a mechanism that we test empirically using household-level survey data.

While early cross-sectional empirical studies typically failed to find evidence of a positive link between income or wealth inequality and conflict (Lichbach, 1989), our results are consistent with more recent work. Macours (2011), for instance, finds that rebel recruitment was more intensive in Nepali districts where inequality between landlords and landless has previously increased. We also contribute to the debate on the effect of inequality within or across ethnic groups. While some studies argue that between-group inequality is a cause of conflict (Cederman *et al.*, 2011; Guariso and Rogall, 2017), other argue that it decreases conflict probability (Mitra and Ray, 2014).[7] Within-group inequality could matter as well (Huber and Mayoral, 2019), for instance if it made it easier for the rich to hire fighters within their own ethnic group (Esteban and Ray, 2008, Esteban and Ray, 2011a).[8] Our final set of results suggest that both between and within ethnic groups inequality shocks (in terms of soil fertility) have a conflict-inducing effect in SSA countries, between-group inequality being especially important in densely populated areas. This

[7] Guariso and Rogall (2017) provide cross-country evidence that economic inequality shocks (rainfall) between ethnic groups increase the likelihood of conflict.

[8] Using a theoretical model from a different perspective, De Luca and Sekeris (2012) show that the intensity of the fight between a rebel group (landless individuals) and landlords is greatest for intermediate values of land inequality between the landlords.

is in line with Mwesigye and Matsumoto (2016) who find, based on data from rural Uganda, that land conflicts are more likely to occur in areas characterized by high population growth and ethnically diverse communities. In general, our conclusions lend support to the view that land related violence must be analyzed in conjunction with wider processes of socio-ethnic divisions and discrimination, and with demographic changes. Our findings on the role of population density echo the recent cross-country analysis of Acemoglu *et al.* (2017).

Finally, this paper sheds light on the potential effects of the recent skyrocketing of fertilizer prices and contribute to the debate about technology adoption in SSA agriculture. Some literature has argued that access to modern inputs such as fertilizers were a key factor on the difference between the rapid growth of agricultural yields in Asia and the stagnation of yields in Africa (Morris *et al.*, 2007); this has led some authors to argue in favor of fertilizer subsidies for African countries (Duflo *et al.*, 2011). Our findings imply that, despite the relatively limited use of fertilizers in SSA countries, variations in fertilizer prices do have a significant effect on agricultural yields, income, and political stability. More generally, our results support the view that fertilizer use, or the lack thereof, can be a trigger of conflict. For instance, Eltahir (2017) describes the conflict in the Nile basin in the following way: "In order to expand agricultural production in Africa, there are two possible routes: horizontal expansion using more land and more water, or vertical expansion using the same land and water volume, but producing more crops aided by fertilizers [...]. The first route usually leads to conflicts over land or water (or both). The second route can help countries avoid these conflicts."

In the following section, we present our model of land heterogeneity and conflict. Section 3 describes the data and the methodology used to construct our main variables of interest. Section 4 contains our econometric approach, the baseline results, and a number of sensitivity analyses. In section 5 we investigate the role of ethnic boundaries in the link between soil fertility and conflict. The last section concludes.

2 A Model of Land Heterogeneity and Conflict

In this section we develop a dynamic model of conflict among two groups that control an area of land characterized by heterogeneous soil fertility. We build the model in two parts. The first part explores the general dynamics of conflict between the two groups which enables us to make predictions about the relationship between economic shocks, inequality, and conflict. The second part focuses on agricultural output and links fertilizer price, soil fertility, and land rents. This enables us to deliver our two main testable predictions regarding the relationship between fertilizer price, the distribution of soil fertility and the likelihood of conflict.

2.1 Inequality Shocks and Conflict

This component of the model builds on Chassang and Padró i Miquel (2009), who assume that land productivity is homogenous and focus on the relationship between wealth and conflict.[9] Unlike Chassang and Padró i Miquel (2009), however, we consider land to be heterogeneous with respect to soil fertility. In this section, we extend their model to incorporate heterogeneity in land productivity in order to study the relationship between this measure of inequality and conflict.

[9] They show that the relationship between poverty and the likelihood of conflict is ambiguous while negative income shocks increase the likelihood of conflict.

Consider two groups $i \in \{1,2\}$ that share a territory of size 2. Assume that each group controls 1 unit of land. The total rent from land i at time t is given by r_{it}. The amount of rent depends on fertilizer use and on soil fertility (we formalize these relationships later).

One group may decide to use violence in order to seize the land of the other group. For the sake of simplicity, we exclude the possibility of peaceful (costless) land transfers. We assume that if a group attacks, it has a first mover advantage and wins the conflict with probability $\mu > 1/2$.[10] If both groups decide to attack, then the probability of winning the conflict is 1/2 for both groups. When conflict occurs, there is a probability, denoted $d \in (0,1]$, that all existing agricultural production is completely destroyed.[11]

In each period of time t, rents from agricultural lands vary, because *fertilizer prices and output prices vary.* Income shocks are captured by the fact that rent r_{it} is independently drawn from a cumulative distribution function $F_i(.)$ over $(0,+\infty)$. The expected value of r_{it} is denoted $\overline{r}_i$, with $\overline{r}_2 < \overline{r}_1$. Each group discounts the future by a factor δ.

The timing of the game is the following. First, r_{1t} and r_{2t} are observed by the two groups. If neither group chooses to attack, then each group produces and consumes their production, and the next period begins. If at least one group decides to attack, there is a decisive war, and the winner of the conflict uses all land to produce, consumes the yields produced, and controls all land forever. While this assumption is convenient, it can be relaxed: our results are qualitatively unchanged if the defeated group regains its land more than one period after the conflict occurred (see the appendix for the proof).

Consider the choice of whether to attack for group $i \in \{1,2\}$ at time t. If peace is reached at time t, then group i obtains the following expected payoff:

$$r_{it} + \delta V_i^P, \tag{1}$$

where V_i^P is the expected continuation value when peace is reached.

If group i decides to deviate and launch an attack, its expected payoff is given by:

$$\mu\left(\left(r_{1t} + r_{2t}\right)(1-d) + \delta V_i^V\right), \tag{2}$$

where V_i^V is the expected continuation value when war occurs and i is victorious.

This continuation value is:

$$V_i^V = E\left[\sum_{\tau=0,\dots,+\infty} \delta^\tau r_{1\tau}\right] + E\left[\sum_{\tau=0,\dots,+\infty} \delta^\tau r_{2\tau}\right], \tag{3}$$

or,

$$V_i^V = \frac{\overline{r}_1 + \overline{r}_2}{1-\delta} \equiv V^V. \tag{4}$$

[10] One could alternatively make the assumption that the richest group is also the strongest, i.e. it has a larger first mover advantage. Our results hold as long as inequalities are sufficiently large and/or the level of rents is small. A sufficient condition is $|r_{1t} - r_{2t}|/(r_{1t} + r_{2t}) > (\frac{\delta}{1-\delta} + 1 - d)|\mu_1 - \mu_2|$ for all t, where μ_i is the probability of winning for group $i = 1,2$ if it decides to attack first. Our results are also unchanged if there is no first mover advantage ($\mu = 1/2$) as long as the rents are not symmetric, i.e. $r_{1t} \neq r_{2t}$ for all t. See Dow *et al.* (2017) for a conflict model in which the winning probability is endogenous and depends on agricultural income.

[11] One may also interpret d as the proportion of agricultural production that is destroyed.

Hence, peace is reached at time t only if:

$$r_{it} + \delta V_i^P > \mu \left((r_{1t} + r_{2t}) (1 - d) + \delta V^V \right), \tag{5}$$

for $i \in \{1, 2\}$.

To elaborate on this condition, we make the following assumption:

Assumption [no switching]: *The most profitable land (on average) is also the most profitable land at each point in time:* $\Delta r_t = r_{1t} - r_{2t} \geq 0$ *for all* t.

This assumption is sufficient to show that the group with less fertile soil (group 2) has a greater incentive to attack than the other group (group 1). Indeed, by this assumption, we can show that $V_1^P \geq V_2^P$, that is, the expected continuation value in the event of peace cannot be larger for the group who owns the less profitable land than for the group who owns the more profitable land.[12] Hence, using condition (5), we deduce that peace occurs at time t only if group 2 has no incentive to launch an attack, that is:

$$(1 - \mu (1 - d)) \, r_{2t} - \mu (1 - d) \, r_{1t} > \delta \left(\mu V^V - V_2^P \right), \tag{6}$$

Condition (6) illustrates the trade-off between the *opportunity cost* of conflict and the *rapacity gain* (a benefit of conflict) in the current period. To see this, let Ψ_t denote the likelihood that a conflict occurs, independently of expected future play:

$$\Psi_t = \underbrace{\mu (1 - d) \, r_{1t}}_{\text{Rapacity gain}} - \underbrace{(1 - \mu (1 - d)) \, r_{2t}}_{\text{Opportunity cost}}. \tag{7}$$

Conflict is more likely (i.e. group 2 has a greater incentive to launch an attack) if the rent of the land-rich (group 1) is temporarily large or if the rent of the land-poor (group 2) is temporarily small. Indeed, independently from future play, group 2 faces a trade-off between the expected current loss from conflict, i.e. the opportunity cost, $(1 - \mu (1 - d)) \, r_{2t}$, and the expected current gain from conflict, i.e. the rapacity gain, $\mu (1 - d) \, r_{1t}$. The opportunity cost of conflict increases with the rent from its land, r_{2t}, and the rapacity gain increases with the rent from land controlled by group 1, r_{1t}.

Notice that the expected continuation value V_2^P is bounded above: $V_2^P \leq \frac{1}{2} \frac{\overline{r}_1 + \overline{r}_2}{1 - \delta}$. Hence, the right hand side in condition (6) is non negative. Thus, a necessary condition for peace is $1 - 2\mu (1 - d) > 0$. This condition can be rewritten as $1 - \mu (1 - d) > \mu (1 - d)$. This implies that the probability that a group loses its current rents is larger than the probability of winning the current rents of the other group. We maintain this assumption throughout the rest of the paper. This assumption excludes the trivial case in which conflict occurs immediately.

The likelihood of conflict defined in (7) can also be written in terms of average rents and the difference between rents:

$$\Psi_t = \frac{1}{2} \Delta r_t - [1 - 2\mu (1 - d)] \, \overline{r}_t, \tag{8}$$

[12] More precisely, this holds for the subgame perfect equilibrium in which players use threshold strategies and launch an attack only when the realizations of the left-hand side in condition (6) are lower than a given constant threshold. We also show that such a subgame perfect equilibrium exists.

where $\overline{r}_t \equiv (r_{1t} + r_{2t})/2$ is the average rent at time t. This leads to the following result regarding the relationship between average rents, rent inequality, and conflict:

Proposition [Inequality and Conflict]: *Conflict occurs if current rents ($\overline{r}_t$) are low enough or if current rent inequality (Δr_t) is sufficiently large.*

The first part of this Proposition, i.e. conflict occurs if current rents are low enough, echoes Chassang and Padró i Miquel (2009). The second part of the Proposition, i.e. conflict occurs if current rent inequality is sufficiently large, however, differs from the results in the literature. Indeed, while existing studies argue that a higher average level of inequality increases the likelihood of conflict (Esteban and Ray, 2011b; Fearon, 2005), we find that a higher average level of inequality, measured by $\overline{r}_1 - \overline{r}_2$ (holding the average rent constant), may be associated with either more conflict (if V_2^P decreases) or less conflict (if V_2^P increases). Rather, our results suggest that, conflict is more likely to occur *when* current inequalities are high.

This general result cannot be easily tested because agricultural rents are difficult to measure accurately in developing countries and are moreover likely to be endogenous to conflict (or correlated with other co-determinants of conflicts). In the empirical section of the paper, we consider fertilizer price variation and the distribution of soil fertility as sources of exogenous and heterogeneous economic shocks. To derive our predictions, we complement our theory with a simple model of agricultural production.

2.2 Soil Fertility, Fertilizer and Conflict

We now specify how rents depend on fertilizer prices and soil fertility. For simplicity, we assume that agricultural production only depends on soil fertility and the quantity of fertilizer used (at the end of the present Section, we discuss why not considering other inputs such as land quantity is not crucial in our context). Let the rent from land i at time t be given by:

$$r_{it} \equiv \pi_t g(s_i, f_{it}) - c_t f_{it}, \tag{9}$$

where π_t is the output price, g is the production function, s_i is soil fertility, c_t is the price of fertilizer and f_{it} is the quantity of fertilizer used at time t. The production function is nondecreasing in both s_i and f_{it} and strictly concave in f_{it}, i.e. $g_s \geq 0, g_f \geq 0$ and $g_{ff} < 0$. Because fertilizers are comprised of nutrients (nitrate, phosphorus and potassium) and our empirical measure of soil fertility is the natural availability of nutrients in the soil (see section 3), fertilizers and soil fertility are assumed to be substitutes, i.e. $g_{sf} < 0$. Existing empirical evidence supports this assumption as long as soil fertility is not extremely low.[13,14] Assuming that the price of agricultural output is π_t, group i's optimal choice of fertilizer is given by:

$$\text{Max}_{f_{it} \geq 0} \ \{\pi_t g(s_i, f_{it}) - c_t f_{it}\}. \tag{10}$$

[13]The assumption is reasonable since the returns to nutrients are decreasing (Halliday and Trenkel, 1992) and fertilizers are composed of nutrients. In Appendix D.1.1, we provide a more detailed discussion of the link between returns to fertilizers and soil fertility.

[14]Marenya and Barrett (2009b) provide evidence of an S-shaped relationship between marginal agricultural yields and fertilizer inputs and soil fertility (soil carbon stocks) in Western Kenya. Therefore, as a robustness check in the empirical section, we drop the regions where soil fertility is below a certain threshold.

The first order condition for an interior solution is given by:[15]

$$g_f\left(s_i, f_{it}\right) = \frac{c_t}{\pi_t}. \tag{11}$$

Hence, f_{it} is a decreasing function of fertilizer price, i.e. $\partial f_{it}/\partial c_t = 1/\left(\pi_t g_{ff}\right) < 0$. It is also a decreasing function of soil fertility:

$$\partial f_{it}/\partial s_i = -g_{sf}/g_{ff} < 0. \tag{12}$$

This condition implies that *farmers use lower amounts of fertilizer on fertile soils.*

Notice that, as expected, *rents from land decrease when the price of fertilizers increases.* Indeed, the effect of a marginal increase in the price of fertilizer on agricultural rents is given by:

$$\partial r_{it}/\partial c_t = -f_{it}. \tag{13}$$

The increase in the rent from land i generated by a marginal increase in the price of fertilizer equals minus the amount of fertilizer used.

We are now able to examine the effect of changes in fertilizer price on the likelihood of conflict. The derivative of the likelihood of conflict (7) with respect to fertilizer price is:

$$\frac{\partial \Psi_t}{\partial c_t} = \mu\left(1-d\right)\frac{\partial r_{1t}}{\partial c_t} - \left(1-\mu\left(1-d\right)\right)\frac{\partial r_{2t}}{\partial c_t}. \tag{14}$$

Since an increase in the price of fertilizer decreases rents for both groups, the resulting effect on the likelihood of conflict is a priori ambiguous. However, the marginal decrease in the rents from the land with the most fertile soil is smaller than the marginal decrease in the rents from the land with the less fertile soil. Indeed, using (12) and (13), we obtain:

$$\frac{\partial r_{2t}}{\partial c_t} = -f_{2t} < \frac{\partial r_{1t}}{\partial c_t} = -f_{1t} < 0. \tag{15}$$

This condition implies that *the negative effect of fertilizer prices on agricultural rents is magnified for less fertile soils.*

Since the weight placed on rents from soils with lower fertility is larger than the weight placed on rents from soils with greater fertility, $1-\mu\left(1-d\right) > \mu\left(1-d\right)$, the right-hand side in (14) is always positive. This result is summarized in the following proposition:

Proposition [Fertilizer Price and Conflict]: *An increase in fertilizer price makes conflict more likely. Formally,*

$$\frac{\partial \Psi_t}{\partial c_t} > 0. \tag{16}$$

This result can be interpreted in terms of current opportunity cost and rapacity gain. An increase in the price of fertilizer decreases the rents provided by the less fertile soil, hence the opportunity cost of fighting decreases. An increase in the price of fertilizer also decreases the rents provided by the soil with greater fertility, which decreases the incentive to seize this land.

[15] Our results are not qualitatively affected if one take corner solutions into account.

In other words, the rapacity gain also decreases. Since larger quantities of fertilizer are used on the less fertile soil, the rents from the poorer quality land more sensitive to an increase in fertilizer price. As a result, the former effect is stronger than the latter, which makes conflict more likely.

Next we explore how the impact of an increase in fertilizer price on conflict is affected by the initial distribution of soil fertility. Specifically, we consider the effect of a change in the difference in soil fertility (the effect of a change in average soil fertility level is relegated to the Appendix). To do so, let us denote $\overline{s}$ and Δs as the average and the difference of soil fertility between groups, respectively, with $\overline{s} = \frac{1}{2}(s_1 + s_2)$ and $\Delta s = s_1 - s_2$. Let us (re)define s_1 and s_2 as functions of $\overline{s}$ and Δs with $s_1 = \overline{s} + \frac{1}{2}\Delta s$ and $s_2 = \overline{s} - \frac{1}{2}\Delta s$. Condition (11) becomes:

$$g_f\left(\overline{s} + \frac{1}{2}\Delta s, f_{1t}\right) = \frac{c_t}{\pi_t} \text{ and } g_f\left(\overline{s} - \frac{1}{2}\Delta s, f_{2t}\right) = \frac{c_t}{\pi_t}. \tag{17}$$

These conditions characterize the amount of fertilizer used by each group as a function of the prices, the average soil fertility and the difference in soil fertility.

Now consider the effect of an increase in the difference in soil fertility on $\partial\Psi_t/\partial c_t$. Differentiating (14) with respect to the difference in soil fertility, we obtain:

$$\frac{\partial^2\Psi_t}{\partial c_t \partial \Delta s} = \mu(1-d)\frac{\partial^2 r_{1t}}{\partial c_t \partial \Delta s} - (1 - \mu(1-d))\frac{\partial^2 r_{2t}}{\partial c_t \partial \Delta s}. \tag{18}$$

The sign of the effect depends on the weighted difference between the cross derivatives of the rents with respect to the price of fertilizer and the difference in soil fertility. Using (17) and differentiating (13) with respect to the difference in soil fertility, these cross derivatives can be written as:

$$\frac{\partial^2 r_{1t}}{\partial c_t \partial \Delta s} = -\frac{1}{2}\frac{\partial f_{1t}}{\partial s_1} > 0 \text{ and } \frac{\partial^2 r_{2t}}{\partial c_t \partial \Delta s} = \frac{1}{2}\frac{\partial f_{2t}}{\partial s_2} < 0. \tag{19}$$

An increase in the difference of soil fertility dampens the negative effect of fertilizer price on the rents from the more fertile soil and it magnifies the negative effect of fertilizer price on the rent from the less fertile soil. This leads to the following result:

Proposition [Soil Fertility Heterogeneity and Conflict]: *The interaction effect of an increase in fertilizer price and in the difference in soil fertility on the likelihood of conflict is always positive. Formally,*

$$\frac{\partial^2\Psi_t}{\partial c_t \partial \Delta s} > 0. \tag{20}$$

The intuition of this result is the following. An increase in the difference of soil fertility amplifies the decrease in opportunity cost and attenuates the decrease in rapacity gain. Hence, the cross-effect of increased fertilizer price and inequality in soil fertility on the likelihood of conflict is positive.

Notice that the last proposition is obtained holding the average level of soil fertility constant. How average soil fertility itself affects the relationship between fertilizer price and conflict is theoretically unclear. Section B.4 of the appendix provides a detailed discussion of this issue. The general conclusion is that a change in average soil fertility may increase or decrease the likelihood of conflict following a fertilizer price shock depending on how soil fertility is measured. For instance, a nonlinear increasing transformation of the variable can reverse the sign of the relationship. Empirically, we indeed find that the sign of this effect varies depending on the indicator used to measure soil fertility.[16]

2.3 Discussion

The two main theoretical predictions we investigate can be summarized as follows. First, an increase in fertilizer prices makes conflict more likely. This is because more costly inputs lead to a drop in the opportunity cost of engaging in conflict for the land-poor, which is greater in magnitude than the decrease in the rents that stand to be appropriated from the land-rich. Second, the probability of conflict increases to an even greater extent if fertilizer prices increase in areas where soil fertility is more heterogeneous. When soil fertility is more heterogeneous, the decrease in the opportunity cost for the land-poor is magnified, and the drop in the rapacity gain is dampened.[17] Before turning to the tests of these core predictions, we discuss the empirical relevance of several intermediate implications of the model, as well as the results implied by extending the model in various directions.

2.3.1 Assumptions and implications of the model: empirical evidence

In our agricultural production model, increases in fertilizer prices trigger conflict partly because the most fertile soils require less fertilizer, which makes the rent from these lands less sensitive to variations in the price of this input. In section D.1 of the online appendix, we discuss existing evidence and provide new estimates supporting these assumptions and intermediary results. First, we discuss the assumption that returns to fertilizers decrease when soil fertility increases in light of existing evidence and using geo-coded data from the World Bank LSMS surveys. Second, we discuss three implications of our agricultural production model: (a) farmers use lower amounts of fertilizers on fertile soils (an implication of equation 12), (b) agricultural yields and rents from land decrease when the price of fertilizer increases (an implication of equation 13), (c) the negative effect of fertilizer prices on agricultural yields and rents is larger for less fertile soils (an implication of equation 15). Concerning the implication (a), existing papers find at most weak support for this relationship (Sheahan and Barrett, 2014, 2017) but they use measures of self-assessed, *perceived* soil quality. Combining geo-coded data from the World Bank LSMS surveys with our measure of nutrient availability (see section 3.3), we find stronger support for our assumption, though the results are sensitive to the specification (online appendix section D.1.1). In the case of the implication (b), we find that our cell-specific measure of fertilizer prices correlates significantly with agricultural yields at the aggregate and local levels (online appendix section D.1.2). We use several measures of yields or agricultural output: a sub-country measure from FAO-AGROMAPS, a cell-level proxy based on a standard vegetation index (Normalized

[16] See Prediger *et al.* (2014) for a study on pastoralists' likelihood to engage in antisocial behavior towards their fellow commons users when they are located in low-yield areas rather than in high-yield areas.

[17] Our main predictions therefore relate conflict likelihood to changes in rents triggered by variations in fertilizer prices. How soil fertility heterogeneity affects conflict independently of fertilizer price variations is theoretically ambiguous. The online appendix B provides more discussion of this relationship. We show that, in contrast with fertilizer prices which only influence the tradeoff between current payoffs (left hand side in condition 6), soil fertility heterogeneity affects both the tradeoff between current payoffs and between future payoffs (right hand side in condition 6). The resulting effect is ambiguous. We however provide some suggestive evidence that, within our sample, soil fertility heterogeneity is positively correlated with conflicts across space.

Difference Vegetation Index, NDVI) and household-plot level information from the World Bank LSMS surveys. This is important because one could have argued that the relatively low usage of fertilizers by SSA countries could have made agricultural output insensitive to fertilizer price fluctuations. Finally, thanks to the LSMS data, we also find support for the implication (c): different measures of land value correlate negatively with our measure of fertilizer prices, especially in regions where land is nutrient-poor.

2.3.2 Extensions of the model

We have assumed that both groups use fertilizers. In fact, if the price of fertilizers is sufficiently high, the land-rich (group 1) may stop using these inputs. This would not affect our two main predictions: in that case, the rents of group 1 become insensitive to fertilizer price variations. The rapacity gain would remain constant while the opportunity cost of group 2 would still vary with the price of fertilizer. In the online appendix (section C), we also consider an extension of the model in which the land-poor group (group 2) faces budget constraints, and as a result stops using fertilizers when the price goes beyond a certain level. This implies that the rents from the less fertile soil become insensitive to fertilizer price variations when the price of fertilizers is sufficiently high. Fertilizer prices now have a non-monotonic effect on conflict while the cross-effect of fertilizer price and soil fertility heterogeneity is still always positive. We provide some evidence of such non-monotonicity; we however find that in the data, the impact of fertilizer price changes on conflict is always positive, as predicted by our baseline model.

