MYANMAR

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Urban proximity, conflict, and agricultural development: Evidence from Myanmar

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ABSTRACT

Urbanization and violent conflict have been two global trends gaining more and more momentum in recent years. This has important implications for agricultural development, which unfortunately are still not well understood. Urban proximity is generally associated with agricultural intensification and improved market participation, while farming systems in remote areas are characterized by larger shares of subsistence production. Such differences along the remoteness gradient likely also play a role in how conflict exposure affects agricultural production. That is, we must assume that the effect of conflict on agricultural development is location-dependent—a fact that is generally neglected in empirical analysis. We address this gap by drawing from a unique nationally representative data set of 2,292 paddy farmers in Myanmar and estimating the effect of conflict exposure and travel times on agricultural production during the monsoon season of 2021. By applying multivariate additive models, we allow for nonlinear and interacted effects of conflict exposure and urban proximity, thereby explicitly exploring spatial variation in the effect of conflict exposure. We find strong positive effects of urban proximity on paddy rice intensification and sales, while conflict exposure has disproportionately negative effects in direct proximity to urban centers and very remote areas. For agricultural development—and smallholder incomes in general—this means that productive areas, on the one hand, and the poorest areas of the country, on the other hand, are especially affected by conflict.

Keywords: Market access, Conflict, Paddy/rice production, Myanmar, Southeast Asia

1. INTRODUCTION

Improving agricultural productivity, technology adoption, and market participation—i.e., agricultural development—is the cornerstone of many efforts to improve welfare and economic growth in low- and middle-income countries. One factor that is closely linked to higher levels of agricultural development is market access (Gollin & Rogerson, 2014; Minten, Koru, & Stifel, 2013; Stifel & Minten, 2017; Van- dercasteelen, Minten, & