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Hidden Costs of War: Evidence from Nepal's Maoist Insurgency

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Abstract
This paper uses a unique longitudinal dataset to examine the costly behavioral changes adopted by agricultural households in response to the 1996–2006 Maoist insur- gency in Nepal. After the war onset, agricultural households that were exposed to high conflict intensity expand their crop cultivation choices—from mainly cereals to cereals and non-cereals—in order to avoid the Maoist tax on cereals. A one standard deviation increase in conflict exposure induced the average household to expand its number of non-cereal crops from 4.36 to 6.01, a 37.84% increase, while continuing to cultivate the same number of cereal crops. This behavioral change exposed households to greater income risk because the value of non-cereal crops is much more volatile. A risk-averse agricultural household would, as a consequence, suffer a 16.35% decline in welfare.

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1 Introduction

In 2016, approximately 12% of the world's population lived in a conflict zone (Bahgat et al., 2018). Most of these were zones of civil conflict that resulted in massive socioeconomic costs with huge impacts on daily lives (Blattman and Miguel, 2010). During a long-lasting civil conflict, households attempt to survive and often change their behavior to mitigate their losses; however, little attention has been paid to these changes and how costly they are. Failure to take this aspect into account might lead one to draw inaccurate conclusions about the costs of conflict.

In this paper, I document a channel through which conflict induced sizeable risk to income during the 1996–2006 Maoist insurgency in Nepal. Using a unique panel dataset that follows the same households before and after the onset of war, I show that agricultural households changed their crop cultivation choices from a less risky portfolio (mostly cereal crops, whose value is less volatile) to a more risky portfolio (a larger amount of non-cereal crops, whose value is more volatile) during the conflict. As a consequence, these households faced higher income risk. Further investigation suggests that avoidance of the rebel tax on cereal may have been the primary driver of such costly behavioral changes.

Empirically, I employ a difference-in-differences strategy whereby the change in household crop cultivation choices across districts that experienced different conflict intensities (as measured by total casualties per thousand district population) are compared before and after war onset while controlling for household-specific differences and aggregate time shocks. I find that agricultural households exposed to high conflict intensity cultivated many more non-cereal crops relative to those in districts that endured a lower intensity of conflict. In particular: a one standard deviation increase in conflict exposure (which translates into 0.676 more casualties per thousand district population) led a household to expand its number of non-cereal crops from about 4.36 to 6.01, a 37.84% increase, while retaining its former number of cereal crops. This result is robust to various ways of measuring conflict intensity and alternative empirical specifications, including a finer-level analysis. The result also holds when I use the value of timber resources–an important source of funding for regional Maoist autonomous government–as an instrument for conflict intensity to address the remaining endogeneity concerns.

In addition, I show that this behavioral change exposed households to increased income risk because the value of non-cereal crops is much more volatile. If one assumes mean-variance preferences, then households' welfare losses associated with one standard deviation increase in conflict intensity could be as high as 16.35%. This welfare loss is in addition to socioeconomic costs that have been well documented by the literature.

Why would these agriculture households choose to cultivate—during the conflict—more non-cereal crops, which places their income at greater risk? Subsequent analysis suggests that these changes were adopted to avoid the Maoist tax on cereal, which was frequently imposed on local households during the conflict and used to feed Maoist soldiers. Specifically, I show two pieces of suggestive evidence. Firstly, I detect more salient changes in districts with greater Maoist presence, especially when conflict intensity was high; this finding supports the idea that households expanded their crop choice disproportionately in areas where Maoists had greater "need" (more intense conflict) and "capacity" (a greater presence) to tax. Here the Maoist presence is measured by two proxies: total number of Maoist abductions during the war; and the placement of United People's Front (UPF) candidates in the 1994 parliamentary election (UPF was the "mother" party of the Maoist Communist Party of Nepal before the two split in 1994). Secondly, I find that the increase in cultivated types is more salient among high-caste households, who were the main targets of Maoist tax. Moreover, I show that alternative channels, such as market disruptions and land transfers, are unlikely to explain these results.

This paper identifies another channel through which war can have an adverse effect on household, one associated with households' active adaptation strategies when facing the war: they actively change their behavior to mitigate their losses—although doing so results in their facing extra costs. These costs may be unobservable to researchers, but failing to account for them leads to underestimates of the costs of war.

Although the Maoist insurgency in Nepal is unique in many ways, it is not uncommon for non-state armed conflict agents (here, Maoists) to levy taxes on local peasants (as occurred in Vietnam, Colombia, Liberia, Nigeria, the Democratic Republic of Congo, etc.). Hence this paper not only addresses the understudied survival strategies adopted by households in a conflict but also reveals a critical phenomenon that has recurred across many episodes of civil war.

This paper contributes to the growing empirical literature that addresses the consequences and costs of civil conflicts (Bundervoet et al., 2009; Blattman and Miguel, 2010; Bozzoli et al., 2010; Kondylis, 2010; Akresh et al., 2011; Shemyakina, 2011; Molina, 2019). As far as the Nepalese civil war alone is concerned, several papers (e.g., Valente, 2013; Menon and Van der Meulen Rodgers, 2015; Pivovarova and Swee, 2015; Mitra and Mitra, 2020) have focused on understanding the war's direct consequences in terms of education, labor market outcomes, and the allocation of post-conflict resources. Yet households' behavioral changes during war, and their consequences, have received scant attention. Verpoorten (2009), Libois (2016) and Arias et al. (2019) show that households do take actions to mitigate losses during war and suggest that such actions can be consequential. This paper adds to the literature by using panel data to understand households' behavioral changes in a prolonged (11-year) civil conflict, during which households had ample opportunities to learn about rebel group activities and to adopt coping actions. Moreover, to the best of my knowledge, this paper is the first to identify certain indirect costs associated with households' survival strategies in wartime.

Along these lines, this paper also improves our understanding of an insurgency's detrimental effects on the agricultural sector, which is the primary economic sector in most areas under conflict (FAO, 2018). Although studies in this field are scarce, they have reported adverse effects on inputs and output markets, on access to land and credit, and on household reactions to war—for example, changing the crop portfolio, hiding livestock and other visible assets, and re-allocating land and labor (Verpoorten, 2009; Rockmore, 2015; Adelaja and George, 2019; Arias et al., 2019; Brück et al., 2019; Verwimp et al., 2019). Findings in this paper suggest that (a) the rules of conduct imposed by armed non-state actors can severely affect agricultural households and (b) the indirect welfare costs associated with household coping behavior could well be significant.

This paper is related to the large development economics literature on households' coping behaviors in response to large macroeconomic and income shocks, such as natural disasters and financial crises (Corbett, 1988; Rosenzweig, 1988; Paxson, 1992; Cameron and Worswick, 2003; Thomas et al., 2005; Gröger and Zylberberg, 2016, e.g.,). Civil conflicts can certainly be viewed as a type of shock, but many peacetime coping strategies (e.g., mutual insurance, remittance) might not be feasible during wartime.[1] Thus my paper also contributes to the literature on understanding households' resilience in the face of shocks.

The rest of this paper is proceeds as follows. Section 2 constitutes the background on Nepal's agricultural sector and that country's civil conflict. Section 3 gives an overview of the data used in this paper. Section 4 presents the empirical framework. Empirical results are contained in section 5 and section 6 concludes.

2 Background

Nepal is mainly an agrarian economy where the agriculture sector accounts for 75% of its population and 40% of its Gross Domestic Production (FAO, 2007).

For much of its modern history, Nepal was as an absolute monarchy until 1990, when a new constitution was promulgated and constitutional monarchy was established. However, the new regime—despite multi-party democratic elections—was marred by political instability. Advantaged castes such as the Brahman, Chhetri, and Newar still controlled most political

[1]War is in many ways strongly similar to a natural disaster: it damages markets, reduces output, and so forth. Of course, there are many differences. Natural disasters tend to be of a short-term nature (though they may be recurring), whereas civil conflict tends to be a long-term continuing event (the average duration of a civil conflict is about 10 years; Swee, 2016). War-related damages to local civilians are usually much less predictable than are the damages due to natural disasters.

power and resources. The traditional elite leadership in the parliament failed to provide equal access and opportunities to all sections of the society. Long-standing ethnic oppression and inequality sowed the seeds of war.[2]

In February 1996, a civil war (a.k.a. the People's War) broke out in the Rolpa district of western Nepal. It turned out to be a decade-long armed conflict between the Communist Party of Nepal (Maoist), or the CPN-M, and the government of Nepal. The Maoist rebel group's aim was to overthrow the monarchy and to establish a so-called People's Republic. Maoists positioned themselves as a voice for all marginalized groups—which included the poor, women, *Dalits* (the low-caste population), and *Janajatis* (the country's indigenous population)—and they demanded abolition of special privileges for the advantaged castes.

The government initially responded with police repression, but it was unable to prevent the rise of insurgents. By 2000, the insurgency has spread to at least 35 of 75 districts. Maoists gained almost total control of five mid-western hill districts by mid-2001. The level of violence escalated quickly.

On 26 November 2001, the King declared a national state of emergency. An official death toll of 1,045 was announced by the ministry of defense during the emergency's first three months (Hutt, 2004). The insurgency peaked in 2002, when the number of attacks from both sides increased dramatically and more people died than in any other year of the war. By the end of 2002, conflict-related casualties were recorded in 74 out of 75 districts. Several rounds of peace negotiations then led to a decrease in violence. Violent conflict was largely replaced by pro-democracy demonstrations in 2006, and a peace agreement was eventually signed on 21 November 2006. Estimates of the death toll ranged from 13,000 to 17,800 (BBC News, 2009; Nepal News, 2012). Throughout this conflict, the government controlled Nepal's cities, towns, and district headquarters while Maoists dominated in rural areas.

The war brought substantial disruptions to the conflict-ridden areas over 11 years of

[2] Poverty, income inequality, food insecurity, grievance from landless farmers, and caste polarization have been identified as determinants of the conflict (Bray et al., 2003; Murshed and Gates, 2005; Tiwari, 2009; Do and Iyer, 2010).

conflict. Agriculture was perhaps the sector most affected. In Maoist-controlled areas, the insurgents frequently imposed taxes on, or forced "donations" (primarily cereals) from, households in order to feed their soldiers. Refusal to cooperate was met with kidnapping or life-threatening behavior.

According to a food security bulletin from World Food Programme (2004),

> "CPN(M) collects compulsory donations of 2 kg of cereals per household every season. For example in Jupu VDC (Achham) alone, the CPN(M) reportedly collected 4.5 MT of paddy this reporting cycle. In addition, households report that they are required to feed one or two CPN(M) cadre on a daily basis."

Furthermore, World Food Programme (2007) reports that:

> "[Farmers] were required to pay certain amounts of their production to the CPN(M), ranging from 20–60 kg of cereals or seven days of household food consumption."

Such taxation would naturally reduce a household's income and could even threaten its food security—that is, since many farmers were engaged in subsistence farming (Upreti et al., 2010). Notably, districts that suffer the most from these taxes, such as Bajura, Doti, Achham, Dolpa, and Jumla, as pointed out by a World Food Program's food security bulletin, also suffer from high conflict intensity (i.e., high per capita casualties). This is likely because Maoists relied on taxing local civilians to feed their combatants and sustain the contest with the state (i.e., Maoists had higher "needs" to tax local people in high conflict intensity districts).

Market access was also much reduced during the conflict. Both *Bandhs* (the enforced closure of markets, industries, and transport) and *naka-bandhi* (the closure of routes, forbidding movements within declared areas) had a major effect on local markets. Violence also caused severe damage to infrastructure—such as market centers, roads, vehicles, and so forth—which likewise considerably impaired transportation, market access, and the agriculture sector in general.

It is worth noting that one of the Maoist slogans was "land to its tillers", which dictated taking land away from landowners and giving it to landless farmers. Land is one of the most valuable natural resources, and in rural Nepal its ownership symbolized power, prestige, and social status. Thus it became a target for Maoist exploitation. The "land to its tillers" slogan entailed that land should be redistributed from rich landlords to poor people, thereby improving the latter's living standards. Local landlords were subsequently unable to cultivate that land, yet the poor were reluctant to cultivate because they feared security forces. Hence the country's limited land resources were not well utilized (Upreti, 2006).

3 Data

This paper relies on two sources of data: the Nepalese Living Standard Survey (NLSS) and Nepalese conflict data. The NLSS is conducted by the Nepal Central Bureau of Statistics with assistance from the World Bank as a part of the latter's Living Standards Measurement Study. The two waves of Nepalese Living Standard Survey used here were undertaken during 1995–1996 (NLSS I) and 2003–2004 (NLSS II). Nepalese conflict data are from the Informal Sector Service Center (INSEC), an independent non-governmental organization concerned with human rights and based in Kathmandu.

NLSS:

The NLSS is a nationally representative household survey, and NLSS I was conducted just before the war onset in 1996. Indeed, more than 96% of households were surveyed before any war-related casualties occurred in their district; hence NLSS I is an excellent source for baseline observations. The NLSS II was conducted during 2003–2004, seven years after the war began, and so it allows me to observe how households changed their behavior during the war. A timeline of the war and these surveys is presented as Figure 1.

Both NLSS I and NLSS II give detailed information on household demographics and consumption expenditures as well as on farming households' production, distribution, earnings, and landholdings. Two types of questionnaires were used: a household questionnaire; and a community questionnaire (by urban/rurual). I make use of data on individuals (household head's age, gender, caste, language, religion), households (crop choices, landholdings, farm revenue), and rural communities (monsoon rainfall).

The NLSS I covers 3,373 households from 274 sampling units in 72 districts.[3] By design, NLSS II has two components: a cross-sectional sample including 3,912 households from 326 sampling units in 72 districts; and a panel sample that traces the households surveyed in NLSS I.[4] Prior to NLSS II, 1,232 households from 100 sampling units in 60 districts were drawn randomly from NLSS I to be re-interviewed. In the end, a total of 962 households from 95 sampling units in 60 districts were successfully traced. This paper focuses on 717 agricultural households in the panel sample. The issue of potential attrition is addressed in Section 4.

For my empirical analysis, the main outcome variable is *Number of Cultivated Crop Types*. I define this variable as the number of crop types that the household reports cultivating—out of the 67 possible crops listed by the survey (see Figure A1 in Appendix A). Of these crops, 10 are cereals and 57 are non-cereals. Non-cereal crops include various oilseed crops, vegetables, fruits, and cash crops (e.g., sugar cane, jute, tobacco).

Table 1 reports the descriptive statistics. The number of cultivated crop types increased from 7.3 in 1996 to 10.5 in 2004. That increase in crop choice was due mostly to the increase in non-cereal types (from 4.3 to 7.6), since the number of cereal types was essentially stable (3.0 in 1996 vs. 2.9 in 2004). I further break down the change in crop cultivation choice by quartiles of total conflict intensity experienced until 2004 in Figure 2. Before the onset of war, there was not much difference in non-cereal crop types across the respective quartiles. But after the onset of war, non-cereal crop types were much more prevalent in high-intensity districts (middle panel in Figure 2). Although there were some systematic differences in number of cultivated cereal crops before the war, the pattern did not change during the war

[3] Namely, all 75 districts except for Rasuwa, Mustang, and Dolpa.

[4] The NLSS II cross-sectional sample includes all 75 districts except for Rasuwa, Mustang, and Achham.

(lower panel in Figure 2).

Nepalese Conflict Data:

The INSEC's Annual Human Rights yearbooks provide, in effect, a census of war casualties—including detailed information on the dates and locations of events involving conflict-related casualties.[5] This database is widely used by scholars researching the conflict in Nepal (see e.g. Do and Iyer, 2010; Valente, 2013; Menon and Van der Meulen Rodgers, 2015; Pivovarova and Swee, 2015; Libois, 2016; Mitra and Mitra, 2020). The death toll recorded by INSEC was 13,239 which is consistent with other estimates (e.g. BBC News, 2009; Human Rights Watch, 2007). Figure 3 plots the number of conflict-related casualties and deaths for each year. Casualties peaked in 2002 and 2004, which renders the 2003–2004 NLSS II surveyed especially relevant for examining how households reacted to the war.

I define *conflict intensity* as the cumulative casualties in each district from the beginning of the war until NLSS II was conducted (2003-2004), normalized by district population (in thousands) according to 1991 census data (see Section 4 for additional details). The mean is 0.714 casualties per thousand district population, and the standard deviation is 0.676 for the 60 districts in the sample.[6] Conflict intensity varies widely across districts, as can be seen in Figure 4 top panel.[7] Conflicts are most intense in Nepal's mid-western and far-western regions. The lower panel in Figure 4 shows the conflict intensity in the 60 panel districts. Even though 15 districts are not in the panel sample (mainly districts in western regions), the high number of districts in each quartile of conflict intensity indicates that there is enough spatial variation to identify a conflict effect using these panel data.

Auxiliary Data

Two additional variables – number of Maoist abductions in 2002-2004 and 1994 Parliamentary Election data are used in this paper to measure Maoist presence.

[5] See Joshi and Pyakurel (2015) for a detailed description of these data. Much of this information is cross-referenced in the UN Human Rights Office of the High Commissioner's Nepal Conflict.

[6] When all 75 districts are considered, the mean is 0.887 and the SD is 0.933.

[7] Casualties per thousand district population, by quartile, are represented by different intensities of shading on the map.

The number of Maoist abductions is taken from Pivovarova and Swee (2015) and is used to measure the Maoist *wartime* presence. These data cover the total number of Maoist abductions, in each district, during the 2002–2004 period. Just as for conflict intensity, I normalize the figures by district population (based on the 1991 census). On average, there were 1.921 abductions per thousand district population with standard deviation of 2.930 in a district.

Data on Nepal's 1994 parliamentary election are compiled from the work of Krämer (1994). I thus construct a proxy for the Maoist *pre-war* presence: proportion of constituencies within a district that had a United People's Front (UPF) candidate in 1994 Nepalese Parliamentary Election. Recall that UPF was the mother party of the CPN-M before they split in 1994 and that the 1994 parliamentary election was the last before the war started.[8] Each district was home to multiple constituencies and the UPF placed 49 candidates in 48 constituencies among 24 districts in the 1994 parliamentary election.[9]

4 Empirical Framework

To see how households changed their behavior during the war, I employ the following difference-in-differences specification:

$$Y_{ijtm} = \alpha_i + \lambda_t + \beta_1 Conflict_{jtm} + \delta_1 X_{ijtm} + \varepsilon_{ijtm} \tag{1}$$

where Y_{ijtm} denotes outcome variable Y for household i in district j surveyed in month m of year t. Recall from Section 3 that the outcome variable of interest is the number of cultivated crop types, which is represented here by Y. The $Conflict_{jtm}$ term stands for the conflict intensity in district j experienced by household i surveyed in month m of year t. So

[8] In mid-1994, UPF split into two fractions—one led by Pushpa Kamal Dahal and the other by Nirmal Lama. However, the Election Commission recognized only the Nirmal Lama–led party. The unrecognized faction renamed itself the Communist Party of Nepal (Maoist) in 1995 and declared war in February 1996.

[9] There were 205 constituencies in total, so the per-district average was 2.733 constituencies.

by definition, $\mathit{Conflict}_{jtm} = 0$ for all observations from interviews conducted before February 1996. For observations collected after February 1996, $\mathit{Conflict}_{jtm}$ is equal to the cumulative casualties in district j from the beginning of the war (February 1996) until the month m of year t when household i was interviewed—normalized by district population (in thousands) based on 1991 census data. The α_i are household fixed effects, which account for all time-invariant, household-level characteristics that are correlated with conflict intensity and with the number of cultivated crop types; α_i also incorporates any district-specific, time-invariant characteristics (e.g., elevation, forest coverage, crop suitability). The λ_t are survey-year fixed effects, which accommodate any year-specific but spatially invariant effects.[10] The X_{ijtm} are control variables. I include community-level monsoon rainfall to control for weather shocks that could affect both conflict in a district and household crop cultivation choices.[11] Rainfall was reported, in rural community surveys by community heads, in terms of whether rainfall during the monsoon season (June–August) was too low, sufficient, or too high.[12] The X_{ijtm} term also includes household demographics: household size (number of people in a household) as well as the household head's gender, age, education level, and literacy (a dummy variable indicating whether or not the household head can read.[13] The standard errors are clustered at the district level.

The coefficient of interest is β_1. The identification assumption is that the difference in number of cultivated crop types across districts experiencing different conflict intensity would have been stable in the absence of war. As I only have a single pre-war survey, I cannot

[10] A specification with district–year fixed effects that account for any time-*varying* district-level changes would be preferable, but including district–year fixed effects would wipe out nearly all of the variation in $\mathit{Conflict}_{jtm}$. Because district–year fixed effects alone explain 99.68% of the variation in $\mathit{Conflict}_{jtm}$, they are not included in the model. Region–year fixed effects are likewise excluded given that conflict intensity tends to be clustered at the regional level, as shown in Figure 4).

[11] This also helps to control for the weather-induced selective migration often observed in an agrarian economy.

[12] More specifically, I include two dummy variables: $\mathit{Monsoon}_{\text{low}}$ is set to 1 if monsoon rainfall is too little (and set to 0 otherwise); $\mathit{Monsoon}_{\text{sufficient}}$ is set to 1 if monsoon rainfall is sufficient (otherwise, it is set to 0). The omitted category is the case of too *much* monsoon rainfall.

[13] These household characteristics might be affected by the conflict, and therefore are bad controls. In Table A1 in Appendix A, I exclude these household characteristics as controls, and the results are quantitatively very similar, albeit slightly larger.

check for parallel trends before the war onset. One concern is that the change in crop types captured by β_1 might simply be due to convergence: high–conflict intensity districts that are poorer and initially produce less (non-cereal) crop types may eventually cultivate as many non-cereal crop types as their low–conflict intensity counterparts even if the war had not occurred. I explore this possibility by testing for whether number of cultivated crop types differed systematically, before the war, across districts that ended up experiencing different degrees of conflict intensity during the war. Thus I regress the number of cultivated crop types (reported in NLSS I) on the conflict intensity experienced by households by the time they were interviewed in NLSS II. Because this test is based on NLSS I data only, I cannot include household fixed effects. I additionally control for time-invariant household characteristics including the household head's caste, religion, and language spoken.

Table 2 presents results from the balance test just described. Columns (1), (3), and (5) give the results with standard controls only; columns (2), (4), and (6) include both the standard controls and additional time-invariant household characteristic controls. I find no systematic differences in pre-war crop types across districts with different conflict intensities (see columns (1) and (2)). In particular, the cultivation of pre-war non-cereal crop types is similar across districts (columns (3) and (4)) even though more cereal types were cultivated in districts that later experienced relatively high conflict intensity (columns (5) and (6)).

Identification might also be compromised by sample selection. Specifically, there are two types of sample selection of concerns: selective migration and selective attrition. Selective migration (i.e., migration induced by the war) would be an issue if households who migrated away from high-conflict districts tended to cultivate fewer (or more) types of crops. For example, Pivovarova and Swee (2015) find that households with less land or with no land are more likely to leave a high-intensity district. If these households produced fewer (resp. more) crop types, then β_1 would be biased upward (resp. downward). To address such selective migration, I focus on households in the panel data and include household fixed effects, which would capture unobserved household characteristics that might be correlated with both migration and cultivation decisions (Pivovarova and Swee, 2015).[14]

However, my use of panel data raises the issue of selective attrition. As described in Section 3, 1,232 households in 60 districts were randomly selected from NLSS I (for purposes of tracing) but ultimately just 962 of those households were re-interviewed in NLSS II; thus the attrition rate is about 22%. In order to see whether the households that were successfully traced differed systematically from the untraced households—that is, to test for selective attrition—I compare pre-war attributes of the panel sample's 962 households with those of non-panel households from the same 60 districts in the NLSS I cross-sectional data. Table 3 summarizes the results of this comparison. In general, the pre-war attributes are balanced. Of even more importance is that households in the panel sample cultivated about the same number of crop types as did those in the cross-sectional sample. That said, there are some differences. Households in the panel sample were less likely to have ever migrated before NLSS I, and the household heads in that sample were less likely to be literate (despite no differences in their level of education). There were systematic differences in the religious composition (e.g., Hindu, Buddhist), but there were no statistically significant differences in any other household characteristics.

5 Empirical Results

In this section, I provide empirical evidence of households expanding their crop choices—specifically, by choosing more non-cereal crops—in response to war. This behavioral change exposed households to higher risks because non-cereal revenue is much more volatile than the revenue generated from cereal crops. Assuming a mean-variance preference, results suggest that households' welfare losses associated with a one standard deviation increase in conflict intensity (i.e., 0.676 more casualties per thousand population) could be as high as 16.35%.

I then present some suggestive evidence that avoiding rebel tax on cereal is likely to be the main channel through which conflict intensity might lead to an expansion of crop choices.

[14] Among the focal 717 agricultural households, 34 of them migrated after the war onset.

I also show evidence against two alternative channels: market disruptions and land transfers. Those two factors, along with Maoist taxes on cereals, are the most widely documented causes of distortions in rural Nepal's agriculture sector during the war.

In addition, I show that the disproportional increase in crop choices in high conflict intensity districts does not persist after the war ends. Lastly, robustness checks are also presented in this section.

5.1 Crop Cultivation Choice

Table 4 reports the estimates of Equation (1). Columns (1), (3), and (5) are estimated using district fixed effects, instead of household fixed effects, in order to capture the district-level determinants of crop types that also correlate with conflict intensity. I then estimate using household fixed effects, as specified in Equation (1) (see columns (2), (4), and (6)) to account for any household-level unobserved characteristics. Robust standard errors are clustered at the district level.

After the war onset, the number of cultivated crop types (out of a possible 67) increased significantly in high–conflict intensity districts (columns (1) and (2)). This increase was driven almost entirely by the increase in non-cereal crops (columns (3) and (4)), since the cultivation of cereal-type crops remained quite stable (columns (5) and (6)). The estimates are statistically significant at the 1% level (column (4)) and also economically large: a one standard deviation increase in conflict intensity (0.676 more casualties per thousand population) raised the number of non-cereal crop types cultivated from 4.36 to 6.01, an increase of 37.84%.

One possible interpretation is that households expand their crop choices to more non-cereal crops in order to avoid the Maoist taxes on cereals.[15] These results show that households deliberately altered their behavior, taking actions to mitigate possible losses. During the 11-year conflict, Nepalese farmers learned about Maoist rebel group activities and changed their behavior accordingly.

[15]Appendix B presents a simple model that offers one possible rationale for the expansion of households' crop choices in response to such Maoist taxation. Suggestive empirical evidence is presented in Section 5.3.

5.2 Welfare Implications

So far, I have documented that households expanded their crop choices when facing conflict. Such behavioral changes could be costly in the sense that households thereby took on more income risk, since the revenue from non-cereal crops is much more volatile than that from cereal crops.[16,17] This hypothesis is motivated by data from the Indian states bordering Nepal during the period 1966–1995 (Nepalese farm revenue data are unavailable).[18,19] The Indian data shows that the standard deviation of the per-hectare average revenue from non-cereal crops is more twice that from cereal crops.[20] These data suggest also that non-cereal crop revenue per hectare is highly correlated with that of cereal crop revenue (correlation coefficient as high as 0.90); the implication is that households, by adding more non-cereal crops to their portfolio, assume a big risk with little diversification benefits.[21] Hence it is reasonable to conclude that Nepalese agricultural households faced much greater income risk after deciding to cultivate more non-cereal crops.

To quantify this welfare loss, I assume that agricultural households have mean-variance preferences with the following utility function:

$$U = \mu - \frac{\lambda}{2}\sigma^2$$

[16]This difference is especially relevant because agricultural households are strongly risk averse (Dillon and Scandizzo, 1978; Binswanger, 1981).

[17]Cereal revenues may be less volatile than non-cereal revenues because the former are less perishable (Joshi et al., 2006; Birthal et al., 2015).

[18]And even if Nepalese farm revenue data were available, they might be endogenous to the conflict—in which case, using data from the Indian states bordering Nepal would actually be preferable. I similarly choose the pre-war time period to ensure that prices are exogenous.

[19]Huchet-Bourdon (2011) use world data to document that prices for non-cereals (e.g., soybeans and sugar) are more volatile than those for cereals (e.g., rice and wheat). Di Falco and Chavas (2009) also find that, in Ethiopia, income variance is increasing in the biodiversity of crops.

[20]In 1965, the standard deviations for average cereal and non-cereal revenue per hectare were (respectively) 67.27 and 147.45 Indian rupees. Both price and quantity are more volatile for non-cereal crops, factors that result in more volatile revenue. See Appendix C). for additional details.

[21]One could argue that India's minimum support price (MSP) for crop production might work better with cereal production, thus rendering cereal prices less volatile. However, Aditya et al. (2017) show that Indian households are largely unaware of the MSP and that this lack of awareness is similar for cereals and non-cereals.

here μ denotes expected farm revenue, σ^2 is the variance of farm revenue, and λ is the parameter for household risk aversion.

Farm revenue here is the sum of crop sales and the value of home-produced agricultural food consumption reported by the household.[22] I use the mean of household farm revenue reported in NLSS I to calculate the value of μ, and I assume (based on column (1) in Table 5) that this value does not vary in response to conflict.[23] Therefore, $\frac{dU}{d\text{ conflict}} = -\frac{\lambda}{2}\frac{d\sigma^2}{d\text{ conflict}}$. It is worth mentioning that the households did not experience farm revenue decline during the war is very surprising at first glance. This is likely because households actively change their behavior during the war to mitigate losses. However, it would be wrong to conclude that household mitigation strategies prevented losses during the war even though their farm revenue remained stable. As I will show in the following, the mitigation strategy exposes them to higher income risks.

The risk aversion parameter λ in mean-variance preferences represents absolute risk aversion (ARA). However, I approximate ARA as relative risk aversion (RRA) divided by the mean (RRA/μ) to account for the scale dependence of ARA (Raskin and Cochran, 1986).[24] I follow the literature (e.g., Ligon and Schechter, 2003; Cruces and Wodon, 2007) in assigning the value of RRA to be 2.[25]

Because I have only one observation for each household at each time, it is impossible to measure the change in farm revenue variance at the household level; therefore, I consider the variance of farm revenue across households within a district. The idea here is that, since households in high conflict intensity districts start cultivating different crops and hence bear greater revenue risk, those districts should exhibit greater variance of farm revenue than

[22]Farm revenue is spatial-year deflated. The regressions incorporate year fixed effects to account for nationwide inflation, but Nepal features considerable spatial variation in prices. I account for this variation by deflating nominal farm revenue using the spatial price index provided by the World Bank. To eliminate outliers in farm revenue, I winsorize household farm revenue at the 95th percentile.

[23]Column (1) in Table 5 estimate Equation (1) using household farm revenue (in log) as dependent variable.

[24]ARA $= -u''(w)/u'(w)$, and RRA $= -w(u''(w)/u'(w))$.

[25]Values of RRA between 1 and 4 are viewed as reflecting typical forms of risk behavior for agricultural households (Binswanger, 1981; Gollier, 2004). My results do not vary much for values of RRA in the range 1–4. If I instead use ARA values (from the literature), then the result is an even larger figure for welfare loss.

that observed in low conflict intensity districts.[26] I therefore run the following regression to estimate the change in variance:

$$ln\sigma_{jt}^2 = \eta_j + \lambda_t + \beta_3 Conflict_{jt} + \delta_3 X_{jt} + e_{jt} \tag{2}$$

The dependent variable, $\ln\sigma_{jt}^2$, is the (log of the) variance of household farm revenue for district j in year t. Because $\ln\sigma(\epsilon)_{jt}^2$ varies only at the district–year level, I also use conflict (measured at that level)—or cumulative casualties in district j from the beginning of the war until survey year t (equal to zero for wave 1)—to run district-level regressions.[27]

To address the concern that conflict might increase the within-district variance of farm revenue even without any changes in crop choice—as might occur, for instance, if Maoists targeted only certain groups of households (e.g., high-caste households, households with large landholdings) when taxing—I adopt a two-step procedure as follows:

$$R_{ij} = \eta_j + \pi W_{ij} + \epsilon_{ij} \tag{3}$$

I first regress farm revenue R_{ij} of household i in district j on district fixed effects η_j and household characteristics W_{ij} for each survey wave separately; this approach is intended to eliminate—at the district level and for each wave—the effects of household characteristics on farm revenue. Hence this regression controls for the effects of district-specific conflict intensity (e.g., the Maoist tax targeting just described) on household farm revenue. The household characteristics term, W_{ij}, includes dummy variables indicating the household head's caste (high or low) and land ownership as well as the head's religion and spoken language; also included is the total land owned by the household before the war. I extract the residual $\hat{\epsilon}_{ij}$,

[26] According to NLSS I, households cultivated on average 20.93 different types of crops in each district (SD = 5.40), among which were 15.63 non-cereal types (SD = 5.21). By NLSS II, each district cultivated 28.03 different types of crops (SD = 6.67), of which 22.70 (SD = 6.19) were attributed to non-cereal crops. On average, households planted 10.55 types of crops, including 7.65 non-cereals in NLSS II and 7.30 different crop types (with 4.30 non-cereal types) in NLSS I.

[27] In theory, the variance of household farm revenue can be constructed at the district-survey month level. However, only 11 households, on average, were surveyed during the same district month, and therefore $\ln\sigma_{jt}^2$ is constructed at district-year level.

which represents the part of a household's farm revenue that is *not* explained by these factors, to construct the district-level revenue dispersion $\hat{\epsilon}_{jt}$ for each period t.

In the second step, I construct the variance of $\hat{\epsilon}_{jt}$ for each district j in year t and take the natural logarithm as the dependent variable. In Equation (4), η_j denotes district fixed effects, the λ_t are year fixed effects, and X_{jt} represents monsoon rainfall controls. Since the variance is constructed using a different number of households, all these regressions are weighted by that number. Formally,

$$ln\sigma(\hat{\epsilon})^2_{jt} = \eta_j + \lambda_t + \beta_4 Conflict_{jt} + \delta_3 X_{jt} + e_{jt} \tag{4}$$

Results for this second step are reported in Table 5.[28] Unexplained farm revenue is more dispersed in higher–conflict intensity districts (column (2)). The table shows that a one standard deviation increase in conflict intensity would lead to 26.77% more dispersion in unexplained farm revenue within a district. According to column (3), the increased variance in unexplained farm revenue is driven mostly by the increased dispersion of unexplained *non-cereal* revenue; there is no statistically significant change in unexplained *cereal* revenue volatility (column (4)). These results suggest the increase in unexplained farm revenue dispersion is probably not caused by a disproportionate Maoist tax, because cereals were the crops targeted by the insurgents.[29]

Taken together, the values reported in Table 5 indicate that a one standard deviation increase in conflict intensity would induce 16.35% welfare loss.[30] Of course, this reduction in welfare might not have resulted entirely from altered crop choices. Other features of the war undoubtedly contributed, notwithstanding the use here of a two-step procedure to control

[28]Bootstrapped standard errors are reported in {braces} and account for the generated regressor bias.

[29]Table A2 in Appendix A presents the results when farm revenue is used to construct district-level farm revenue variance directly (i.e., without the first step). That table reports a much greater increase in variance, which means that the two-step approach effectively controls for the increase in farm revenue dispersion due to other aspects of the war.

[30]This calculation is based on a pre-war average farm revenue of $\mu = 16{,}240.4$ Rupees and a farm revenue variance of $\sigma^2 = 1.0 \times 10^8$. Pre-war utility was therefore $U = 16240.4 - (1/16240.4) \times 10^8$ and post-war utility was $U = 16240.4 - (1/16240.4) \times 10^8 \times 1.2677$.

for households' revenue changes—due to observed characteristics—after the war onset. But considering that the standard deviation of revenue from non-cereal crops is (on average) more than twice as high as the standard deviation for cereal crops and that households' non-cereal varieties increased by 37.85%, it is reasonable to conclude that households in higher–conflict intensity districts took on extra risk and thus could have suffered a large loss of welfare.

It should also be acknowledged that an increase in the number of cultivated crop types, especially increased varieties of non-staple crops, could actually benefit agricultural households. For example, such increases could have the effect of diversifying output risk—that is, since different crops are typically subject to different weather shocks and/or susceptible to different insect diseases. Increased numbers and varieties of crops could also generate more employment and increase farm income (Ali and Abedullah, 2002; Barghouti et al., 2004; Weinberger and Lumpkin, 2007). Yet these benefits depend on the low marketing risks enabled by adequately functioning markets, especially since most non-cereal crops are relatively perishable (Fafchamps, 1992; Joshi et al., 2006; Chhatre et al., 2016; Auffhammer and Carleton, 2018). It follows that households are unlikely to enjoy such benefits during wartime.

Another question of interest is whether cultivating more types of non-cereal crop led to a reduction in cereal output. If so, that would suggest the existence of additional welfare costs to these agriculture households. However, testing for this possibility is precluded by the poor data quality of the output module in the survey.

5.3 Channels

5.3.1 Maoist Tax Avoidance Channel

So far, I have shown that households expanded their crop choices (mainly non-cereal varieties) after the war onset. A prime suspect is the Maoist taxes on cereal. The Maoists taxed more in districts that had more fighting because that is where more provisions were needed. Due to the absence of quantitative data on the Maoist tax, I cannot provide direct evidence that the Maoist tax is the main channel. Instead, I provide some suggestive evidence to support this channel.

First, I examine the tax avoidance channel by estimating heterogeneous war effects as a function of the Maoist presence. It is reasonable to suppose that, conditional on their need to collect tax (i.e., on conflict intensity), Maoists would have taxed more in districts where they had more presence and hence were more able to collect such taxes . Hence I will show that the increase in types of cultivated crops is more pronounced in districts where Maoists had a greater presence and thus a greater need and capacity to tax.

I start by constructing two proxies for Maoist presence: the number of Maoist abductions during 2002–2004 (per thousand district population); and proportion of constituencies within a district that had a United People's Front candidate in the 1994 Nepalese parliamentary election. The former is a measure of *wartime* Maoist presence across districts; the latter measures the *pre-war* Maoist presence.[31] These two measures are complementary. On the one hand, Maoist abductions can be viewed as a proxy for the willingness to exploit local peasants—which in turn is a reasonable proxy for the capacity to tax.[32] However, admittedly, it might be endogenous. On the other hand, UPF candidacy captures the ground-level presence of Maoists before the war and so is arguably more exogenous.[33] I then augment Equation (1) with an interaction term of Maoist presence $Presence_j$ with $Conflict_{jtm}$, where the coefficient of interest is ψ_1:

$$Y_{ijtm} = \alpha_i + \lambda_t + \beta_5 Conflict_{jtm} + \psi_1 Conflict_{jtm} \times Presence_j + \delta_4 X_{ijtm} + \xi_{ijtm} \tag{5}$$

Results are presented in Table 6. Panel A uses the number of Maoist abductions (per thousand population) as the measure of Maoist presence, and Panel B uses the proportion of constituencies with a UPF candidate. Regardless of which proxy is used, this table confirms

[31] Pivovarova and Swee (2015) also use Maoist abduction as a measure of Maoist presence.

[32] Maoists only started to abduct local civilians in the later stage of the war, and thus there is no data available prior to 2002.