Finally, we have assumed that the only exogenous difference in agricultural productivity between the two groups is soil fertility. This leads us to conclude that the group with more fertile soil gets larger agricultural rents than the other group. This intermediate results is consistent with existing evidence (Marenya and Barrett, 2009a,b; Liverpool-Tasie *et al.*, 2017), and thus we believe that our simple agricultural production model is sufficient to capture the main intuitions. Notice that, from a theoretical point of view, exogenous characteristics that influence agricultural productivity beyond soil fertility (such as land quantity) may lead to a situation where the group with more fertile soil gets smaller rents than the other group (if the group with more fertile soil owns a much smaller land surface for instance). In this case, our first prediction could be reversed (to the extent that the weights $1-\mu(1-d)$ and $\mu(1-d)$ are of sufficiently similar magnitude) and our second prediction would be reversed. These alternative predictions are, however, based on an assumption that is not supported by existing empirical evidence and they are not consistent with our main empirical results.

3 Data

Testing the predictions of the model first requires defining a level of spatial aggregation. At this level of aggregation, we must then build measures of (i) conflict events, (ii) natural soil fertility, and (iii) variations in fertilizer prices. In this section we summarize the main variables used in our baseline estimations. For each of these variables, we also use alternative measures in our sensitivity analysis; their description appears in the online appendix A.

3.1 Unit of analysis

Our units of analysis are cells of size 0.5×0.5 degrees latitude and longitude (around 55×55 kilometers at the equator), covering the entire set of SSA countries. Most of the data we use throughout the paper are available at a more disaggregated level. For this reason, we aggregate the data in order to generate a dataset at the *cell-year* level. We use this level of aggregation rather than administrative boundaries in order to ensure that our unit of analysis is not endogenous to conflict events. We assign a country to each cell based on the end-of-period boundaries. Note that we check that our main results are not sensitive to our choice of spatial scale, by reproducing our analysis using 0.25×0.25 and 1×1 degree cells.

3.2 Conflict data

We use conflict event data from the *Armed Conflict Location and Event dataset* (ACLED) which contains information on the geo-location of conflict events in all African countries over the period from 1997 to 2013 (Raleigh and Dowd, 2014). These data, that have been widely used in recent conflict literature, contain information about the date, the location (longitude/latitude) of conflict events within each country, and the nature of the actors on both sides of the conflicts. Events are compiled from various sources, including press accounts from regional and local news, humanitarian agencies, and research publications. Geographic precision specifies at least the municipality level in more than 95% of cases, and is even finer (i.e. village level) for more than 80% of observations. For each data source, we aggregate the data by year and by 0.5×0.5 degree cell.[18] We focus on Sub-Saharan African countries only; North African countries possess significant reserves of phosphate (in particular Morocco and Western Sahara), which would affect our identification strategy.

We construct a dummy variable equal to one if at least one conflict occurs in the cell during the year; we interpret this variable as cell-specific *conflict incidence*. As an alternative measure of conflict, we compute a variable containing the number of events observed in the cell during the year. Note that our results are also robust to modeling the onset and ending of cell-specific conflicts separately. Figure 1.A provides a visual representation of our data across cells (a larger version appears in the online appendix section A.7, figure A2). Events are observed over the entire Sub-Saharan African continent, with some clusters appearing in the Great Lakes Regions, Nigeria, and West Africa.

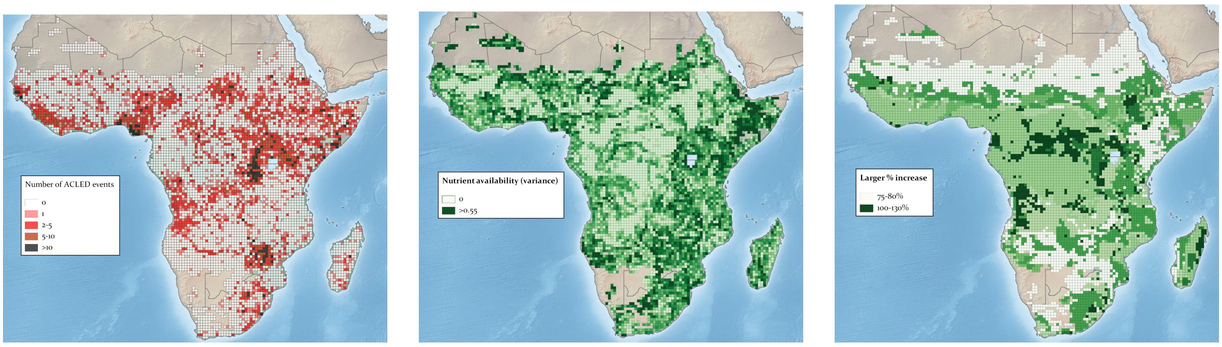
A unique feature of the ACLED dataset is that it includes information about the characteristics of the actors on both sides of the conflicts as well as – for a large subset of observations – a description of the event. As an alternative measure of conflict incidence, we make use of the richness of the ACLED dataset in order to identify conflicts that are likely to be land-related as well as those that are likely to have occurred between local actors. We thus define "land conflicts" as events (i) involving communal militias (i.e. local armed groups, fighting for a local objective) on both sides and/or (ii) whose description include specific keywords related to land.[19] Figure A2.B

[18]See Besley and Reynal-Querol (2014), Michalopoulos and Papaioannou (2016), or Berman *et al.* (2017) for papers combining data that is structured similarly to our own with the same conflict data we use. We only keep events that are geolocalized at the finer precision level for our analysis. We also drop duplicated events, i.e. events for which all of the ACLED variable's content (precise date, location, actors, description, etc.) is the same for several observations – in these cases we retain only one observation for the event. This eliminates 1.7% of events. Finally, we drop from our baseline estimates events related to riots and protests in order to conform to the objectives of our model.

[19]ACLED refers communal militias as groups whose "goal [...] is often for the defense of localized territories, livelihoods, community wealth, etc.". We include events whenever the descriptions include the following keywords: "land dispute", "dispute over land", "control of land", "over land", "clash over land", "land grab", "farm land",

Figure 1: Data visualization

A. ACLED data | B. Soil fertility | C. Fertilizer price change



Note: Only the cells included in our final sample (i.e. the cells for which all of our main variables are non-missing) appear in these figures. Figure A: *Armed Conflict Location and Event dataset* (ACLED) events (all events). Figure B: cell-specific soil fertility variance. Data obtained from the International Institute for Applied System Analysis. Soils are ordered in five categories ranging from 1 ("no or slight constraints") to 5 ("very severe constraints"). Figure C: largest increase in the cell-specific fertilizer price index over the 1997-2013 period.

in the online appendix (section A.7) shows the spatial distribution of our measure of land-related conflicts. These conflicts tend to be geographically concentrated, and mostly occur in East Africa, which illustrates a limitation of our measure of land-related conflicts. Specifically, the measure relies on the event description provided in the ACLED data, for which the methods and quality of coding vary widely across countries. In some countries, the description may be absent or very short, or may use a different terminology, which may have prevented us from identifying potential land-related events. For this reason, we use the broader measure of violent conflicts described above in our baseline, and focus on land-related events for comparison purposes. Note that the ACLED dataset does not include information on who attacked in the first place.

3.3 Soil fertility

One of our objectives is to understand how the heterogeneity in soil fertility within regions affects the transmission of agricultural input price shocks to conflict. As an empirical counterpart to our model of soil fertility, we use the quantity of nutrients naturally available in the soil. When soil quality is poor, fertilizers can be used as substitutes.

Our baseline data source is the Harmonized World Soil Database (HWSD) built jointly by the FAO (Food and Agriculture Organization) and IIASA (International Institute for Applied System Analysis). This data uses models that incorporate location-specific soil attributes (texture, organic carbon, pH, and total exchangeable bases) to compute, among other measures, an index of nutrient availability.[20] The index assigns soils to one of five categories ranging from 1 ("no or slight constraints") to 5 ("very severe constraints"). Although, the data are available by spatial units of 5 arc-minutes (approx. 9km $\times$ 9km at the equator), while our units of observation are cells of 30 arc-minutes. For each cell, we thus compute the average value, the mode, as well

"land invaders", "land invasion", "land redistribution", "land battle", "over cattle and land", "invade land", "over disputed land", "over a piece of land".

[20] Each soil attribute is associated with a rating. The nutrient availability index is calculated as the average of the rating of the attribute with the smallest rating and the average rating of the three other attributes. See Fischer *et al.* (2008) for a detailed description.

as the standard deviation and the variance of this variable, which we use as a measure of the heterogeneity of soil fertility. We also compute the share of soil fertility in each category and define high fertility cells as those for which the share of soil with "no or slight constraints" is above 50%. Figure 1.B plots the spatial distribution of heterogeneity in soil fertility (see Figure A3 in the online appendix section A.7, for larger maps and the distribution of average soil fertility). Figures A7 to A10 in the online appendix (section A.8) focus on four specific countries for which we plot the distribution of the mode, average, standard deviation and Herfindahl index of nutrient availability. In a country such as Ethiopia, soil fertility is relatively concentrated across cells, with most regions displaying a high level of average fertility (Figures A7 and A8); fertility within cells, in contrast, appears to be highly heterogeneous (Figures A9 and A10). In Zimbabwe, however, nutrient availability is more concentrated, both across and within cells.

3.4 Measuring local variations in fertilizer prices

The final piece of information required to test our predictions are cell-specific fertilizer prices. Direct information on local fertilizer prices is not widely available, and if it were, these prices would likely be endogenous to conflicts. To identify exogenous local variations in fertilizer prices, we combine three types of data: (i) data on crop specialization (what crops are produced in each cell), (ii) information on crop-specific nutrients uptakes (what mix of nutrients should be included in the fertilizers used for each crop), and (iii) data on the annual price of each nutrient.

The general idea behind our measure is the following. Different cells are specialized in different crops, and the content of the fertilizers used to produce these crops should, in theory, differ (see the end of the present section for further discussion). Fertilizers typically contain a mix of nitrogen, phosphate and potassium (N-P-K), but this mix varies across different types of fertilizers in order to meet crop-specific needs.[21] Hence, combining data on local crop specialization with the international market price of each fertilizer component, we are able to construct a fertilizer price that varies across locations and over time.

First, we identify the main crop(s) produced by each cell using data from the FAO's Global Agro-Ecological Zones (GAEZ). This data is constructed from models that use location characteristics such as climate information (for instance, rainfall and temperature) and soil characteristics. This information is combined with crop' characteristics in order to generate a global GIS raster of the suitability of a grid cell for cultivating each crop. The main advantage of this data is that crop suitability is exogenous to conflicts, as it is not based on actual production. In our benchmark estimations, we use the main crop produced in the cell, which is defined as the crop with the highest suitability level.

Second, we gather information about the required N-P-K mix of nutrients (measured in kg/ha) for each crop. Our benchmark data are generated by the International Plant Nutrient Institute (IPNI) and include information on the nutrient requirements of 42 crops (Table A2, online appendix section A.4).

Finally, we obtain the real international market prices of each nutrient from the World Bank Commodities Dataset. A graph of each price series over time is shown in the online appendix (section A.4), Figure A1. The three price spikes that occurred between 2008 and 2009 were due

[21] Most fertilizers contain multiple nutrients. Each fertilizer has a N-P-K rating that consists of three numbers ($\alpha^N, \alpha^P, \alpha^K$). The first number is the percentage of nitrogen (N), the second number is the percentage of phosphorus pentoxide (P_2O_5) , and the third number is the percentage of potassium oxide (K_20).

to a rise in demand triggered by US biofuel programs and to the imposition of a 135% Chinese export tariff on phosphate (see Schröder *et al.*, 2010).

Equipped with these data, we compute, for each cell, the international market price of a kilogram of local fertilizer based on the identified main crop and the required N-P-K mix for this crop:

$$P_{ct} = P_t^N \alpha_{i(c)}^N + P_t^P \alpha_{i(c)}^P + P_t^K \alpha_{i(c)}^K, \tag{21}$$

where the $\{P_t^N,\ P_t^P,$ and $P_t^K\}$ represent the real international market prices of nitrogen, phosphate, and potassium, $i(c)$ is the crop with the highest suitability in the cell, and $\{\alpha_{i(c)}^N,\ \alpha_{i(c)}^P,$ and $\alpha_{i(c)}^K\}$ are the required proportion (%) of the three nutrients for crop $i(c)$. These proportions are computed from the quantities of nutrients that are removed from the soil at the time of harvest (in kg/ha), with $\alpha_i^N + \alpha_i^P + \alpha_i^K = 1$, for each crop i. We use the main crop in our baseline estimations as re-weighting equation (21) across crops may introduce some noise. However, because multiple cropping practices may be prevalent in many regions, we demonstrate that our results are robust to using the five most suitable crops in the computation of our price index.[22]

Figure 1.C above shows the largest yearly fertilizer price change observed for each cell over the period (see online appendix section A.7 Figure A3 for additional maps on fertilizer prices), which lies between 70% (for cells in which suitable crops require fertilizers with low amounts of phosphate) and almost 130% (for cells in which suitable crops require phosphate intensive fertilizers). As we will show later, the average change in fertilizer price is positive but relatively low (around 6%), which implies that drops in prices are not uncommon.

3.5 Identification assumptions

When interpreting P_{ct} as a measure of exogenous changes in local fertilizer prices, we make several implicit assumptions. Section D of the online appendix lists these assumptions and section D.2 provides a detailed discussion of various pieces of empirical evidence supporting them. We summarize this discussion here.

Our first identification assumption is that the international market prices of nutrients are exogenous to conflict. Reverse causality could be an issue in our case only if the use of a specific mix of nutrients in conflict-affected cells in SSA impacts the international market price of this mix. This seems very unlikely: SSA countries are not large consumers nor producers of fertilizers. Consumption of fertilizer relies mostly on imports and almost all of the world production occurs in Europe, North America, and Asia (Hernandez and Torero, 2013). Taken together, the countries in our dataset represent only 4% of world imports and 2% of world consumption of fertilizer.[23]

Second, we assume that changes in the international market prices of nutrients are transmitted to local markets. We investigate the validity of this assumption using data on a subset of countries and nutrients in section D.2.1 of the online appendix. We gathered data for urea and phosphate, at the market level, for about 350 markets located in 17 countries over a 4-year period (2010-

[22] When identifying the most suitable crop using GAEZ, we need to restrict our sample to the crops for which we observe the ideal NPK mix. For 78% of the cells, this has no incidence as the most suitable crop is one for which we have NPK data. Removing other 22% of the cells has little impact on our results (if anything these are marginally reinforced).

[23] Authors' computations based on FAO-STAT data. Note also that, since fertilizer use is an investment, more conflict or anticipated conflicts (i.e. insecure property rights) should be associated with less fertilizer use (Jacoby *et al.*, 2002) and lower prices. We find the opposite: variations in international market prices and conflicts are positively correlated.

2013)[24] and regressed local market-level prices on the international market price of the nutrient, both in logs. Controlling for various sets of fixed effects, we confirm that variations in international market prices do have a significant impact on local prices. Online appendix section D.2.1 provides additional details and discussion.[25]

A last identification assumption we make is that the fertilizers used by local farmers should indeed reflect, at least to some extent, the "ideal" mix of nutrients they should use given the crop(s) they grow. This assumption is weaker than it might appear at first: we do not need to assume that farmers systematically use the ideal mix. Our only requirement is that the fertilizers that are locally available partly reflect the specialization of the cell – that is, that the nutrient composition of fertilizers available in, say, a maize producing cell should be closer to the mix of nutrients suitable for growing maize than the composition of fertilizers in other cells. In section D.2.2 of the online appendix, we provide evidence that this is indeed the case, i.e. that our measure of fertilizer price indeed correlates with the actual (unobserved) local prices of fertilizers. We build on the results of section D.1.2, where we find that our measure of fertilizer prices indeed correlates strongly with various measures of agricultural yields: a sub-country measure from FAO-AGROMAPS; a cell-level proxy based on a standard vegetation index (NDVI) and household-plot level information for six countries covered by the World Bank LSMS surveys. These measures systematically correlate negatively with our fertilizer prices. Given that in all estimations we control for common time shocks, our identification arises from differences in fertilizer prices across crops, which are themselves driven by different mixes of nutrients. If farmers all used the same mix across regions producing different crops, or used simply urea for instance, or used a random mix of locally available fertilizers, we would expect these estimates to be insignificant.

3.6 Other data

We complement our dataset with additional cell-specific information. In particular, we add cell-level information from PRIO-GRID v.2 (Tollefsen *et al.*, 2012): geographical characteristics, population, and weather. We also control for economic shocks such as variations in the prices of produced and consumed agricultural commodities (Berman and Couttenier, 2015, McGuirke and Burke, 2018) or in the price of locally produced natural resources such as oil and minerals (Berman *et al.*, 2017). Finally, in the last part of the paper we make use of information on ethnic homelands boundaries from Murdock (1959). More details about these variables and their sources are provided in the corresponding robustness section, and the full description appears in the online appendix, section A.5.

3.7 Final sample statistics

Table 1 provides descriptive statistics for our main variables (section A.6 of the online appendix provides additional statistics about the variables used in our sensitivity analysis). Our sample contains 6,565 cells belonging to 43 SSA countries, and covers the period from 1997 to 2013.

[24] We do not use this data directly in our conflict estimations because: (i) these local prices are likely to be endogenous to conflicts, and (ii) the time frame and geographical coverage are limited.

[25] Note that even in countries where fertilizers were subsidized over the period, we expect variations in the world prices of fertilizers to have an impact on the price paid by farmers, as the subsidies typically represent only a share of the total cost.

Pr(conflict) equals 1 if at least one conflict event occurs within the cell-year.

At least one conflict event occurred in 7% of the 111,605 cell-year units. Unsurprisingly, the unconditional probability of land-related conflicts is much lower at 1%. Conditional on at least one conflict event being observed, the number of conflicts is 1.25 on average. The average level of soil fertility, computed from our baseline data on nutrient availability, is equal to 2.11, which is close to 2, the value defined as "moderate constraints" in our dataset (1 denotes "no or slight constraints", 5 denotes "very severe constraints"). The correlation between the mean and the variance of soil fertility is around 12%. Finally, the average fertilizer price in a cell is around \$210 per metric ton, with significant year-to-year variations observed during our time period: the third quartile of the log-change in this variable shows a 22% increase in price, and the largest observed increase is as high as 130%. Negative price shocks also occur often – the median of the variable is close to zero.

Table 1: Descriptive statistics

	Obs.	Mean	S.D.	1^{st} Quartile	Median	3^{rd} Quartile
Pr(conflict> 0)	111605	0.07	0.26	0.00	0.00	0.00
Pr(conflict> 0) (land-related)	111605	0.01	0.08	0.00	0.00	0.00
# conflicts	111605	0.09	0.38	0.00	0.00	0.00
# conflicts (if > 0)	7945	1.25	0.75	0.69	1.10	1.61
Soil fertility (mean)	111588	2.11	0.79	1.42	2.00	2.81
Soil fertility (mode)	111588	2.07	0.92	1.00	2.00	3.00
Soil fertility (variance)	111588	0.38	0.29	0.16	0.42	0.50
Fertilizer price (\$/ton)	111605	209.97	106.89	116.27	180.96	286.68
Δ ln fertilizer price	105040	0.06	0.24	-0.10	0.01	0.22
Share irrigated	111605	0.33	1.84	0.00	0.00	0.04
Share agriculture	111605	22.27	26.33	1.53	11.33	33.94

Source: Authors' computations. See main text and online appendix A for data sources. Pr(conflict> 0) is a dummy taking the value 1 if at least one conflict is observed in the cell that year. # conflicts is the number of conflict events observed. Soil fertility (mean), Soil fertility (mode) and Soil fertility (variance) are respectively the mean, mode and variance of nutrient availability within the cell. Fertilizer price (\$/ton) is our measure of fertilizer price from equation (21).

4 Econometric strategy and results

4.1 Empirical specification

We denote cells by c and years by t. Our first prediction states that variations in fertilizer prices have a positive impact on the likelihood of violence within a cell. We estimate the following specification:

$$\text{Conflict}_{ct} = \alpha_1 \ln P_{ct} + \mathbf{D'_{ct}}\beta + \eta_c + \mu_t + \varepsilon_{ct}, \tag{22}$$

where Conflict_{ct} is our conflict variable at the cell-year level, with conflicts being measured in terms of incidence (i.e. a binary variable coding for non-zero events) in our baseline specification, although we also estimate specifications using conflict intensity (number of events), onset and ending as alternative dependent variables. We also study the specific subset of events that we consider to be land-related. P_{ct} is our measure of cell-specific fertilizer price shocks from equation (21), which measures the price of the fertilizer for the main crop produced by the cell c at time t, or, in our sensitivity analysis, the price of the fertilizers for the 5 main crops produced by the cell. P_{ct} varies across cells and time because the fertilizers needed for different crops are characterized by different nutrient composition and the prices of these nutrients vary through time, as explained above. $\mathbf{D'_{ct}}$ is a set of potential time-varying cell-specific co-determinants of conflicts that we consider in our robustness analysis. These include weather-related conditions, and other world demand or price shocks, related to mineral or agricultural output. Finally, η_c and μ_t are cell and year fixed effects, respectively. η_c accounts for any time-invariant or slow-moving cell characteristics, such as geography, institutions, or culture, that may affect conflict; μ_t captures common time shocks, in particular global commodity price variations, that might be correlated with fertilizer prices.

According to prediction 1, estimates of α_1 should be positive, e.g. spikes in fertilizer price make conflict more likely.[26] In our theoretical model, this is due to the fact that, in an environment where soil fertility is unequally distributed, an increase in the price of fertilizer diminishes the opportunity cost of conflicts more than it decreases the rapacity gain, i.e. the production that can be appropriated through violence for groups who possess less fertile soils. Hence, conflict probability rises.

Our second prediction relates soil fertility heterogeneity to the effect of fertilizer price changes on conflict. We therefore augment equation (22) with an interaction term between fertilizer prices and a measure of soil fertility heterogeneity:

$$\text{Conflict}_{ct} = \alpha_1 \ln P_{ct} + \alpha_2 \ln P_{ct} \times \mathbb{V}(\text{Fertility}_c) + \alpha_3 \ln P_{ct} \times \overline{\text{Fertility}}_c + \mathbf{D'_{ct}}\beta + \eta_c + \mu_t + \varepsilon_{ct}, \quad (23)$$

where $\mathbb{V}(\text{Fertility}_c)$ is a measure of the heterogeneity of soil fertility in cell c. In our baseline estimations, this measure represents the variance of nutrient' availability within the cell. Note that we control for $\overline{\text{Fertility}}_c$, the average fertility level in the cell, as required by the model (see condition (20) and the paragraph before equation (17)). $\mathbf{D'_{ct}}$ includes interaction terms between $\ln P_{ct}$ and cell-specific variables that may be correlated with $\mathbb{V}(\text{Fertility}_c)$, and which we also consider in our robustness checks. These include various geographical and socio-economic characteristics.

Following the second prediction of the model, we expect α_2 to be positive, e.g. increases in fertilizer prices trigger more conflicts in cells in which natural soil fertility is more heterogeneous. This is because, keeping average fertility constant, in regions where soil fertility is more heterogeneous, the drop in the opportunity cost resulting from an increase in fertilizer prices is greater than in more homogeneous regions, and the decrease in the rapacity gain is lower. However, as discussed in the appendix, we note that the sign of α_3 is theoretically ambiguous and may depend on our measure of soil fertility.