[33] Correlations between the measures of Maoist presence and conflict intensity are 0.161 (for abductions) and −0.224 (for candidates).

that—conditional on conflict intensity—the number of cultivated crop types increases more in districts where Maoist had more of a presence (column (1)). Households cultivate more non-cereal types in districts with a greater Maoist presence (column (2)), but there is no such effect on cereal types (column (3)).

These results are consistent with the idea that, conditional on the *need* to tax (conflict intensity), Maoists' *capacity* to tax (presence) strongly affected household crop choice. Hence, this tax avoidance channel is the likely culprit driving my main result.

In addition, I show that the increase in types of cultivated crops is more salient among high-caste households, who were the main targets of Maoist tax during the war. One of Maoist's slogans is to achieve caste equality and abolish privileges for the high-caste people. Therefore, people whose ethnicity belong to the high-caste were the prime victims of the Maoist (Hutt, 2004; Libois, 2016). As such, we would expect high caste households to have more incentives to change their crop choices to avoid Maoist taxes.

To this end, I estimate a similar heterogeneous war effects with household caste status by interacting $Conflict_{jtm}$ with a dummy variable indicating high-caste households. The results are shown on Table 6 Panel C. Indeed, high caste households adopted more types of (non-cereal) crops holding conflict intensity constant. Similar to other sets of results, we don't see this effect on the number of cereal crops.

Although this result is consistent with the tax avoidance channel, I would like to point out that there are other factors that can also drive this result. For example, it could be the case that high caste households have more resources to allow them to change their cultivation decisions. Hence, this result should be interpreted with caution.

5.3.2 Alternative Channels

Here I present evidence against two alternative channels: market disruptions and land transfers. Massive market disruptions during the war limited market access, which could induce a transformation from a market economy to self-sufficiency. In that case, there would be an increase in crop choices because households must then cultivate all their necessities. Maoist land transfers constitute another possible channel that would lead to increased numbers of cultivated crop types. Inspired by their "land to its tillers" slogan, wartime Maoists aimed to take land away from landowners and distribute it to landless farmers. Since the new landowners would probably be poor subsistence farmers, they might cultivate more crop types upon receiving the transferred land. However, I show that neither of these channels is likely to be the primary driver of households' crop choice expansion.

Market disruption:

During the war, market access was limited as a result of ruined infrastructure as well as frequent *Bandhs* (forceful closure of markets, industries, and transport) and *Naka-bandhi* (closure of routes, forbidding of movement within declared areas). Market disruptions can force an economy into self-sufficiency. Hence households might respond by broadening their crop portfolios because of the need to home-produce necessary foodstuffs. That said, it is possible that households would *reduce* their range of crop choices given that perishable and/or cash crops would then be no longer cultivated. Although the net effect of these dynamics on the number of cultivated crop types cannot be known ex ante, one should expect fewer households to sell their produce—and fewer crop types to be sold—if households were responding primarily to market disruptions. Thus more subsistence farming would be expected. To assess that possibility, I re-estimate Equation (1) after replacing the outcome variables with (i) the number of crop types sold by a household; (ii) a dummy variable indicating whether (or not) a household sold at least one crop type; and (iii) household revenue from selling harvested crops.

However, the results run counter to the market disruption hypothesis. Column (1) in Table 7 shows that the number of crop types (out of 67) that households sold in higher–conflict intensity districts increased after the onset of war, although the difference is not statistically significant. Yet the extensive margin on sales—as measured by the proportion of households that sold at least some of their harvested output—did increase significantly (column (2)), and household revenue from selling harvested crops also increased (column (3)).[34]

Given the massive war-related market disruptions, that households still managed to sell more is surprising. One possible explanation is that, even though markets were disrupted, farmers were incentivized to sell their output before the Maoists could come and tax it. So out of desperation, then, a household might well increase its effort to sell the harvest whenever an opportunity arose—despite reduced market access. Households might also dispose of their output in other ways: via local exchange or bartering with neighbors or extended family.

Land Transfer

Another possible channel is that of land transfers. The Maoist "land to its tillers" program could drive the results if land was redistributed to those who were formerly landless (most likely, subsistence farmers) and who would therefore cultivate more crop types once they owned land. But if the expansion of crop choice was indeed due to such land transfers—that is, if land was redistributed into smaller plots among more landowners who subsequently cultivated more crop types—then we should see an increase in the number of landowners in high–conflict intensity districts and/or smaller landholdings among existing landowners after the war onset.

To examine this alternative channel, I first re-estimate Equation (1) after changing the outcome variable to a dummy that indicates whether or not the household is a landowner. The result is presented column (4) of Table 7, which reveals that there is no significant change in the wartime proportion of landowners in high–conflict intensity districts. And because more than 97% of the agricultural households in my sample were landowners before the war, it is unlikely that the increase in cultivated crop types resulted from new landowners.[35] Next, I replace the dependent variable with household landholdings (in hectares). The regression

[34] Sale values are spatial-year deflated.

[35] Appendix A Table A3 reports the proportion of households that owned land before the war, but lost land after the war began, as well as the proportion of households that were landless before the war yet owned land afterwards. Only a few such cases are found in the NLSS panel sample, but—among that limited number—most cases are from districts in the lowest quartile of conflict intensity. This finding provides further support for my claim that selective land transfer is unlikely to be the channel through which the increase in types of cultivated crops occurred.

results show no significant change in the amount of land held by existing landowners in high–conflict intensity districts (column (5)). These findings are a good indication that systematic land transfer is *not* likely to explain the observed increase in crop types.

Although my results are consistent with the existence of a tax avoidance channel, I cannot rule out other channels and say unequivocally that tax avoidance explains the expansion in crop choices. In fact, it is almost certain that Nepalese agricultural households considered many factors when deciding to cultivate more non-cereal crop types. Yet the totality of my results does suggest that tax avoidance is most probably the key factor leading households to expand their crop choices.

5.4 Long Run Outcomes

Do we continue to observe the differences in the number of crop types cultivated by households after the war ends? I use the panel component of the third wave of NLSS (NLSS III) to answer this question. This survey round was conducted in 2011, 5 years after the war ended. This dataset allows me to compare the same household's cultivation decisions in 2011 with that in 1996 and re-run Equation (1).[36]

However, many post-conflict reconstruction programs and various types of aid flowed into Nepal, mostly in conflict-intensive regions. These programs might also have an impact on households' cultivation decisions. We need to bear this in mind when interpreting the long-run results.

Results are shown in Table 8. Notice that the number of observations dropped by roughly a half. This is by survey design that only half of the households from NLSS I & NLSS II panel were traced and is not due to attrition. Nevertheless, we don't observe a significant difference across households in the number of both cereal and non-cereals crop types. The coefficients' size are smaller and they are no longer statistically significant at conventional levels. This could suggest that households did not adopt more types of crops voluntarily. As

[36]I use conflict intensity household experienced by the time that NLSS II was surveyed to ensure that the regression results are comparable to that in Table 4.

a result, we stop observing the differential crop adoption patterns across districts after the war ends.

5.5 Robustness Checks

This subsection is devoted to several robustness checks.

Alternative ways to measure conflict intensity:

It could be the case that households might not respond and change their behavior to events in the same district but far away from where they were living. To address this concern, I conduct a more granular-level (village-level) analysis. I replace the district-level $Conflict_{jtm}$ in Equation (1) with village-level cumulative casualties. That is, I now look at how households' cultivation decisions have changed in response to their own village's conflict experience. It is worth pointing out that in this village-level analysis, the cumulative casualties are not normalized by population size, as the data is not available at the village level. Results are shown in Table 9 Panel A. We continue to see the positive effects for the total number of cultivated crop types (column (1)) and are entirely driven by the increase in non-cereal crops (column (2)) while, the cultivation of cereal crops remains stable. In Panel B, I consider the cumulative casualties in both households' own villages as well as their neighboring villages.[37] Results are still similar.

As the primary mechanism explored in this paper is households avoiding Maoist taxes on cereals, one might argue that casualties inflicted by the Maoists is a better measure for households' conflict experience. Table 9 Panel C shows that the results are still robust when restricting our attention to casualties (normalized by district population (in thousands)) where Maoists were the perpetrators.[38]

Another concern is that some districts may experience high conflict intensity only during the war's earlier years. If so, then using cumulative casualties from the beginning of the war

[37]Neighbourhood villages are defined as villages that share a common border.

[38]The mean value for Maoists inflicted casualties (per thousand population) is 0.068 with a standard deviation of 0.140.

might not be an appropriate measure of conflict intensity. When conflict intensity declines, the households in these districts could change their behavior in response to other (unobserved) factors—which means that using cumulative casualties from the beginning of the war could also be capturing such non–conflict-related factors. According to Figure 3, however, conflict intensity was not high overall during the war's earlier years; hence the described scenario is rather improbable. Nevertheless, as a robustness check, I use an alternative measure of conflict intensity: cumulative casualties from 2001 (i.e., two years before NLSS II was conducted) to the month that households were surveyed. The results are consistent with those using the baseline measure (Panel D in Table 9).

Alternative Specifications and Sample:

Moreover, I adopt an instrumental variable approach to address the concerns that casualties were not randomly assigned across districts. Following Mitra and Mitra (2020), I use the value of each district's timber resources as an instrument for conflict intensity.[39] Selling timber to India was an important source of local funding for the Maoists. In contrast to some centralized fund-raising efforts, such as building international networks, trading timbers is primarily a mean for Maoist regional autonomous governments seeking financial self-sufficiency (International Crisis Group, 2005). Therefore the value of each district's timber resources would affect the Maoists' fighting strategies in each region.

To construct the instrumental variable, the vegetation types were classified into four categories: coniferous, non-coniferous, non-coniferous tropical forest, and other timber. The cross-sectional variation comes from the vegetation coverages in each district (i.e. proportion of each vegetation type). It is then interacted with the average price changes in India for each vegetation type to create the temporal variation.

The identification strategy relies on the changes in the export value of forest resources—owing to the changes in prices in India—has no direct effect on households' cultivation decisions. This is likely true given that only 2% of households have a non-agricultural business in the

[39] I am grateful to Anirban Mitra for sharing their data on timber prices and district-level vegetation types in Nepal.

forestry sector (Libois, 2016), and therefore the export value of timber is unlikely to affect other channels, such as income, which would alter households' cultivation decisions. Furthermore, conflict in Nepal is unlikely to change the timber prices in India, given that Nepal is a minor timber exporter to India.

Results are presented in Table 10 Panel A. The Cragg-Donald Wald F statistics are all above the commonly accepted threshold, suggesting that the relevance condition is satisfied. We continue to see a positive effect on the total number of cultivated (non-cereal) crop types but no effect on cereal crop types. The IV estimators are even larger than the difference-in-differences estimates in Table 4. Although this could be because there is an omitted variable, such as differential trends in the socioeconomic changes across different districts that being positively correlated with conflict intensity and crop choices, it can also be because the IV estimator reveals a larger local average treatment effect (LATE). In other words, households adopted more types of crops in districts where the Maoist used timber revenue to finance the war. This is very likely, since the local Maoist government could only use timber revenue to raise funds in districts where they had a strong presence, and these were also the districts where they were more able to tax local civilians and resulting in a larger effect.

Next, I incorporate different sets of fixed effects as robustness checks. Panel B of Table 10 gives the results when regressions control for region–year fixed effects instead of just year fixed effects. This is to address the concerns that there might be region-year varying unobservables that correlate with conflict intensity and also affect crop choice.[40] Incorporating this control has little effect on the results. In Panel C, I also include month fixed effects to capture potential seasonality; the results still hold.

In addition, the NLSS classification of crop types into 67 categories might be too detailed and so have led to reporting errors. For example: the survey considers sweet lime and lime to be two different crops, yet a survey respondent might not distinguish one from the other.

[40]Regions are an administrative level that are higher than districts. Nepal comprises five such regions: eastern, central, western, mid-western, and far-western. I do not control for region–year fixed effects in the main specification (Equation 1) because conflict intensity tends to cluster at the regional level (see Figure 4); hence controlling for region–year fixed effects could wash out most of the variation in conflict intensity.

Even though it is hard to believe such reporting errors would be correlated with conflict intensity, I address this possible concern by instead using 10 crop groups that aggregate the 67 crop types. Those 10 crop groups are: cereals, pulses and legumes, tuber and bulb crops, oilseed crops, cash crops, spices, vegetables, citrus fruits, non-citrus fruits, and "other" (see Figure A1 in the Appendix A for details). When regressing the number of cultivated crop group on conflict intensity, I still find that households in high–conflict intensity districts expand their cultivation choices (column (1) in Panel D of Table 10). In column (2), which focuses on non-cereal crop groups, the results are qualitatively similar. The implication is that my main results are robust to the aggregate classification of crop types.

Lastly, as discussed in Section 4, one benefit of focusing on the panel sample is that it enables me to account directly for selective migration. However, this could introduce the issue of selective attrition. Even though Table 3 shows that pre-war attributes are generally balanced—that is, between panel versus non-panel households in cross-sectional data from the same districts—there could still be selective attrition on unobservables. Having cross-sectional data allows for re-estimating Equation (1) while replacing household fixed effects with district fixed effects, and I find that the results are robust (see Panel E in Table 10).