Econometric issues. As a benchmark, equations (22) and (23) are estimated using a linear probability model (LPM), and include cell (η_c) and year (μ_t) fixed effects. A LPM more natu-

[26] An alternative approach would be to focus on price growth over time (i.e. difference in log-prices). Section F.2 in the online appendix discusses this alternative specification. We argue that the use of levels is consistent with our theory, and show that it is statistically supported by unit root tests.

rally handles multiple fixed effects and spatial correlation, and better deals with rare events than, for instance, a logit model (King and Zeng, 2001). We do, however, check the results we obtain using nonlinear estimators, specifically logit when the dependent variable is conflict incidence, or Poisson when the dependent variable is the number of events. We also consider a number of alternative specifications, adding in particular country-specific time trends or country×year fixed effects to equations (22) and (23).

Given the high spatial resolution of the data, and because both conflicts and crop specialization are geographically clustered, we allow the error term to be spatially correlated, and autocorrelated in our baseline estimations.[27] More precisely, we apply a spatial HAC correction to our standard errors, allowing for both cross-sectional spatial correlation and location-specific serial correlation, following the method developed by Conley (1999). As in Berman *et al.* (2017), we impose no constraint on the temporal decay for the Newey-West/Bartlett kernel that weights serial correlation across time periods. The horizon at which serial correlation is assumed to vanish can be infinite (i.e. 100,000 years). In the spatial dimension we retain a radius of 500km for the spatial kernel.[28] We also provide robustness results allowing for different radiuses and temporal decays.

The main potential threat to causal identification in equations (22) and (23) is arguably the existence of other shocks correlated with variations in fertilizer prices, or of cell characteristics correlated with soil fertility heterogeneity (in equation (23)). We therefore perform extensive robustness exercises, including time-varying variables such as variations in mineral prices, agricultural commodity demand, and climate, as well as time-invariant variables that reflect the geography and other characteristics of the cell, interacted with P_{ct}.

4.2 Baseline results

Our baseline results appear in Table 2 below. Columns (1) and (2) consider the full set of conflict events, and columns (3)-(4) restrict the dependent variable to land-related conflicts. We find support for our two theoretical predictions. First, variations in local fertilizer price are positively and significantly correlated with conflict probability (columns (1) and (3)). Second, this effect is magnified in cells characterized by more heterogeneous soil fertility (columns (2) and (4)). The coefficient of the interaction between the average soil fertility level and fertilizer price is significant only in column (2).

When all conflicts events are considered, our estimates from column (1) imply that a standard deviation increase in fertilizer price (i.e. an increase of approximately 0.5 in logs) raises conflict probability by 5.9 percentage points, a moderate impact. In cells where soil fertility is one standard deviation more heterogeneous than the sample average, the same standard deviation increase in fertilizer price rises conflict probability by 9.5 percentage points. Interestingly, these figures – relative to average conflict probability – are much larger in the case of land-related conflicts.[29] We come back to the quantitative interpretation of our results in section 4.5 below.

[27]A related issue is related to temporal and spatial spillovers in the effect of fertilizer prices. We come back to this question in our robustness section below.

[28]We employ the recent Stata routine `acreg` developed by Collela *et al.* (2018) based on Hsiang (2010) and Conley (1999).

[29]The coefficients displayed in Table 2 are lower in columns (3) and (4), but this is only due to the very low probability of this type of event in our sample.

Table 2: Baseline results

	(1)	(2)	(3)	(4)
Dep. var.	Conflict incidence			
Conflicts	—— All events ——		—— Land-related ——	
ln fertilizer price	0.119^a	0.156^a	0.018^b	0.019^b
	(0.041)	(0.043)	(0.007)	(0.007)
$\times$ $\mathbb{V}$(Fertility)		0.058^a		0.007^a
		(0.009)		(0.003)
$\times$ $\overline{\text{Fertility}}$		0.021^a		0.001
		(0.004)		(0.001)
Cell and Year FE	Yes			
Countries	42			
Period	1997-2013			
Observations	111605	111588	111605	111588
Average predicted conflict prob.	0.071	0.071	0.006	0.006
Increase in conflict prob. after a one s.d. increase in fertilizer price[1]				
Average cell	0.059	0.062	0.009	0.009
1 s.d. more heterogeneous cell		0.096		0.043

[c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. ln fertilizer price is our baseline fertilizer price shock, computed using the required NPK mix (from IPNI) for the main crop produced by the cell (from GAEZ). $\overline{\text{Fertility}}$ is the mean of nutrient availability of the cell, i.e minus the categorial variable with values ranging from 1 to 5 (from HWSD). $\mathbb{V}$(Fertility) is the variance of the nutrient availability level within the cell (from HWSD). In columns (1) and (2) the dependent variable is a dummy taking the value 1 if at least a conflict event is observed in the cell during the year, 0 otherwise. In columns (3) and (4), the dependent variable is a dummy taking the value 1 if at least a land-related event is observed in the cell during the year, 0 otherwise. [1] In columns (1) and (3), we compute the effect of a standard deviation increase in fertilizer prices given the estimated coefficient. In columns (2) and (4), we compute the effect of a standard deviation increase in fertilizer prices, respectively for the average cell – a cell with the average value of $\overline{\text{Fertility}}$ and $\mathbb{V}$(Fertility) –, and then for a cell with the average value of $\overline{\text{Fertility}}$ and a value of 1 standard deviation above the mean of $\mathbb{V}$(Fertility).

4.3 Sensitivity analysis

In this section we first discuss specification issues; we then show that our main results of Table 2, columns (1) and (2) are robust to a large battery of sensitivity checks. Most of the tables are relegated to the online appendix (section F), in which we discuss these results at length.

4.3.1 Omitted variables

In the first important set of robustness checks we control for potential omitted variables (online appendix section A.5 provides the source of each variable). In Table 3, we add country×year fixed effects (or country-specific time-trends) to filter out all time-varying country characteristics that could be correlated to both the dynamics of conflicts and with global changes in fertilizer prices (columns (1) to (4)). Such fixed effects capture for instance the fact that in 2008, in the midst of the spike of fertilizers' and other commodities' prices, the stock exchange collapsed in South Africa and Nigeria. They can also capture country-specific abilities to subsidize fertilizers during bad times. It is reassuring that our results were not driven by unobserved heterogeneity across country×year. Columns (5)-(6) show even more restrictive specifications, where time-varying fixed effects are defined at the sub-national level (second administrative units). This rules out the possibility that our results are caused by regional characteristics correlated with conflicts and fertilizer prices (e.g., fertilizer subsidies).

Table 3: Alternative specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			Conflict incidence			
ln fertilizer price	0.085^{b}	0.071^{b}	0.112^{a}	0.094^{a}	0.064^{b}	0.072^{b}
	(0.034)	(0.034)	(0.035)	(0.035)	(0.032)	(0.032)
$\times$ $\mathbb{V}$(Fertility)		0.025^{a}		0.023^{a}		0.003^{a}
		(0.006)		(0.007)		(0.001)
$\times$ $\overline{\text{Fertility}}$		-0.004		-0.006		0.003^{a}
		(0.003)		(0.004)		(0.001)
Cell FE	Yes	Yes	Yes	Yes	Yes	Yes
Country$\times$Year FE	Yes	Yes	No	No	No	No
Country-specific time trends	No	No	Yes	Yes	No	No
Country$\times$Region$\times$Year FE	No	No	No	No	Yes	Yes
Observations	111588	111571	111605	111588	109599	109582

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. Regions are defined as the country-specific second administrative units.

Table 4 controls for cell-specific time-varying factors such as commodity prices and weather conditions. In recent literature conflict likelihood has been shown to be associated to fluctuations in the prices of agricultural commodities, produced (Dube and Vargas, 2013, Berman and Couttenier, 2015, McGuirke and Burke, 2018) or consumed (McGuirke and Burke, 2018), to changes in mineral prices (Berman *et al.*, 2017) or to rainfall variations (Harari and Ferrara, 2018, Guariso and Rogall, 2017, Adhvaryu *et al.*, 2017). These shocks could be correlated to our fertilizer prices. Similarly, soil quality might correlate with production and consumption patterns. We sequentially include agricultural price shocks, local rainfall variations, oil and mineral prices. The producer prices of agricultural goods are computed as the sum of the world price of all crops produced in the cell, weighted by the share of each crop in cultivated land (in the spirit of Berman and Couttenier, 2015 and McGuirke and Burke, 2018). Consistent with these papers, we find a negative impact of such shocks (column 2). The crop consumption price index is computed as the weighted sum of the world prices of consumed crops, with weights being defined at the country-level by nutritional intake shares from FAO Food Balance Sheets data (McGuirke and Burke, 2018). Its coefficient is positive but less precisely estimated.[30] In all instances our coefficients of interest remain statistically significant and of similar magnitude as in our benchmark specification. Similarly, including rainfall, the world price of oil for oil-producing cells or the price of the main mineral produced in the cell (as in Berman *et al.*, 2017) has little impact on our estimates.[31]

[30]Note that the statistical significance of the coefficients on the producer and consumer price indexes is quite sensitive to our choice of spatial clustering of the standard errors. When clustering at the cell-level, for instance, the producer price is significant at the 1% level.

[31]The number of observations is lower than in our baseline sample for several reasons. First, not all countries have consumption data in the FAO Food Balance Sheets, and so the consumer price index cannot be computed for

Table 4: Additional time-varying controls

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.	Conflict incidence					
ln fertilizer price	0.119^b	0.121^b	0.122^b	0.121^b	0.119^b	0.174^a
	(0.056)	(0.056)	(0.056)	(0.056)	(0.058)	(0.067)
$\times$ $\mathbb{V}$(Fertility)						0.042^b
						(0.017)
ln producer price index		-0.076^c	-0.076^c	-0.076^c	-0.010	-0.111
		(0.043)	(0.043)	(0.043)	(0.044)	(0.088)
$\times$ $\mathbb{V}$(Fertility)						-0.006
						(0.067)
ln consumer price index		0.028	0.027	0.030	-0.006	0.053
		(0.063)	(0.064)	(0.063)	(0.061)	(0.092)
$\times$ $\mathbb{V}$(Fertility)						-0.005
						(0.065)
ln rainfall			0.010	0.011	-0.000	-0.035^c
			(0.010)	(0.010)	(0.010)	(0.018)
$\times$ $\mathbb{V}$(Fertility)						-0.008
						(0.016)
ln oil price $\times$ oil field				0.035^c	0.029^c	-0.075^c
				(0.019)	(0.017)	(0.040)
$\times$ $\mathbb{V}$(Fertility)						0.033
						(0.050)
ln main mineral price $\times$ mine					0.054^b	0.159^a
					(0.023)	(0.055)
$\times$ $\mathbb{V}$(Fertility)						0.104
						(0.076)
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	85680	85680	85680	85680	70560	70546

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. ln producer price index is computed as in Berman and Couttenier (2015) and McGuirke and Burke (2018) using M3-crop data as the sum of the world price of all crops produced in the cell, weighted by the share of each crop in cultivated land. ln consumer price index is computed as in McGuirke and Burke (2018) as the weighted sum of the world prices of consumed crops, weights being defined at the country-level by nutritional intake shares from FAO Food Balance Sheets data. ln oil price equals the world price of oil interacted with a dummy denoting onshore petroleum deposits (from Prio-Grid v.2). ln price mineral is price of the main mineral produced by the cell during the period, and equals zero if no active mine is recorded in the cell over the period – see Berman *et al.* (2017). Finally, rainfall is the yearly total amount of precipitation (in millimeter) in the cell, based on monthly meteorological statistics from the Global Precipitation Climatology Centre (as appearing in Prio-Grid v.2).

Our measures of soil fertility could also conceivably be correlated with a number of local characteristics affecting the response of the cell to economic shocks. This might be especially true of time-invariant geographical / topographic characteristics; section A.9 of the online appendix indeed shows that our measure of the variance of soil fertility correlates with the presence of water and forest in the cell. Socio-economic characteristics (e.g. income or, population density) can also correlate with fertility and affect conflicts. Table 5 shows that indeed, some of these

our entire sample. Second, the data on minerals from Berman *et al.* (2017) stops in 2010.

characteristics do affect the impact of fertilizer prices on conflicts. In columns (1)-(2), we therefore add to our baseline specification a set of interaction terms between fertilizer prices and time-invariant geographical characteristics. Quite intuitively, we find that fertilizer price variations have a stronger impact in cells where agricultural or harvested area represent a larger share of the total surface. Agricultural specialization could also correlate with cell-specific characteristics that affect the prevalence of malaria. In column (3), we find that the inclusion of the interaction between fertilizer price and malaria suitability at the cell-level leaves our result unchanged.[32] In columns (4) to (9), we control for local socio-economic characteristics, specifically: population density and nighttime lights (which could serve as a proxy for either GDP or population density).[33] We find that conflict is more responsive to fertilizer price changes in denser cells, as measured by population or nighttime luminosity. However, in all estimations our coefficients of interest remain remarkably stable.[34]

Finally, despite the wide array of fixed effects and additional controls that we have included, it could be the case that the residual unobserved heterogeneity still co-moves with the world prices of fertilizers. We perform a placebo analysis to exclude this last concern and check the validity of our approach. We replace the price of fertilizer in the cell with the price of a fertilizer whose mix of nutrients is different from the one of the main crop of the cell. More precisely, we randomly assign a main crop to each of the cells and estimate specification (1) of Table 2 with this fake fertilizer price variable. We repeat this Monte Carlo procedure in 1,000 draws. Figure F1 in the online appendix (section F.1) displays the sampling distribution of the coefficient of fertilizer price for each estimation. Reassuringly, the Monte Carlo coefficients are distributed far from their baseline estimates and are massively insignificant. This confirms that our baseline results are not driven by unobserved co-movements with fertilizer prices.

4.3.2 Econometric specification

Our main specification uses the level of log fertilizer price, and does not take into account potential lagged effects in the temporal or spatial dimensions. Section F.2 of the online appendix discusses both assumptions. As pointed in Ciccone (2011) in the context of rainfall-induced income shocks, the correct specification of the econometric model involves levels, unless price exhibits non-stationarity. We show that the use of levels is both theoretically founded and supported by unit root tests, which show that our price series are stationary. We also find that allowing for spatial spillovers doubles the estimated impact of fertilizer price variations, while including temporal lags has little influence on the magnitude of the effect. The results on spatial lags echo the findings of Berman *et al.* (2017) and McGuirke and Burke (2018), who study respectively the links between mineral prices and food price variations on conflict at the local-level.

[32] Cervellati *et al.* (2016) show that suitable conditions for malaria increase the incidence of civil violence. We employ the *Malaria Ecology Index* used by Kiszewski *et al.* (2004) and developed by Gordon McCord as a measure of malaria at the cell level.

[33] These data were obtained from PRIO-GRID and the Global Land Survey dataset, respectively. Demographic and economic variables are measured before the start of the period. A complete description of the variables is provided in section A.5 of the online appendix.

[34] Soil quality and its dispersion could affect ethnic diversity in particular, as found by Michalopoulos (2012). If this is the case, then our estimates would confound the magnifying effect of heterogeneous land endowments with that of ethnic divisions. We come back to the role of ethnic divisions in section 5.

Table 5: Additional time-invariant controls

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			Conflict incidence			
Controls	—— Geography ——			Socio-economic		
ln fertilizer price	0.158^{a}	0.147^{a}	0.149^{a}	0.148^{a}	0.148^{a}	0.149^{a}
	(0.044)	(0.047)	(0.042)	(0.047)	(0.043)	(0.046)
ln fertilizer price × $\mathbb{V}$(Fertility)	0.055^{a}	0.056^{a}	0.059^{a}	0.067^{a}	0.054^{a}	0.062^{a}
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.011)
ln fertilizer price × $\overline{\text{Fertility}}$	0.017^{a}	0.020^{a}	0.020^{a}	0.021^{a}	0.019^{a}	0.018^{a}
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)
ln fertilizer price × % agriculture	0.025^{c}					0.018
	(0.015)					(0.016)
ln fertilizer price × % forest	-0.027^{b}	-0.038^{a}				-0.024^{c}
	(0.013)	(0.012)				(0.014)
ln fertilizer price × % barren	-0.015	-0.017				-0.009
	(0.011)	(0.018)				(0.013)
ln fertilizer price × % water	-0.031	-0.033				-0.042
	(0.039)	(0.040)				(0.043)
ln fertilizer price × % mountains	-0.012	-0.005				-0.009
	(0.012)	(0.012)				(0.012)
ln fertilizer price × % harvested		0.136^{c}				
		(0.075)				
ln fertilizer price × Malaria index			0.000			0.000
			(0.000)			(0.000)
ln fertilizer price × Density pop.				0.003^{b}		-0.001
				(0.002)		(0.002)
ln fertilizer price × Lights					0.069^{a}	0.067^{a}
					(0.014)	(0.014)
Cell and Year FE			Yes			
Observations	111486	96951	111588	97682	111588	97580

[c] significant at 10%; [b] significant at 5%; [a] significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. % agriculture, % forest, % barren, % water % mountains and % harvested are the percentage of the cell's area covered respectively by agricultural land, forest, barren land, water, mountainous area and the percentage harvested (all from PRIO-GRID). Malaria index is a measure of the incidence of malaria at the cell-level from Gordon McCord. Density pop. is the log of population density in 1990 from LandScan. lights is the log of nighttime luminosity in 1995 from PRIO-GRID. ln fertilizer price × $\overline{\text{Fertility}}$ is included as a control variable but its coefficient is not reported.

4.3.3 Measurement

In the online appendix section F.3, we show that our results are not sensitive to changes: i) in the level of aggregation, ii) to alternative measure and definition of conflicts, iii) to alternative measure of fertility, and iv) to the required nutrient mix by crop.

First, we show that changes in the level of spatial aggregation of our data does not influence our results qualitatively. We reproduce our baseline estimations using two alternative levels of aggregation, one smaller (0.25×0.25 degree cells) and the other larger (1×1 degree cells) than our baseline.

Second, we use a number of alternative datasets and definition of conflicts. We start with an alternative dataset, UCDP-GED, that records only deadly events pertaining to conflicts associated with more than 25 conflict-related deaths in a given year. We also use a measure of conflict intensity (number of events, number of fatalities), measures of conflict onset or ending instead of incidence and also discuss the results obtained when looking at various subcomponents of ACLED events.

Third, our baseline proxy for natural soil fertility is a measure of nutrient availability based on the soil texture, pH level, and on the amount of organic carbon. This is the closest measure to that described in our model, in which natural soil fertility and fertilizer use are substitutes. We consider the following alternative measures: (i) a classification of soils from fertile to infertile from the EU Commission, (ii) the nitrogen density of the soil, and (iii) the percentage of irrigated land in the cell. Since soil fertility and fertilizer use might be substitutes as long as natural soil fertility does not fall below a certain level (Marenya and Barrett, 2009b), we also check that our results are robust to dropping with very low levels of soil fertility.

Fourth, we compute alternative versions of our fertilizer prices: (i) using an alternative source of data for the "ideal mix" of nutrient, as the required nutrient mix by crop is experimentally measured and may vary from one data source to another (Halliday and Trenkel, 1992); (ii) using the five main suitable crops for each cell weighted by the relative suitability of each crop within the cell, in order to allow for multiple cropping; (iii) using an alternative data source to identify the main crops from actual harvested area (Monfreda *et al.*, 2008).

4.3.4 Other robustness

Estimation. We check whether our baseline results are sensitive to alternative estimations methods of both the coefficients and their standard errors (online appendix F.4). We first replicate the baseline estimates with various cutoffs of spatial correlation of the error term. Second, we estimate our baseline specification using non-linear estimators instead of LPM.

Sensitivity to specific countries, years or crops. In the online appendix F.5, we perform a systematic sensitivity analysis and drop each country, year and main crop one by one from our sample. Our coefficients of interest remain remarkably stable. In particular, dropping the years during which commodities prices spiked (2008-2009) has little effect on our results – if anything it slightly increases our estimates. Across countries, Angola is found to contribute significantly to our estimates, although these remain highly significant when we drop it.

4.4 Underlying mechanisms

As mentioned earlier, section D.1 of the online appendix provides several pieces of empirical evidence that support the main implications of our model. Using LSMS data we find in particular that being located in a fertile area tends to decrease the amount of inorganic fertilizers used by households, and that land value decreases with fertilizer prices, especially in nutrient-poor areas. While these results should be interpreted with caution due to the small number of countries and the likely presence of some degree of noise in the data, they are a favorable indication of our key theoretical mechanisms. Importantly, we also show that our measure of fertilizer prices affects negatively several measures of yields at the local-level, some of them being available for the entire set of SSA countries and over most of our period of study.

The online appendix E contains two additional exercises which again suggest that our results are indeed likely driven by the channels at play in our model.

4.4.1 Violence at the individual-level

We show that our measure of fertilizer prices correlates with several measures of violence at the individual or household levels, using two different datasets (online appendix section E.1). First, we combine 3 waves of the Afrobarometer surveys (rounds 3 to 5) which contain geo-localized information at the individual-level for 28 African countries and around 80,000 individuals over the period 2005-2013. Note that the Afrobarometer is not a panel but a repeated cross-section, hence we cannot track individuals over time. To measure violence, we use the following questions: (i) Q11.a "During the past year, have you or anyone in your family: Had something stolen from your house?" and (ii) Q11.b "During the past year, have you or anyone in your family: Been physically attacked?". Second, we use household-level information from the World Bank LSMS, which cover only six countries but with a panel structure. To measure violence, we use the fact that the surveys ask households wether they did face a number of shocks. We use information on the two following shocks: (i) theft / robbery / other violence; (ii) involuntary loss of house/land. For each type of shock, we construct dummies which equal 1 if the household did face at least once the shock in the previous year(s). As explained in more details in the online appendix, these data are less harmonized and more noisy than the one of the Afrobarometer. We find results broadly consistent with our story, especially in the case of the Afrobarometer and when using the land-related shocks from the LSMS. The latter finding echoes our previous one obtained with our measure of land-related conflict from ACLED (Table 2, columns (3) and (4)).

4.4.2 Heterogeneity across countries

We finally explore whether countries are heterogeneous in the way they react to variations in fertility triggered by fertilizer prices (online appendix section E.2). We first show our coefficients of interest are increasing in country-level fertilizer consumption. We use data on the intensity of fertilizer use for a subset of 30 countries from FAO-STAT. Quantitatively, the direct effect of fertilizer prices on conflict doubles when we compare the country that uses the least fertilizer (Central African Republic) with the country that uses the most (Malawi). Quite reassuringly, we do not detect any significant effect of fertilizer price variations in countries where fertilizer use is close to zero. We then make use of information on the legal security of land tenure. Specifically, we rely on estimates of the extent to which the security of land tenure for indigenous peoples and communities is legally codified in national laws (see section A.5 for more information). We find a smaller effect of fertilizer price on conflict in countries where land tenure is better secured, especially when controlling for broad institutional quality indicators. The coefficients on the triple interaction terms involving the variance of soil fertility are insignificant, which is not surprising given how demanding these specifications are and how noisy our land security proxy is.

4.5 Quantifications

How large is the effect of fertilizer prices on conflict? As shown in Table 4 above, the average effect of fertilizer price changes is quite similar in magnitude to the one found in the case of the world price of agricultural output or in the case of the prices of minerals. This might seem surprising at first given the widespread belief that fertilizers are not frequently used in Sub-Saharan Africa and therefore represent a small fraction of overall production costs in these countries. In fact, recent studies have shown that the use of fertilizers in this region is higher than usually thought. Sheahan and Barrett (2014), using data from the World Bank LSMS surveys on six SSA countries, find that a third of surveyed farmers use inorganic fertilizers, and that this share reaches 55% in Ethiopia and 77% in Malawi. The average amount of fertilizers used is 57 kg/ha, a number twice larger than estimates from previous studies. Available estimates of fertilizer demand price elasticity in Africa range from -0.82 to -1.08,[35] which suggests that the demand of fertilizer is inelastic but still sensitive to fertilizer price variations.