6 Conclusion

This paper investigates agricultural households' behavioral changes in response to war as well as the costs associated with those changes. I study Nepalese farmers' crop choices during the 1996–2006 Maoist insurgency by using a unique panel dataset that brackets the war onset. Comparing households before and after the beginning of that war—across districts that experience different intensities of conflict—reveals that an increase of one standard deviation in conflict intensity (0.676 more casualties per thousand population) increased the cultivation of non-cereal crop types from about 4.36 to 6.01, a 37.85% rise, even as cultivation of cereal crops remained relatively stable. Moreover, I show that a consequence of this change is that households bear more risks because the revenue generated from non-cereal crops is much more volatile. Results sugguest that household welfare losses could amount to 16.35%.

In addition, I show that household avoidance of the Maoist tax on cereals is likely to be the main channel via which changes in crop selection occurred. Thus I detect—consistently with this hypothesis—a greater change in districts where Maoists had more capacity to tax (a stronger presence). I also explain why neither market disruptions nor land transfers can credibly account for the observed behavioral change in crop choices.

Previous research has documented wars' huge socioeconomic costs (in terms of health, education, labor market outcomes, etc.). This paper adds another layer of understanding to those costs, one that reflects households' behavioral changes intended to mitigate their losses during a conflict. Such *indirect* war-related costs—which have too often been overlooked—can be substantial. Failure to account for them results in underestimating the actual costs of war.

Although the mitigation strategies identified in this paper might be specific to Nepal, I believe that households taking actions to minimize losses in wartime—actions that could ultimately prove costly—is a more general phenomenon. So when seeking to quantify the costs of war, scholars would be well advised to focus more of their attention on households' actions and behavioral changes. Such considerations are vital also to the task of designing post-war aid or reconstruction programs.

References

Adelaja, A. and George, J. (2019). Effects of conflict on agriculture: Evidence from the boko haram insurgency. *World Development*, 117:184–195.

Aditya, K., Subash, S., Praveen, K., Nithyashree, M., Bhuvana, N., and Sharma, A. (2017). Awareness about minimum support price and its impact on diversification decision of farmers in india. *Asia & the Pacific Policy Studies*, 4(3):514–526.

Akresh, R., Verwimp, P., and Bundervoet, T. (2011). Civil war, crop failure, and child stunting in rwanda. *Economic Development and Cultural Change*, 59(4):777–810.

Ali, M. and Abedullah, D. (2002). Nutritional and economic benefits of enhanced vegetable production and consumption. *Journal of Crop Production*, 6(1-2):145–176.

Arias, M. A., Ibáñez, A. M., and Zambrano, A. (2019). Agricultural production amid conflict: Separating the effects of conflict into shocks and uncertainty. *World Development*, 119:165–184.

Auffhammer, M. and Carleton, T. A. (2018). Regional crop diversity and weather shocks in india. *Asian Development Review*, 35(2):113–130.

Bahgat, K., Dupuy, K., Østby, G., Rustad, S. A., Strand, H., and Wig, T. (2018). Children and armed conflict: what existing data can tell us. *Oslo: Peace Research Institute Oslo (PRIO)*.

Barghouti, S., Kane, S., Sorby, K., and Ali, M. (2004). Agricultural diversification for the poor guidelines for practitioners. *TW Bank*.

BBC News (2009). Nepal raises conflict death toll. http://news.bbc.co.uk/2/hi/8268651.stm.

Binswanger, H. P. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural india. *The Economic Journal*, 91(364):867–890.

Birthal, P. S., Roy, D., and Negi, D. S. (2015). Assessing the impact of crop diversification on farm poverty in india. *World Development*, 72:70–92.

Blattman, C. and Miguel, E. (2010). Civil war. *Journal of Economic literature*, pages 3–57.

Bozzoli, C., Brück, T., and Sottsas, S. (2010). A survey of the global economic costs of conflict. *Defence and Peace Economics*, 21(2):165–176.

Bray, J., Lunde, L., and Murshed, S. M. (2003). Nepal: Economic drivers of the maoist insurgency. *The political economy of armed conflict: Beyond greed and grievance, ed. Karen Ballentine and Jake Sherman (Boulder, Colorado: Lynne Rienner Publishers).*

Brück, T., d'Errico, M., and Pietrelli, R. (2019). The effects of violent conflict on household resilience and food security: Evidence from the 2014 gaza conflict. *World Development*, 119:203–223.

Bundervoet, T., Verwimp, P., and Akresh, R. (2009). Health and civil war in rural burundi. *Journal of human Resources*, 44(2):536–563.

Cameron, L. A. and Worswick, C. (2003). The labor market as a smoothing device: labor supply responses to crop loss. *Review of Development Economics*, 7(2):327–341.

Chhatre, A., Devalkar, S., and Seshadri, S. (2016). Crop diversification and risk management in indian agriculture. *Decision*, 43(2):167–179.

Corbett, J. (1988). Famine and household coping strategies. *World development*, 16(9):1099–1112.

Cruces, G. and Wodon, Q. (2007). Risk-adjusted poverty in argentina: measurement and determinants. *The Journal of Development Studies*, 43(7):1189–1214.

Di Falco, S. and Chavas, J.-P. (2009). On crop biodiversity, risk exposure, and food security in the highlands of ethiopia. *American Journal of Agricultural Economics*, 91(3):599–611.

Dillon, J. L. and Scandizzo, P. L. (1978). Risk attitudes of subsistence farmers in northeast brazil: A sampling approach. *American Journal of Agricultural Economics*, 60(3):425–435.

Do, Q.-T. and Iyer, L. (2010). Geography, poverty and conflict in nepal. *Journal of Peace Research*, 47(6):735–748.

Fafchamps, M. (1992). Cash crop production, food price volatility, and rural market integration in the third world. *American journal of agricultural economics*, 74(1):90–99.

FAO (2007). Food security assessment mission to nepal. *Special Report*.

FAO (2018). Helping farmers helps peace. Available at: http://www.fao.org/news/story/en/item/1146356/icode/.

Gollier, C. (2004). *The economics of risk and time*. MIT press.

Gröger, A. and Zylberberg, Y. (2016). Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics*, 8(2):123–53.

Huchet-Bourdon, M. (2011). Agricultural commodity price volatility: An overview. *OECD Food, Agriculture and Fisheries Working Papers, No. 52, OECD Publishing*.

Human Rights Watch (2007). Children in the ranks: The maoists' use of child soldiers in nepal. *Human Rights Watch*.

Hutt, M. (2004). *Himalayan people's war: Nepal's Maoist rebellion*. Indiana University Press.

International Crisis Group (2005). Nepal's maoists: Their aims, structure and strateg. *Asia Report N°104*.

Joshi, M. and Pyakurel, S. R. (2015). Individual-level data on the victims of nepal's civil war, 1996–2006: A new data set. *International Interactions*, 41(3):601–619.

Joshi, P., Joshi, L., Birthal, P. S., et al. (2006). Diversification and its impact on smallholders: Evidence from a study on vegetable production. *Agricultural Economics Research Review*, 19(2):219–236.

Kondylis, F. (2010). Conflict displacement and labor market outcomes in post-war bosnia and herzegovina. *Journal of Development Economics*, 93(2):235–248.

Krämer, K.-H. (1994). Parliamentary election. Available at: http://www.nepalresearch.org/politics/background/elections_old/elections1994.htm.

Libois, F. (2016). Households in times of war. *CRED working paper*.

Ligon, E. and Schechter, L. (2003). Measuring vulnerability. *The Economic Journal*, 113(486):C95–C102.

Menon, N. and Van der Meulen Rodgers, Y. (2015). War and women's work: Evidence from the conflict in nepal. *Journal of Conflict Resolution*, 59(1):51–73.

Mitra, A. and Mitra, S. (2020). Redistribution of economic resources due to conflict: The maoist uprising in nepal. *Journal of Comparative Economics*.

Molina, T. (2019). Health-seeking amidst violence: Evidence from the philippines. *Economic Development and Cultural Change*, Forthcoming.

Murshed, S. M. and Gates, S. (2005). Spatial–horizontal inequality and the maoist insurgency in nepal. *Review of development economics*, 9(1):121–134.

Nepal News (2012). Nepal news 18 june 2012. Available at: https://reliefweb.int/report/nepal/17800-people-died-during-conflict-period-says-ministry-peace.

Paxson, C. H. (1992). Using weather variability to estimate the response of savings to transitory income in thailand. *The American Economic Review*, pages 15–33.

Pivovarova, M. and Swee, E. L. (2015). Quantifying the microeconomic effects of war using panel data: Evidence from nepal. *World Development*, 66:308–321.

Raskin, R. and Cochran, M. J. (1986). Interpretations and transformations of scale for the pratt-arrow absolute risk aversion coefficient: Implications for generalized stochastic dominance. *Western Journal of Agricultural Economics*, pages 204–210.

Rockmore, M. (2015). Conflict and agricultural portfolios: Evidence from northern uganda. Technical report, Working Paper.

Rosenzweig, M. R. (1988). Risk, implicit contracts and the family in rural areas of low-income countries. *The Economic Journal*, 98(393):1148–1170.

Shemyakina, O. (2011). The effect of armed conflict on accumulation of schooling: Results from tajikistan. *Journal of Development Economics*, 95(2):186–200.

Swee, E. L. (2016). Economics of civil war. *Australian Economic Review*, 49(1):105–111.

Thomas, D., Osbahr, H., Twyman, C., Adger, N., and Hewitson, B. (2005). *ADAPTIVE: Adaptations to Climate Change Amongst Natural Resource-dependant Societies in the Developing World: Across the Souther African Climate Gradient*. Tyndall Centre for Climate Change Research.

Tiwari, B. N. (2009). 12 an assessment of the causes of conflict in nepal. *The Maoist insurgency in Nepal: Revolution in the twenty-first century*, 20:241.

Upreti, B. R. (2006). *Armed Conflict and Peace Process in Nepal: The Maoist insurgency, past negotiations, and opportunities for conflict transformation*. Adroit-Publ.

Upreti, B. R., Ghale, Y., and Ghimire, S. (2010). Food insecurity and conflict in nepal. *EVELOPMENT IN OUTH SIA*, 18:141.

Valente, C. (2013). Education and civil conflict in nepal. *The World Bank Economic Review*, 28(2):354–383.

Verpoorten, M. (2009). Household coping in war-and peacetime: Cattle sales in rwanda, 1991–2001. *Journal of Development Economics*, 88(1):67–86.

Verwimp, P., Justino, P., and Brück, T. (2019). The microeconomics of violent conflict. *Journal of Development Economics*, 141:102297.

Weinberger, K. and Lumpkin, T. A. (2007). Diversification into horticulture and poverty reduction: a research agenda. *World Development*, 35(8):1464–1480.

World Food Programme (2004). Food security bulletin, number 7, november to december 2004.

World Food Programme (2007). Food and agricultural markets in nepal: Feburary 2007.

Figures and Tables

Figure 1: Timeline of the NLSS and the Maoist Insurgency in Nepal

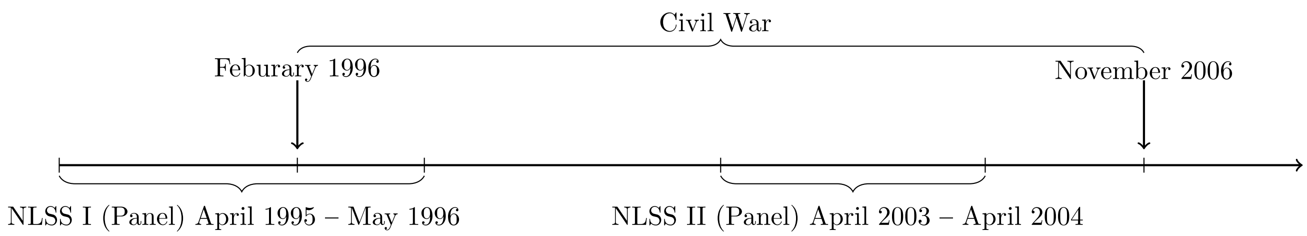
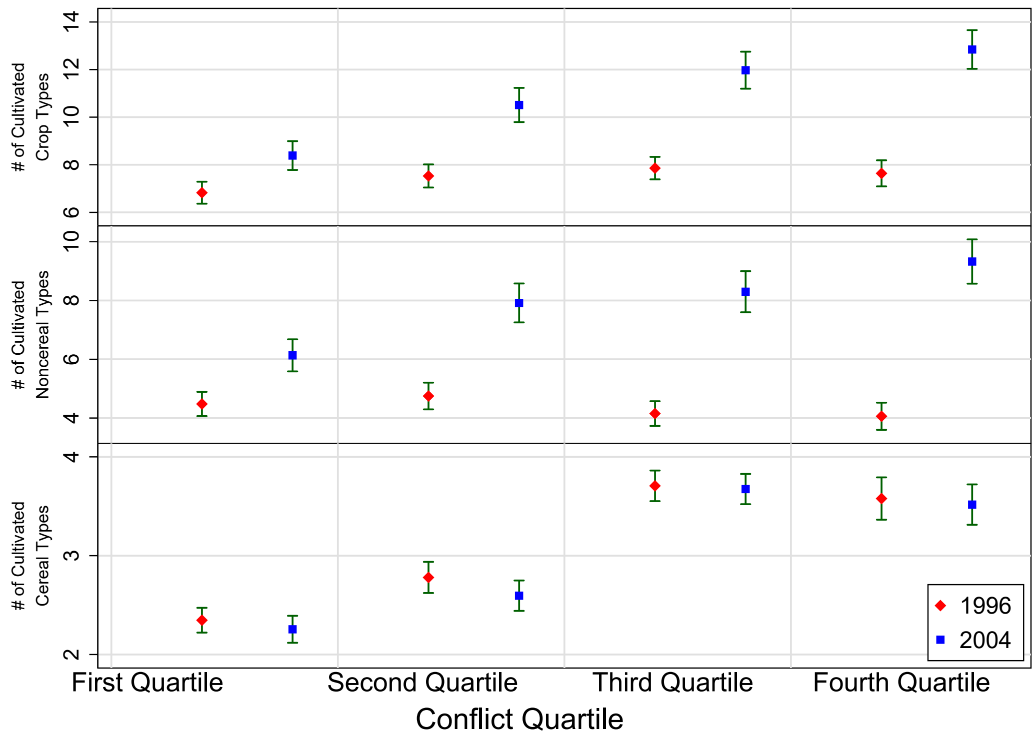


Figure 2: Descriptive Statistics: Changes in Number of Cultivated Crop Types



Notes: Each dot represents the mean number of all cultivated crops (upper panel), non-cereal crops (middle panel), or cereal crops (lower panel) by quartile of conflict intensity and for each wave of the NLSS survey. Districts in the first (resp. fourth) quartile experienced the lowest (resp. highest) conflict intensity. Vertical bars mark the 95% confidence intervals.