All this is consistent with the fact that we find significant effect of fluctuations in our fertilizer prices on yields in our sample of SSA countries (online appendix section D.1.2). These estimates can also be used to quantify the changes in conflict probability implied by fertilizer prices through their effect on agricultural productivity, and to compare these with existing literature. Using the figures from Miguel *et al.* (2004), for instance, we find that a 1% increase in rainfall-induced GDP growth leads to a 9.5% decrease in the probability of conflict. Using the results from Hodler and Raschky (2014), we find that the elasticity of conflict to nighttime lights is 6.5: a 1% increase in GDP growth leads to a 6.5% decrease in the probability of conflict.[36]

In our case, to compute the elasticity of conflict to agricultural productivity, we need an estimate of the elasticity of agricultural productivity to fertilizer price. Using our own estimates from the online appendix Tables D3 and D4 (section D.1.2), we find that the elasticity of conflict to agricultural output lies between 4.4 and 11.3. In other words, a 1% increase in agricultural productivity leads to a decrease in the probability of conflict ranging from 4.4% to 11.3%.[37] When using instead existing estimates of yields response to fertilizer and estimates of the fertilizer demand price elasticity from the literature, we find that the elasticity of conflict to agricultural productivity is lower and lies between 1.75 and 3.8.[38] Overall, these orders of magnitude are consistent with Miguel *et al.* (2004) and Hodler and Raschky (2014).

[35]These elasticities were estimated using data from Malawi (Chembezi, 1990; Komarek *et al.*, 2017) and Tanzania (Brekke *et al.*, 1999).

[36]Miguel *et al.* (2004) find that the effect of the log of GDP growth on the likelihood of conflict is -2.55 (Table 4, column (6)) and the unconditional probability of conflict is 0.27 in their data. Hodler and Raschky (2014) find that the effect of the log of lights on the probability of conflict is -0.3 (Table 2, column (5)) and the unconditional conflict probability is 0.046.

[37]We use our main estimate of the effect of fertilizer price on conflict, 0.119 from Table 2, column (1). We get each bound by dividing 0.119 by the unconditional probability of conflict in our data (0.07) and by our bound estimates of the elasticity of agricultural yield to fertilizer price, -0.39 from Table D4 (in which the analysis covers six countries performed at the household-plot level) or -0.15 from Table D3 (columns (1) and (2), where the analysis covers Africa and is performed at the regional-level), respectively.

[38]Recent estimates of yields response to fertilizer (nitrogen) range from 15 to 25 kg of grain per kg of N. These values were estimated using data from Kenya (Marenya and Barrett, 2009b; Matsumoto and Yamano, 2011; Sheahan *et al.*, 2013), Zambia (Xu *et al.*, 2009), Ghana (Chapoto and Ragasa, 2013) and Burkina Faso (Koussoube and Nauges, 2017). Available estimates of fertilizer demand price elasticity range from -0.82 to -1.08. These elasticities were estimated using data from Malawi (Chembezi, 1990; Komarek *et al.*, 2017) and Tanzania (Brekke *et al.*, 1999). We use the average N fertilizer use of $36.9kg/ha$ provided in Sheahan and Barrett (2014) who use LSMS data. We also consider an average yield of 1 ton/ha (World Bank, see McArthur and McCord, 2017). Using these figures, we find that the elasticity of yields to fertilizers is between 0.55 and 0.9. Multiplying this range by the range of values of the fertilizer demand price elasticities, we find that the elasticity of yields to fertilizer price ranges between -0.97 and -0.45.

5 Crop heterogeneity, ethnic divisions and population pressure

Thus far, in the model as well as in our empirical analysis, we have abstracted from the ethnic dimension of conflicts. The issues of heterogeneous access to fertile soils and of ethnic diversity are however likely to be intertwined. As shown by Michalopoulos (2012), regions where the land characteristics are more heterogeneous are on average more ethnically diverse. Even if it falls beyond the scope of our model, we can nonetheless assess the empirical relevance of two potential mechanisms through which ethnic lines might affect how conflict react to land fertility shocks. First, pre-existing ethnic tensions may exacerbate the effect of rising land inequality. The civil war and subsequent genocide in Rwanda illustrate this possibility, as they have been at least partly triggered by the combination of historical ethnic divisions between Tutsi and Hutu (divisions which are themselves linked to their agricultural practices), population growth and soil depletion (André and Platteau, 1998). We can assess whether between group inequality in soil quality might on the contrary magnify the impact of fertilizer prices on conflicts, especially when combined with population pressure. Second, within an ethnic group, heterogeneity of crop production may help to cope with the adverse impact of fertilizer price variations on conflict by providing opportunities for co-insurance.

5.1 Land inequality within and between ethnic groups

Our baseline results show that land inequality magnifies the effect of negative effect of input prices on conflict. Soil quality inequality could, however, be observed either across or within the homelands of ethnic groups, both of which could in theory affect the likelihood of conflict. Larger between-group inequality could exacerbate grievances, frustrations, and feelings of relative deprivation (Cederman *et al.*, 2011; Guariso and Rogall, 2017), and these issues could coincide with the rapacity gain/opportunity cost channels described in our model. Within-group inequality could matter, as well (Esteban and Ray, 2008, 2011a; Huber and Mayoral, 2019). In Esteban and Ray (2011a), for instance, more inequality within ethnic groups makes conflicts more likely because it makes it easier for the rich to finance them by hiring fighters.

Our methodology is the following. Combining maps of ethnic boundaries with our baseline information on nutrient availability, we construct measures of within- and between-ethnic groups soil heterogeneity using a simple variance decomposition.[39] Specifically, we decompose the total variance of soil quality observed in a given cell over the territories of identified ethnic groups into the variance within groups and the variance across groups:[40]

$$\mathbb{V}(\text{Fertility}) = \mathbb{V}_W(\text{Fertility}) + \mathbb{V}_B(\text{Fertility})$$

Or:

$$\frac{1}{A}\sum_{e\in E}\sum_{j\in T(e)}(s_j - s)^2 = \frac{1}{A}\sum_{e\in E}\sum_{j\in T(e)}(s_j - s_e)^2 + \frac{1}{A}\sum_{e\in E}A_e(s_e - s)^2 \tag{24}$$

[39]The empirical strategy we use in this section is in the same spirit than Guariso and Rogall (2017). They compute a measure of inequality using rainfall on ethnic homelands and aggregate this information in order to provide cross-country evidence that economic inequality shocks (in terms of rainfall) between ethnic groups increase the likelihood of conflict. However, they do not find any significant effect of economic inequality shocks (rainfall) within ethnic groups on the likelihood of conflict.

[40]See for instance Helpman *et al.* (2017) for an application of such a decomposition to within and between sector *wage* inequality.

where e is an ethnic-group, E is the set of ethnic groups observed in the cell, j is our geographical unit of observation of nutrient availability (pixels of 5 arc-minutes), and $T(e)$ is the set of geographical units covered by the homeland of ethnic group e. s_j, s_e, and s denote nutrient availability in area j, average nutrient availability over the area in which group e is observed, and average nutrient availability across all the pixels of the cell, respectively. Finally, A and A_e are, respectively, the sizes (in number of pixels) of the area covered by all ethnic groups and by ethnic group e. In other words, the overall variance of soil fertility in the cell (over the areas covered by at least one ethnic group) is the sum of the average variance within groups and of the variance of the average fertility across groups.

We compute two versions of $\{\mathbb{V}(\text{Fertility}), \mathbb{V}_W(\text{Fertility}), \mathbb{V}_B(\text{Fertility})\}$ based on two alternative datasets that map the borders of ethnic homelands. We use the contours of historical ethnic homelands from Murdock (1959), although we provide robustness exercises in the online appendix F.6 using data from the Geo-referencing of Ethnic Groups (GREG), which is drawn from the Soviet Atlas Narodov Mira (Weidmann *et al.*, 2010).[41] In our baseline specification, we replace the interaction term between fertilizer price and $\mathbb{V}(\text{Fertility})$ by two interaction terms between fertilizer price and each component of the variance of soil fertility. The between-group variance is set to zero in cells where only one ethnic group is present.

Columns (1) to (4) of Table 6 contain the results. We start by reporting the results on the effect of the overall variance in column (1),[42] and then split the variable into its within and between-group components in column (2). The remaining regressions add controls for ethnic polarization (similar results are obtained when controlling for fractionalization instead) and the number of ethnic groups in the cell. Both within and between group land inequality are found to magnify the effect of fertilizer price variations.[43] The coefficient on between-groups inequality is however found to be twice as high as the one on the within-group variance.

The role of population pressure. As mentioned above, anecdotal evidence suggests that competition for fertile lands is more likely to trigger conflict in densely populated areas. Returning to the example of Rwanda, while population pressure has surely been one of the war's causes, several scholars have even argued that this in fact served as the main motivation for a genocide that was purposefully planned by a small Hutu elite (e.g. Diamond, 2005). More recently, Acemoglu *et al.* (2017) used cross-country data to show that exogenous changes in population growth were positively associated with civil wars.

In the last two columns of Table 6, we investigate the links between population pressure, soil fertility shocks, and conflicts. In column (5) we add interaction terms between the log of population density in the cell (in 1990 to mitigate endogeneity concerns) and fertilizer prices. Fertilizer price shocks indeed have a slightly stronger effect in densely populated areas. What is more, this effect is only observed in cells where land is unequally distributed (column (6)).

[41] Figure A6 in the online appendix (section A.7) plots the obtained variances, within and across groups.

[42] Note that the estimated coefficients are not the same as in our baseline table. This is because the variance of soil fertility is computed over the territories wherein at least one ethnic group is identified, which do not necessarily cover the entire cell.

[43] In Table F11 of the online appendix (section F.6), we show that the coefficient estimates on the interaction with between-group inequality are positive but statistically insignificant at conventional levels. A reason that might explain this discrepancy is the highest variability of the measure when using Murdock instead of GREG data due to the largest number of groups present in the Murdock dataset. The contribution of the between-group component is 8% using Murdock, and 4% when using GREG, which is likely insufficient to identify an effect.

Table 6: Soil fertility heterogeneity within and between ethnic groups

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.			Conflict incidence			
ln fertilizer price	0.152^a	0.151^a	0.147^a	0.152^a	0.140^a	0.144^a
	(0.043)	(0.043)	(0.043)	(0.043)	(0.046)	(0.046)
× $\mathbb{V}$(Fertility)	0.047^a					
	(0.008)					
× $\mathbb{V}_B$(Fertility)		0.090^a	0.072^b	0.081^b	0.069^b	0.002
		(0.030)	(0.031)	(0.032)	(0.033)	(0.031)
× $\mathbb{V}_W$(Fertility)		0.044^a	0.046^a	0.045^a	0.051^a	0.044^a
		(0.009)	(0.009)	(0.009)	(0.010)	(0.080)
× Ethn. Pol.			0.037	0.060^b	0.037	0.040
			(0.023)	(0.028)	(0.025)	(0.025)
× # groups				-0.004		
				(0.004)		
× Ethn. Pol.					0.037	0.040
					(0.025)	(0.025)
× Density pop.					0.003^c	-0.000
					(0.002)	(0.002)
× $\mathbb{V}_B$(Fertility) × Density pop.						0.030^b
						(0.014)
× $\mathbb{V}_W$(Fertility) × Density pop.						0.007^b
						(0.003)
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111316	111316	111316	111316	97580	97580

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. ln fertilizer price × $\overline{\text{Fertility}}$ is included as a control variable. $\mathbb{V}_W$(Fertility) is the variance of soil fertility (nutrient availability) within ethnic groups, computed by cell. $\mathbb{V}_B$(Fertility) is the variance of soil fertility between ethnic groups, computed by cell. $\mathbb{V}$(Fertility) is the overall variance of soil fertility, computed by cell. Ethn. Pol. is an index of ethnic polarization in the cell. # groups is the number of ethnic groups present in the cell. Density pop. is the log of population density in 1990. Data on ethnic groups are obtained from Murdock (1959).

When the variance of soil quality is zero, population density no longer has an effect. On the other hand, in denser areas, the impact of both within- and between-group inequality on conflict are stronger. Again, the interaction between population density and between-group inequality has a much larger coefficient than the interaction with inequality within groups.

In a nutshell, the results presented in Table 6 imply that violence is more likely to occur when inequality rises, whether between or within groups, and especially in densely populated areas. Between-group inequality appears to contribute more than within-group inequality when population density is high. Yet, changes in within-group inequality also matter significantly: a larger part of our sample is composed of cells in which a single ethnic group is observed (hence all of the variance is within-group); in these cells, fertilizer prices do have a significant impact on conflict, especially when soil fertility is heterogeneous. More generally, the findings in this section clearly point to the need for more research focusing on the nexus between inequality, population growth, and conflicts.

5.2 Crop heterogeneity within ethnic groups

Within the homeland of an ethnic group, a more diversified crop production may dampen the adverse effect of fertilizer prices shocks. Its impact may be mitigated when the crops produced are heterogeneous in terms of nutrient needs; in this case actual price variations might be negatively correlated across space, generating possibilities of co-insurance.[44] Note that this might not be the case, however, if these price variations increase inequality within and/or between ethnic groups: in this case a price shock might trigger more conflicts.

We explore this potential source of heterogeneity in two different ways. We first construct indexes of crop suitability heterogeneity at the following three alternative levels: i) cell, ii) cell $\times$ ethnic group, and iii) ethnic group. We make use of information on ethnic homeland boundaries from Murdock (1959). An alternative source for ethnic boundaries is the data from GREG. Given our level of spatial disaggregation, our preferred source however is Murdock (1959), which contains many more groups than GREG (835 versus 250 over the geographical area we consider), which is key to be able to identify sufficient variation.

Denote by s_{ni} the share of nutrient n for given crop i from IPNI. We first compute:

$$\text{HET}_i = \sum_{n=N,P,K} \sum_{m \neq n} (s_{ni} - s_{mi})^2 \tag{25}$$

HET_i represents the sum of the squares of the differences in nutrient shares for a given crop, i.e. an indicator of nutrient heterogeneity. We then sum across the five most suitable crops of spatial unit c (which can be a cell, an ethnic-group $\times$ cell, or an ethnic group):

$$\text{HET}_c = \sum_{i=1}^{5} \text{HET}_i \tag{26}$$

We interpret HET_c as an indicator of crop production heterogeneity, i.e. how much the most suitable crops of spatial unit c require different mixes of nutrients.

In columns (1) to (3) of Table 7 we interact our fertilizer price shocks with the three different versions of HET_c. We find that, indeed, fertilizer price variations have significantly smaller effects in cells or ethnic groups producing more heterogeneous – in terms of nutrient shares – crops. When all versions of HET_c are simultaneously introduced in column (4), only the ethnic group version remains statistically significant. This last result has to be taken with caution, however, because all three measures are highly correlated.

A potential issue with the estimates of columns (1) to (4) is that a cell could produce very heterogeneous crops and yet face positively correlated price shocks if the prices of nutrients do not move in opposite directions. Moreover, these indicators do not capture heterogeneity across cells (within or between groups). Therefore, another, perhaps more satisfactory way of looking at this coinsurance mechanism is to include several versions of the fertilizer prices, interacted with each other. The results are provided in columns (5) to (7), the most interesting results being displayed

[44] We thank a referee for suggesting this mechanism.

Table 7: Crop heterogeneity and the impact of fertilizer prices on conflict

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep. var.				Conflict incidence			
ln fertilizer price	0.170^a	0.170^a	0.174^a	0.175^a	0.528^c	0.415	0.520^c
	(0.045)	(0.045)	(0.045)	(0.045)	(0.287)	(0.269)	(0.288)
× $\mathbb{V}$(Fertility)	0.052^a	0.052^a	0.052^a	0.051^a			
	(0.009)	(0.009)	(0.009)	(0.009)			
× HET_c (cell)	-0.044^b			-0.054			
	(0.018)			(0.054)			
× HET_c (cell × ethnic group)		-0.043^b		0.043			
		(0.018)		(0.057)			
× HET_c (ethnic group)			-0.062^a	-0.054^b			
			(0.024)	(0.026)			
ln fertilizer price neighbors					0.746^b		1.450^a
					(0.328)		(0.436)
× ln fertilizer price					-0.095^c		-0.224^a
					(0.053)		(0.077)
ln fertilizer price ethnic homeland						0.415	-0.723^b
						(0.280)	(0.368)
× ln fertilizer price						-0.062	0.131^b
						(0.048)	(0.067)
Cell and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	111588	111571	111588	111571	111588	111588	111588

^{c} significant at 10%; ^{b} significant at 5%; ^{a} significant at 1%. Conley (1999) standard errors in parentheses, allowing for spatial correlation within a 500km radius and for infinite serial correlation. ln fertilizer price is our baseline fertilizer price shock, computed using the required NPK mix (from IPNI) for the main crop produced by the cell (from GAEZ). $\mathbb{V}$(Fertility) is the variance of the nutrient availability level within the cell (from HWSD). Columns (1) to (4) control for an interaction term between fertilizer prices and the mean of nutrient availability of the cell. See equations (25) and (26) for a definition of HET_c. When computed at the cell×ethnic group or ethnic group levels, HET_c is the average of all crop heterogeneity in the homeland(s) of the ethnic group(s) present in the cell. ln fertilizer price neighbors is the fertilizer price of the main crop of the first and second degrees neighboring cells. ln fertilizer price ethnic group is the average fertilizer price of the main crop produced in the homeland(s) of the ethnic group(s) present in the cell.

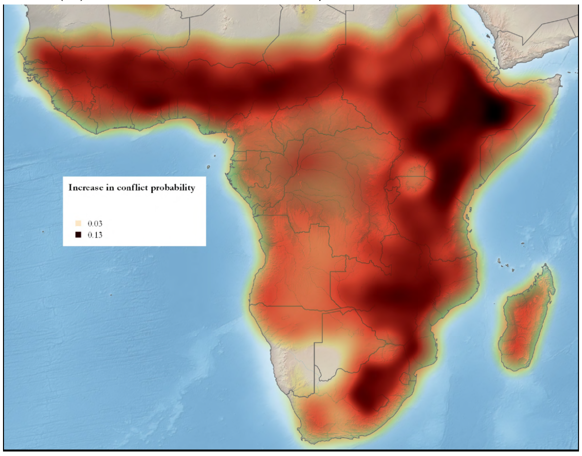
in column (7). In these estimations we include the fertilizer price of the neighboring cells (first and second degrees) and of the ethnic homeland of the group(s) present in the cell, and interact these with our baseline measure. We observe that an increase in the fertilizer price of the cell itself, everything else equal, raises the probability of conflict – our baseline results. If a positive fertilizer price shock occurs at the same time as a negative one in neighboring cells, the effect is reinforced, as shown by the negative coefficient on the interaction between ln fertilizer price in the cell and in the neighbors (columns (5) and (7)). This is consistent with the idea that, cross-cells inequality increases when the prices move in the opposite direction, which triggers more conflict. On the other hand, the interaction with the price in the ethnic homeland is positive in column (7). This finding is consistent with the coinsurance mechanism: if the co-ethnics of the cell's residents face an opposite shock, the likelihood of conflict decreases.

5.3 The geography of soil fertility and conflicts

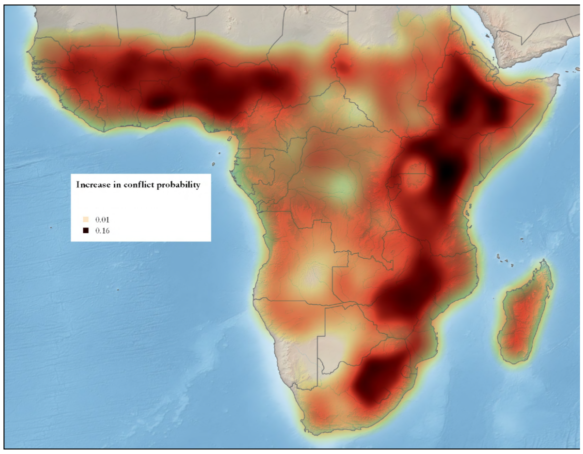
Which areas are more likely to be affected by variations in soil productivity? Figures 2.a and 2.b provide a visual representation of the predicted impact of a one standard deviation increase in fertilizer prices on conflict across Sub-Saharan countries. Figure 2.a is based on column (3) of Table 6: the heterogeneity of the effect arises primarily from differences across regions in terms of land inequality (either between or within ethnic groups). Figure 2.b is constructed from column (6) of Table 6, i.e. we consider also variations in terms of population density. Note that Figures A5 and A6 in the online appendix (section A.7) show the spatial distribution of each of these variables.

Figure 2: Effect of a one standard deviation increase in fertilizer prices on conflict

(a) Inequality within/between groups



(b) Population pressure



Note: These figures represent the predicted increase in the probability of conflict occurring, following a one standard deviation increase in fertilizer prices. Figure (a) plots the predictions obtained from column (3) of Table 6; Figure (b) adds an interaction with population density, and displays the predictions from column (6) of Table 6.

When considering only the variance in soil fertility, a stronger effect is found along a diagonal that begins in Northern Ethiopia, and continues to South Africa. The estimated impact becomes more heterogeneous when population density is taken into account. In particular, the increase in conflict probability becomes much stronger around Nigeria, Rwanda and more generally in the Great Lakes region. It remains high in most parts of Ethiopia, Kenya, and in Eastern South Africa, regions characterized by large populations and heterogeneous land endowments.

These spatial patterns correspond to conflict narratives in these regions. For instance, Peters (2004) writes:

"[...] some of the most intense competition and conflict over land resources and patterns of exclusion are found in the most densely populated areas such as Rwanda and Burundi, where commentators have included land conflicts in the complex causes of 'ethnic' hostility and civil war, and in the Kenyan Highlands and Hausa areas of Northern Nigeria where land sales and landlessness have long been common. Even where overall population density may not be high, intense competition has developed over valued resources, such as wetlands and river valleys in semi-arid regions or in areas with a single annual rainy season. Many of these, dubbed 'key resources' by ecologists working in Southern Africa [...], are coming under intensified use, and generating increased social competition and conflict among farmers [...]" (Peters, 2004, p.293).

6 Conclusion

In this paper, we provide an analysis of the effect of variations in soil productivity on violence at the local level. From a theoretical perspective, we show that changes in land inequality, defined as the level of geographical dispersion of natural agricultural soil fertility, positively affects the likelihood of conflict. Changes in fertilizer prices, through their effect on income and inequality, also increase the likelihood of conflict, especially in regions characterized by high levels of initial inequality. Combining data on local agricultural specialization, soil fertility and conflict events over SSA countries with information on international market prices of fertilizer, we find support for these predictions. We conduct a variety of robustness exercises, controlling for potential omitted factors, changes in estimation techniques, and alternative methods of measuring our key variables. We also find that country characteristics play a role: specifically, the impact of changes in fertilizer price – and hence, the effect of increases in soil fertility heterogeneity – is magnified in countries with weak institutions, or more insecure land tenure arrangements for local communities.

Note that we cannot exclude the possibility that, beyond farmers' incomes, other channels are at work. In particular, food prices might be a channel of transmission of fertilizer price shocks to conflict. Some authors (e.g. Childers *et al.*, 2011) indeed argue that the spike in fertilizer prices was one of the cause of the global food crisis of 2008 which led to violence in many African countries.

In the last part of the paper we incorporate an ethnic dimension to the analysis, and find that the distribution of soil fertility both within and across ethnic groups matters. Between-group inequality matters especially in densely populated areas, a result that accords well with case-specific evidence on several well-known civil war episodes throughout Africa.

Our work has a number of implications and indicates several avenues for future research. With respect to policy, our results suggest that fertilizer price fluctuations have a significant effect on the occurrence of violence because they generate agricultural yields fluctuations. Therefore, policies aiming at limiting such fluctuations and reducing fertilizer prices could be considered as tools to reduce conflict. Land redistribution – an issue often neglected in empirical papers dealing with the roots of civil wars in Africa – should also be a key consideration of strategies to reduce conflict.

In general, our findings imply that inequality in access to fertile lands, both within and across ethnic groups, must be considered as a serious threat to peace at the local-level. The results presented in the last section suggest that complex interactions exist between land inequality both between and across ethnic groups, population density, soil fertility, and conflict. The model presented in this paper features only some of these elements. One specific direction for future research would be to extend our theory to include more than two groups. Such a model could be used to shed light on these complex interactions, as well as to study the emergence and the diffusion of conflicts over space as a result of unevenly distributed economic shocks.

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