Figure 3: Conflict-Related Casualties and Deaths

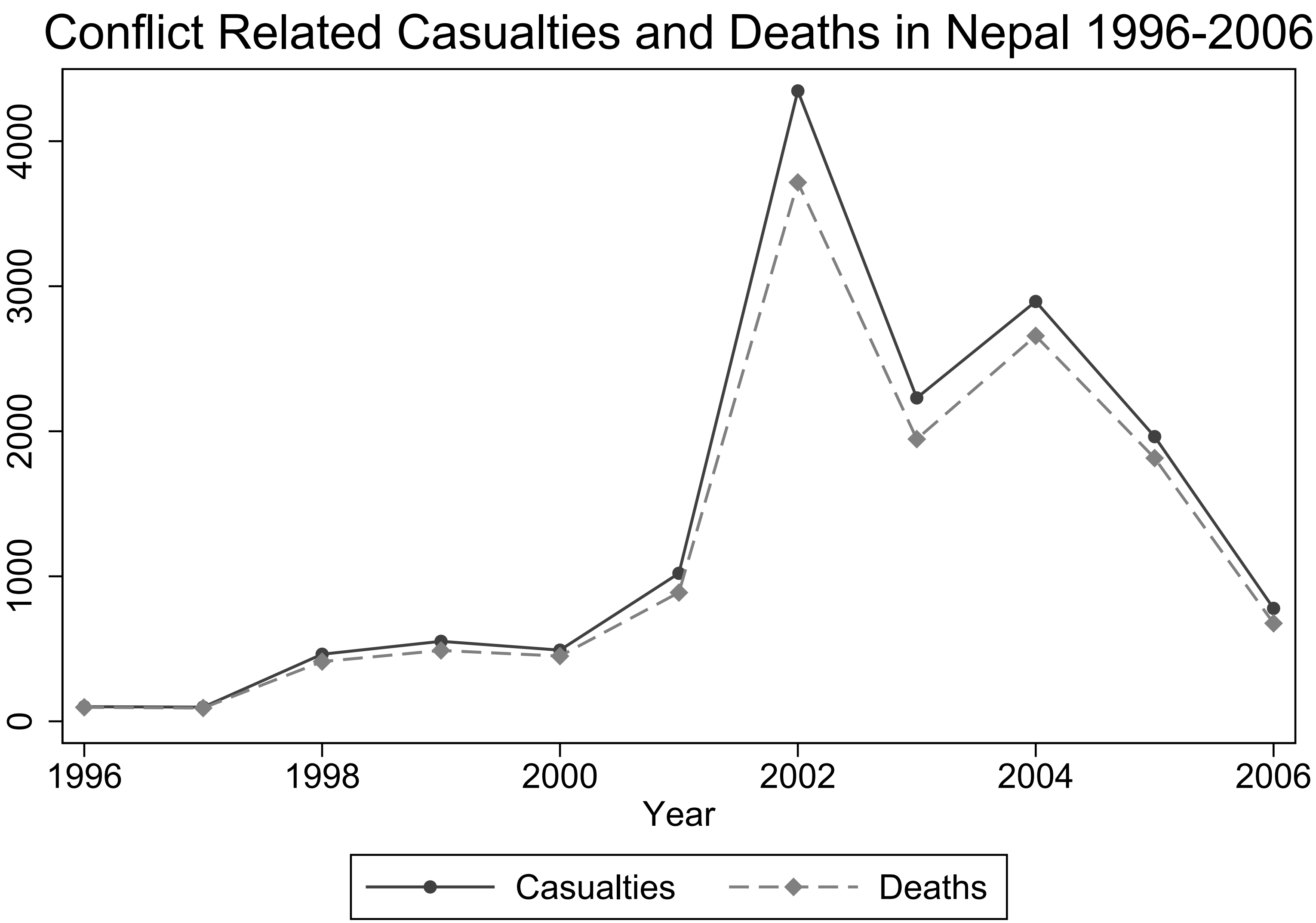
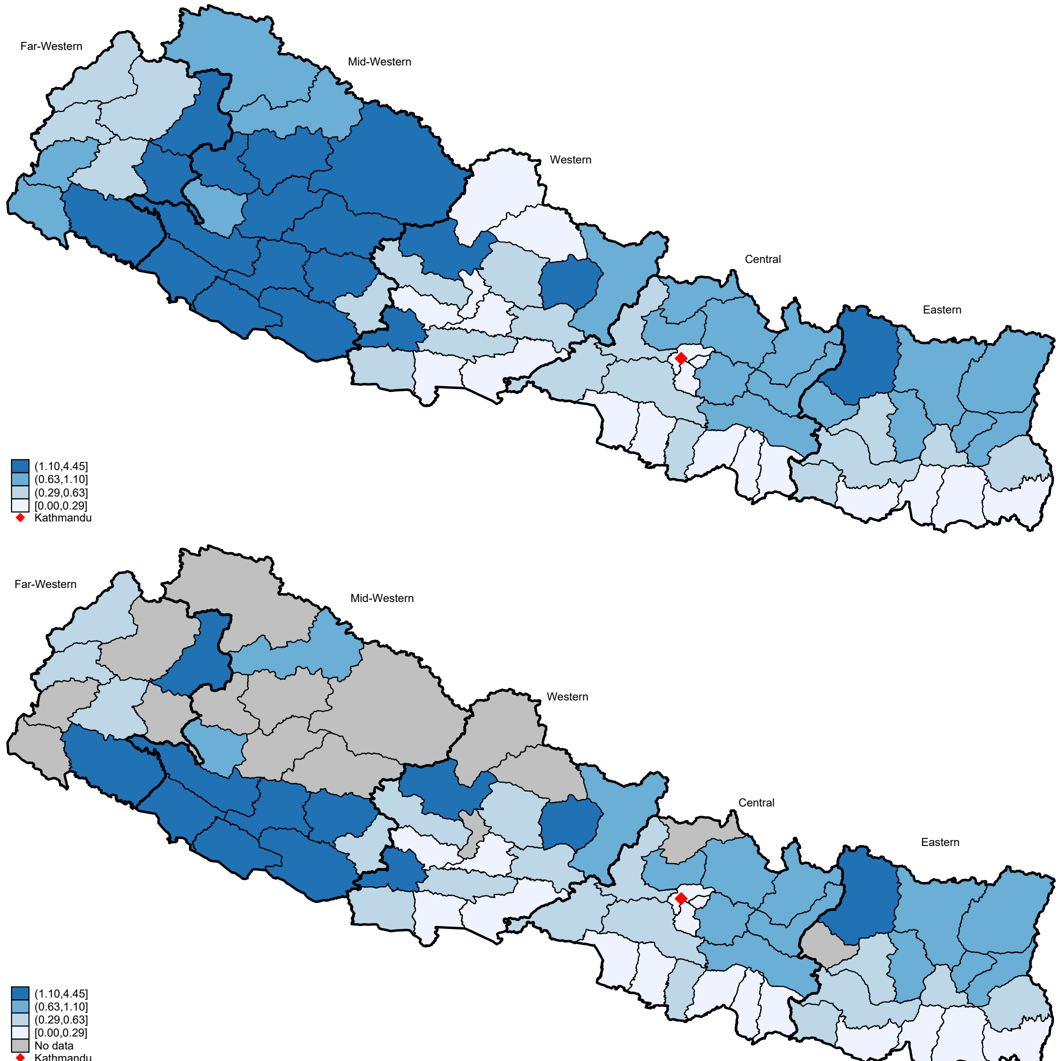


Figure 4: Spatial Variation in Conflict Intensity



Notes: Conflict intensity is defined as total casualties in each district, from 1996 to 2004, normalized by thousand district population in 1991. Districts are categorized into four quartiles of conflict intensity (see legend). Top panel shows all 75 districts and lower panel shows the 60 districts in the panel sample.

Table 1: Descriptive Statistics

	Full Sample (1)	NLSS I (2)	NLSS II (3)	Difference (4)
# of Cultivated Crop Types	8.914	7.296	10.547	3.251***
	[4.648]	[3.333]	[5.187]	(0.226)
# of Cultivated Cereal Types	2.950	3.000	2.900	-0.100
	[1.254]	[1.249]	[1.259]	(0.065)
# of Cultivated Noncereal Types	5.964	4.296	7.647	3.351***
	[4.194]	[2.946]	[4.578]	(0.199)
# of Crop Types Sold	1.274	1.242	1.306	0.064
	[1.704]	[1.648]	[1.759]	(0.088)
Seller	0.537	0.515	0.559	0.044
	[0.499]	[0.500]	[0.497]	(0.026)
ln(Sales)	3.355	3.256	3.454	0.198
	[4.118]	[4.134]	[4.102]	(0.188)
Landowner	0.792	0.806	0.778	-0.028
	[0.406]	[0.396]	[0.416]	(0.019)
Landholdings (hectares)	0.885	0.982	0.788	-0.195*
	[1.478]	[1.784]	[1.081]	(0.081)
ln(per capita Consumption)	8.697	8.587	8.808	0.221***
	[0.695]	[0.665]	[0.707]	(0.031)
ln(per capita Food Consumption)	8.260	8.209	8.311	0.102***
	[0.511]	[0.516]	[0.501]	(0.023)
Observations	1924	962	962	

Notes: Columns (1)–(3) report household means, with standard deviations in brackets; column (4) reports the differences in those means across NLSS II and NLSS I, with standard errors in parentheses. Number of cultivated crop types is a count variable of the number (of a possible 67) crop types that households report cultivating, and number of cultivated cereal (resp. non-cereal) types is the number of cereal (resp. non-cereal) types—out of a possible 10 (resp. 57)—that households report cultivating.

*significant at the 10% level; **significant at the 5% level; ***significant at the 1% level

Table 2: Pre-War Balance Test

Dependent Variable:	# of Cultivated Crop Types		# of Cultivated Noncereal Types		# of Cultivated Cereal Types	
	(1)	(2)	(3)	(4)	(5)	(6)
Conflict	0.599	0.302	0.039	-0.145	0.560**	0.447*
	(0.392)	(0.353)	(0.318)	(0.322)	(0.269)	(0.237)
Observations	661	644	661	644	661	644
Original Controls	Y	Y	Y	Y	Y	Y
Additional Controls	N	Y	N	Y	N	Y
Mean dep var	7.436	7.488	4.357	4.399	3.079	3.089

Notes: Number of cultivated crop types is a count variable of the number (of a possible 67) crop types that households report cultivating, and number of cultivated cereal (resp. non-cereal) types is the number of cereal (resp. non-cereal) types—out of a possible 10 (resp. 57) that households report cultivating. Conflict is the war intensity that households report experiencing when surveyed in NLSS II. Original controls are those included in the main specification (household size; household head's gender, age, literacy, and education level; and two dummy variables indicating whether the community in which the household is located experienced sufficient or insufficient monsoon rainfall). Additional controls include the household head's caste, language spoken, and religion. Odd-numbered columns include the original controls only; even-numbered columns also include the additional controls. All columns use NLSS I data only. Robust standard errors, clustered at the district level, are shown in parentheses.
*significant at the 10% level, **significant at the 5% level; ***significant at the 1% level

Table 3: Sample Selection Test

	Non-Panel Households	Panel Households	Difference (Non-Panel - Panel)
	(1)	(2)	(3)
Household Size	5.877	5.999	-0.122
	[2.946]	[2.718]	(0.108)
High Caste	0.420	0.458	-0.039
	[0.494]	[0.499]	(0.020)
Low Caste	0.115	0.126	-0.011
	[0.320]	[0.332]	(0.013)
Male Household Head	0.858	0.873	-0.016
	[0.350]	[0.333]	(0.013)
Age	44.977	44.198	0.780
	[14.532]	[14.280]	(0.558)
Read	0.500	0.450	0.050*
	[0.500]	[0.498]	(0.019)
Education	2.801	2.638	0.163
	[4.181]	[4.090]	(0.162)
Hindu	0.842	0.911	-0.069***
	[0.365]	[0.285]	(0.012)
Budhist	0.094	0.050	0.044***
	[0.292]	[0.218]	(0.010)
Muslim	0.048	0.032	0.016*
	[0.214]	[0.175]	(0.007)
Other Religion	0.016	0.008	0.008*
	[0.125]	[0.087]	(0.004)
Nepali (Language)	0.728	0.725	0.003
	[0.445]	[0.447]	(0.018)
Maithili (Language)	0.092	0.103	-0.011
	[0.290]	[0.305]	(0.012)
Bhojpuri (Language)	0.010	0.009	0.002
	[0.102]	[0.093]	(0.004)
Tamang(Language)	0.035	0.015	0.020***
	[0.185]	[0.123]	(0.006)
Newari (Language)	0.044	0.058	-0.014
	[0.205]	[0.233]	(0.009)
Other (Language)	0.090	0.090	-0.000
	[0.286]	[0.287]	(0.011)
Migrate	0.136	0.100	0.036**
	[0.343]	[0.300]	(0.012)
Write	0.950	0.956	-0.006
	[0.219]	[0.206]	(0.012)
# of Cultivated Crop Types	6.948	7.296	-0.348*
	[3.544]	[3.333]	(0.152)
# of Cultivated Cereal Types	2.875	3.000	-0.125*
	[1.213]	[1.249]	(0.055)
# of Cultivated Noncereal Types	4.073	4.296	-0.223
	[3.145]	[2.946]	(0.135)
Observations	2121	962	3083

Notes: The non-panel sample includes households in the same 60 districts as in the panel sample in the NLSS I cross-sectional sample (but not panel households). Columns (1) and (2) report household means, with standard deviations in brackets; column (3) reports the differences in those means, with robust standard errors (in parentheses) clustered at the district level.
*significant at the 10% level, **significant at the 5% level, ***significant at the 1% level

Table 4: Conflict Intensity and Number of Cultivated Crop Types

Dependent Variable:	# of Cultivated Crop Types		# of Cultivated Noncereal Types		# of Cultivated Cereal Types	
	(1)	(2)	(3)	(4)	(5)	(6)
Conflict	2.263***	2.512***	2.263***	2.441***	0.013	0.071
	(0.552)	(0.509)	(0.534)	(0.483)	(0.058)	(0.062)
Observations	1,334	1,334	1,334	1,334	1,334	1,334
Number of households	717	717	717	717	717	717
District FE	Y	N	Y	N	Y	N
Household FE	N	Y	N	Y	N	Y
Mean dep var (pre-war)	7.436	7.436	4.357	4.357	3.079	3.079
Mean dep var (post-war)	10.89	10.89	7.920	7.920	2.975	2.975

Notes: Number of cultivated crop types is a count variable of the number (of a possible 67) crop types that households report cultivating, and number of cultivated cereal (resp. non-cereal) types is the number of cereal (resp. non-cereal) types—out of a possible 10 (resp. 57) that households report cultivating. Odd-numbered columns incorporate district fixed effects while even-numbered columns includes household fixed effects. Conflict is defined as cumulative casualties in the district from 1996 to the month that households were surveyed, normalized by district population in thousands (based on the 1991 census). All columns include household-level controls (household size; household head's gender, age, literacy, and education level) and two dummy variables indicating whether the community in which the household is located experienced sufficient or insufficient monsoon rainfall. All columns include year fixed effects. Robust standard errors (in parentheses) are clustered at the district level.
*significant at 10%; *significant at 5%; ***significant at 1%;

Table 5: Variance of Farm Revenue

Dependent Variable:	ln(Farm Revenue)	ln Variance (Farm Revenue)	ln Variance (Farm Non-cereal Revenue)	ln Variance (Farm Cereal Revenue)
	(1)	(2)	(3)	(4)
Conflict	-0.171			
	(0.152)			
Conflict (96-04)		0.396	0.682	-0.166
		(0.216)*	(0.232)***	(0.223)
		{0.207}*	{0.226}***	{0.198}
Observations	1,334	121	121	121
Number of Household	717			
District FE	N	Y	Y	Y
Household FE	Y	N	N	N
Mean dep var	9.440	18.06	16.52	17.12

Notes: In column (1), the dependent variable is (the log of) household farm revenue. Farm revenue is defined as the household's revenue from crop sales *plus* the value of that household's consumption of home-produced agricultural food (Winsorized at the 95th percentile). The dependent variables for columns (2)–(4) are the district-level unexplained farm (total/cereal/non-cereal) revenue (logged) variance among households as obtained by a two-step estimation procedure. Conflict (1996–2004) is the total number of casualties during that time span, normalized by district population reported in the 1991 census. All monetary values are spatial-year deflated. Column (1) includes household-level controls as well as controls for community-level monsoon rainfall; columns (2)–(4) control for district-level average monsoon rainfall. All columns include year fixed effects. Robust standard errors (in parentheses) are clustered at the district level. Bootstrapped standard errors {in braces} are reported for regressions that use the two-step procedure.
*significant at 10%; *significant at 5%; ***significant at 1%;

Table 6: Suggestive Evidence for Tax Avoidance Channel

Dependent Variable:	# of Cultivated Crop Types (1)	# of Cultivated Noncereal Types (2)	# of Cultivated Cereal Types (3)
Panel A: Heterogeneous Effects with Maoist Presence: Maoist Abduction as a Proxy			
Conflict	2.081***	2.006***	0.075
	(0.403)	(0.385)	(0.061)
Conflict × Abduction	0.383*	0.386*	-0.003
	(0.208)	(0.209)	(0.038)
Mean of Abduction	1.921	1.921	1.921
Std Dev of Abduction	2.930	2.930	2.930
Panel B: Heterogeneous Effects with Maoist Presence: UPF Candidacy as a Proxy			
Conflict	2.408***	2.344***	0.064
	(0.435)	(0.413)	(0.062)
Conflict × UPF	5.314***	4.931***	0.383
	(1.736)	(1.660)	(0.235)
Mean of UPF	0.241	0.241	0.241
Std Dev of UPF	0.676	0.676	0.676
Panel C: Heterogeneous Effects with High Caste Households			
Conflict	2.170***	2.054***	0.117
	(0.358)	(0.328)	(0.078)
Conflict × $\mathbb{1}_{\text{high caste}}$	1.522**	1.724**	-0.203
	(0.691)	(0.684)	(0.164)
Number of Households	717	717	717
Mean dep var (pre-war)	7.436	4.357	3.079
Mean dep var (post-war)	10.89	7.920	2.975

Notes: Conflict is cumulative casualties in the district from 1996 to the month that households were surveyed, normalized by district population (in thousands) based on the 1991 census. Abduction—a measure of Maoist *wartime* presence—is the number of Maoist abductions during 2002–2004, normalized by district population (in thousands) based on the 1991 census. The UPF term, a proxy for Maoist *pre-war* presence, is the proportion of constituencies in which the United People's Front (the party to which Maoists belonged before they split) placed a candidate in a district for the 1994 parliamentary election. All columns include household and year fixed effects, household-level controls, and community-level monsoon rainfall controls. Robust standard errors (in parentheses) are clustered at the district level.
*significant at 10%; *significant at 5%; ***significant at 1%;

Table 7: Alternative Channels: Market Disruption and Land Transfer

	Market Disruption			Land Transfer	
Dependent Variable:	# of Crop Types Sold	Seller	ln(Sales+1)	Landowner	Landholdings
	(1)	(2)	(3)	(4)	(5)
Conflict	0.204	0.109***	1.247***	0.007	-0.064
	(0.130)	(0.041)	(0.317)	(0.007)	(0.115)
Observations	1,334	1,334	1,334	1,334	1,210
Number of households	717	717	717	717	677
Mean dep var (pre-war)	1.236	0.516	4.268	0.974	1.015
Mean dep var (post-war)	1.351	0.569	4.838	0.952	0.813

Notes: Number of crop types sold is a count variable of the number of crop types sold by a household. Seller is a dummy variable indicating whether (or not) a household sold at least some of their harvested output, and ln(Sales + 1) is the (log of) sales revenue—plus one rupee to account for cases of zero sales. Landowner is a dummy variable indicating whether (or not) a household owns land. Landholdings represents the land area (in hectares) owned by a household owns. Conflict is cumulative casualties in the district from 1996 to the month that households were surveyed, normalized by district population (in thousands) based on the 1991 census. All monetary values are spatial-year deflated. All columns include household and year fixed effects, household-level controls, and community-level monsoon rainfall controls. Robust standard errors (in parentheses) are clustered at the district level. *significant at 10%; *significant at 5%; ***significant at 1%;

Table 8: Long Run Outcomes

Dependent Variable:	# of Cultivated Crop Types		# of Cultivated Noncereal Types		# of Cultivated Cereal Types	
	(1)	(2)	(3)	(4)	(5)	(6)
Conflict	1.812	1.776	1.822	1.765	-0.005	0.012
	(1.204)	(1.074)	(1.196)	(1.076)	(0.080)	(0.079)
Number of Households	334	334	334	334	334	334
District FE	Y	N	Y	N	Y	N
Household FE	N	Y	N	Y	N	Y
Mean dep var (1996)	7.404	7.404	4.274	4.274	3.130	3.130
Mean dep var (2011)	11.36	11.36	8.528	8.528	2.831	2.831

Notes: Results are based on the panel component of NLSS I and NLSS III. Number of cultivated crop types is a count variable of the number (of a possible 67) crop types that households report cultivating, and number of cultivated cereal (resp. non-cereal) types is the number of cereal (resp. non-cereal) types—out of a possible 10 (resp. 57) that households report cultivating. Odd-numbered columns incorporate district fixed effects while even-numbered columns includes household fixed effects. Conflict is defined as cumulative casualties in the district from 1996 to the month that households were surveyed in NLSS II, normalized by district population in thousands (based on the 1991 census). All columns include household-level controls (household size; household head's gender, age, literacy, and education level) and two dummy variables indicating whether the community in which the household is located experienced sufficient or insufficient monsoon rainfall. All columns include year fixed effects. Robust standard errors (in parentheses) are clustered at the district level.
*significant at 10%; *significant at 5%; ***significant at 1%;

Table 9: Robustness Checks: Alternative Measures

Dependent Variable:	# of Cultivated Crop Types (1)	# of Cultivated Noncereal Types (2)	# of Cultivated Cereal Types (3)
Panel A			
Casualties (Village-level)	0.054*	0.046*	0.008
	(0.027)	(0.026)	(0.005)
Panel B			
Casualties (Own Village & Neighbors)	0.021*	0.017*	0.003
	(0.011)	(0.009)	(0.003)
Panel C			
Conflict (Maoists Inflicted)	7.433***	7.385***	0.048
	(1.429)	(1.393)	(0.196)
Panel D			
Conflict (from 2001)	3.563***	3.464***	0.099
	(0.622)	(0.586)	(0.106)
Mean dep var (pre-war)	7.436	4.357	3.079
Mean dep var (post-war)	10.89	7.920	2.975
Number of households	717	717	717

Notes: Casualties (Village-level) are cumulative casualties in the village from 1996 to the month that households were surveyed; while Casualties (Own Village & Neighbors) are cumulative casualties in both own village and its neighboring village from 1996 to the month that households were surveyed. Conflict (Maoist Inflicted) is defined as cumulative casualties inflicted by the Maoists in the district from 1996 to the month that households were surveyed, normalized by district population in thousands (based on the 1991 census). Conflict ($t-1$) is cumulative casualties but only until the year before households were surveyed. Conflict (from 2001) is cumulative casualties in the district from 2001 only. All columns include household and year fixed effects as well as household-level controls (household size; household head's gender, age, literacy, and education level) and community-level dummies indicating whether monsoon rainfall was too low, sufficient, or too high. Robust standard errors (in parentheses) are clustered at the district level. *significant at 10%; *significant at 5%; ***significant at 1%;

Table 10: Robustness Checks: Alternative Specifications and Sample

Panel A: Using Instrumental Variable (2SLS)			
Dependent Variable:	# of Cultivated Crop Types	# of Cultivated Noncereal Types	# of Cultivated Cereal Types
	(1)	(2)	(3)
Conflict	4.002**	4.275**	-0.272
	(1.750)	(1.695)	(0.286)
Cragg-Donald Wald F statistic	363.1	363.1	363.1
Panel B: Including Region-Year Fixed Effects			
Dependent Variable:	# of Cultivated Crop Types	# of Cultivated Noncereal Types	# of Cultivated Cereal Types
	(1)	(2)	(3)
Conflict	1.971***	1.962***	0.009
	(0.595)	(0.634)	(0.099)
Panel C: Including Month Fixed Effects			
Dependent Variable:	# of Cultivated Crop Types	# of Cultivated Noncereal Types	# of Cultivated Cereal Types
	(1)	(2)	(3)
Conflict	2.197***	2.111***	0.087
	(0.656)	(0.632)	(0.061)
Panel D: Using Crop Group			
Dependent Variable:	Crop Group	Non-cereal Group	
	(1)	(2)	(3)
Conflict	1.102***	1.110***	–
	(0.208)	(0.210)	–
Mean dep var (pre-war)	3.811	2.831	–
Mean dep var (post-war)	5.413	4.423	–
Panel E: Using Cross-sectional Data			
Dependent Variable:	# of Cultivated Crop Types	# of Cultivated Noncereal Types	# of Cultivated Cereal Types
	(1)	(2)	(3)
Conflict	1.411***	1.548***	-0.137
	(0.418)	(0.391)	(0.083)
Observations	4,196	4,196	4,196
Mean dep var (pre-war)	7.555	4.262	3.293
Mean dep var (post-war)	9.833	6.907	2.926

Notes: Conflict is the cumulative casualties in the district from 1996 to the month that households were surveyed, normalized by district population (in thousands) based on the 1991 census. Crop group reflects the classification of 67 types of crops into 10 groups, of which 9 are non-cereal groups. Panels A–D use the panel sample and include household and year fixed effects; Panel E uses the cross-sectional sample and include district and year fixed effects. All columns include household-level controls (household size; household head's gender, age, literacy, and education level) and community-level dummies indicating whether monsoon rainfall was too low, sufficient, or too high. Robust standard errors (in parentheses) are clustered at the district level.
*significant at 10%; *significant at 5%; ***significant at 1%;

A Appendix

Figure A1: All Possible Crop Choices

CROP CODES

CEREALS:

EARLY PADDY	01
MAIN PADDY	02
UPLAND PADDY	03
WHEAT	04
SPRING/WINTER MAIZE	05
SUMMER MAIZE	06
MILLET	07
BARLEY	08
BUCKWHEAT	09
OTHER CEREALS	10

PULSES AND LEGUMES:

SOYBEANS	11
BLACK GRAM	12
RED GRAM	13
GRASS PEA	14
LENTIL	15
GRAM	16
PEA	17
GREEN GRAM	18
COARSE GRAM	19
COW PEA	20
OTHER LEGUMES	21

TUBER AND BULB CROPS:

WINTER POTATO	22
SUMMER POTATO	23
SWEET POTATO	24
COLOCASIA	25
OTHER TUBERS	26

OILSEED CROPS

MUSTARD	27
GROUND NUT	28
LINSEED	29
SESAME	30
OTHER OILSEED	31

CASH CROPS:

SUGARCANE	32
JUTE	33
TOBACCO	34
OTHER	35

SPICES:

CHILIES	36
ONIONS	37
GARLIC	38
GINGER	39
TURMERIC	40
CARDAMOM	41
CORIANDER SEED	42
OTHER SPICES	43

VEGETABLES:

WINTER VEGETABLES	44
SUMMER VEGETABLES	45

CITRUS FRUITS:

ORANGE	46
LEMON	47
LIME	48
SWEET LIME	49
OTHER CITRUS	50

NON-CITRUS FRUITS:

MANGO	51
BANANA	52
GUAVA	53
JACK FRUIT	54
PINEAPPLE	55
LICHEE	56
PEAR	57
APPLE	58
PLUM	59
PAPAYA	60
POMEGRANATE	61
OTHER FRUIT	62

OTHER:

TEA	63
THATCH	64
FODDER TREES	65
BAMBOO	66
OTHER TREES	67

Table A1: Conflict Intensity and Number of Cultivated Crop Types: Without Household-level Controls

Dependent Variable:	# of Cultivated Crop Types		# of Cultivated Noncereal Types		# of Cultivated Cereal Types	
	(1)	(2)	(3)	(4)	(5)	(6)
Conflict	2.423***	2.629***	2.378***	2.538***	0.046	0.091
	(0.576)	(0.513)	(0.557)	(0.487)	(0.056)	(0.057)
Observations	1,334	1,334	1,334	1,334	1,334	1,334
Number of households	717	717	717	717	717	717
District FE	Y	N	Y	N	Y	N
Household FE	N	Y	N	Y	N	Y
Mean dep var (pre-war)	7.436	7.436	4.357	4.357	3.079	3.079
Mean dep var (post-war)	10.89	10.89	7.920	7.920	2.975	2.975

Notes: Number of cultivated crop types is a count variable of the number (of a possible 67) crop types that households report cultivating, and number of cultivated cereal (resp. non-cereal) types is the number of cereal (resp. non-cereal) types—out of a possible 10 (resp. 57) that households report cultivating. Odd-numbered columns incorporate district fixed effects while even-numbered columns includes household fixed effects. Conflict is defined as cumulative casualties in the district from 1996 to the month that households were surveyed, normalized by district population in thousands (based on the 1991 census). All columns include two dummy variables indicating whether the community in which the household is located experienced sufficient or insufficient monsoon rainfall. All columns include year fixed effects. Robust standard errors (in parentheses) are clustered at the district level.
*significant at 10%; *significant at 5%; ***significant at 1%;

Table A2: Variance of Farm Revenue

Dependent Variable:	ln(Farm Revenue)	ln Variance (Farm Revenue)	ln Variance (Farm Non-cereal Revenue)	ln Variance (Farm Cereal Revenue)
	(1)	(2)	(3)	(4)
Conflict	-0.171			
	(0.152)			
Conflict (96-04)		0.708**	0.806***	0.048
		(0.299)	(0.291)	(0.247)
Observations	1,334	121	121	121
Number of Household	717			
District FE	Y	Y	Y	Y
Household FE	N	N	N	N
Additional District's Controls	-	Y	Y	Y
Mean dep var	9.440	18.36	16.80	17.40

Notes: The dependent variables are (logged) variance of district-level farm (total/cereal/non-cereal) revenue among households. Farm revenue is defined as the household's revenue from selling crops *plus* the value of that household's consumption of home-produced non-animal agricultural food food (Winsorized at the 95th percentile). Conflict (1996–2004) is the number of casualties during that time span, normalized by district population reported in the 1991 census. All monetary values are spatial-year deflated. DV = dependent variable. Standard errors (in parentheses) are clustered at the district level.
*significant at 10%; *significant at 5%; ***significant at 1%;

Table A3: Land Transfer

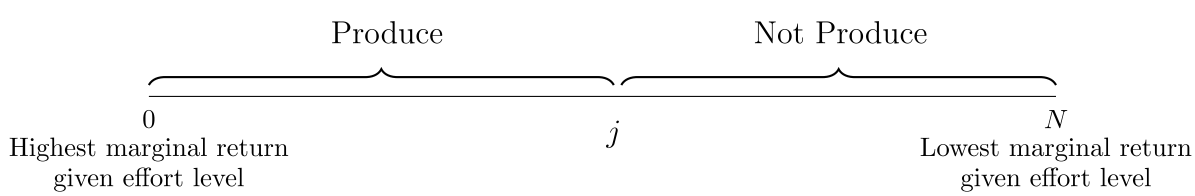
	1st quartile (lowest)	2nd quartile	3rd quartile	4th quartile (highest)
	(1)	(2)	(3)	(4)
New Landowner	0.065	0.027	0.011	0.019
	[0.020]	[0.010]	[0.007]	[0.011]
Lose Land	0.051	0.016	0.021	0.006
	[0.017]	[0.008]	[0.012]	[0.006]

Notes: New landowner captures households that are landless in NLSS I but own some land in NLSS II. Lose land represents households that own some land in NLSS I but own landless in NLSS II. Reported values are the means of the proportion of households in these two groups by quartile of conflict intensity, where the 1st (resp. 4th) quartile is the lowest (resp. highest). Standard deviations are reported in brackets.

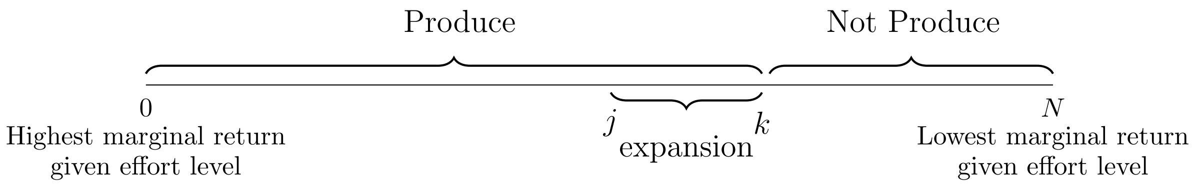
B Appendix: Conceptual Framework

In this section, I develop a simple model to explain one possible rationale for households' crop choice expansion when facing a Maoist tax. The intuition is summarized as follows.

I assume that a representative agricultural household has a fixed plot of land that it can use to cultivate multiple crops (out of a total of N types). Each household is endowed with an exogenous level of resource—namely, effort. The household's objective is to allocate that effort in a way that maximizes total output. Crops have different marginal return given the level of effort allocated, but households experience a diminishing marginal product for each crop. Hence the household will allocate its effort to crops in descending order of profitability. That is: after the marginal product of the most profitable crop diminishes sufficiently, the household will start producing the next most profitable crop. Once the whole unit of endowed effort is used up, crops for which no effort has yet been allocated will not be produced. So if we rank crops according to their marginal return (given the level of effort allocated), from the highest to the lowest, then in equilibrium the first j crops with highest marginal return will be produced. This dynamic is illustrated by the following diagram. In the case of a mainly subsistence agrarian economy like Nepal's, cereals are likely to have the highest return because they are (in terms of calories) the most important source of food consumption.



If cereals are taxed, then their marginal return will decline given the amount of effort allocated to them. Therefore, maximizing retained output requires that less effort be allocated to cereal production before households start to produce the next crop—even if cereals still have the highest return. It follows that effort would be re-allocated to more types of crops. In other words, a tax will lead to the expansion of crop choice and so, in equilibrium, the first k crops will be produced (where $k > j$); see the following diagram.



In short: when there was a Maoist tax on cereal, some effort that would have been allocated to cereal production was instead devoted to crops that households would not otherwise have cultivated. The implication is that households reallocated their effort—and thereby expanded their crop portfolio—in attempting to minimize their losses.

C Appendix: Revenue Volatility

Indian crop prices, quantities, and total land size associated with production are from the ICRISAT Village Dynamics in South Asia Macro-Meso Database (ICRISAT for short).[41] This data base contains the yearly prices and quantities of—as well as the area of land used to cultivate—16 major crops (including 7 cereal crops and 9 non-cereal crops) across all districts in India for the period 1966–2011.[42] I shall focus on four states (Bihar, Uttar Pradesh, Uttarakhand, and West Bengal) that shared borders with Nepal during the latter's 1966–1995 pre-conflict period.[43]

To measure the volatility of revenue derived from cereal and non-cereal crops, I calculate the standard deviations of the average revenue of cereals and non-cereals per hectare along the time trend. For that purpose, I first deflate revenue for each crop per hectare using Indian consumer price data from the World Bank and take the average revenue across all districts. This procedure yields the deflated revenue for each crop during 1966–1995.

I then de-trend the revenue R generated from each crop by regressing it on year T:

$$R_{it} = \omega_{i0} + \omega_{i1}T + \vartheta_{it}.$$

The standard deviation of the residual, $\hat{\vartheta}_i$, is the revenue volatility for each crop.

Next, I classify crops into cereals and non-cereals in order to calculate the average volatility for these types. The ideal way of measuring the relative revenue volatility of cereal versus non-cereal crops would be to find the standard deviations of the average revenue along the time trend for each crop in NLSS, thus measuring the additional revenue risk due to an expansion of crop choices. Yet as mentioned previously, ICRISAT contains only 16 major crops, which do not correspond to the 67 crops in NLSS. Hence I measure only the standard

[41] The reason I use Indian (rather than Nepalese) data is explained in Section 5.2.

[42] The 16 crops are rice, wheat, sorghum, pearl millet, maize, finger millet, barley, chickpea, pigeon-pea, sugar cane, groundnut, sesame, rapeseed and mustard, linseed, castor, and cotton; among these, the cereals are rice, wheat, sorghum, pearl millet, maize, finger millet, and barley. Prices are in Indian rupees per quintal (100 kg).

[43] There are 86 districts within these four states.

deviations of average cereal and non-cereal revenue. Non-cereal crops in ICRISAT data only include pulses (chickpea, pigeon-pea) and oil seeds (groundnut, sesame, rapeseed and mustard, linseed, castor) as well as two cash crops (sugar cane and cotton), of which are arguably less volatile—because they are relatively less perishable— than the NLSS non-cereal crops. In this sense, using ICRISAT data might understate the income risk of non-cereal crops. The average standard deviations for cereal revenue and non-cereal revenue are, respectively, 67.27 and 147.45.

To see whether the observed revenue volatility is driven by price and/or yield risk, I repeat the foregoing procedures for price and quantity (per hectare) separately. Regression results establish that yield and—to a greater extent—price are more volatile for non-cereal crops than for cereal crops.[44]

[44]The standard deviation of average de-trended cereal (resp. non-cereal) prices is 32.23 (resp. 99.55) Indian rupees, and the standard deviation of average cereal (resp. non-cereal) yields is 0.20 (resp. 0.25) tons.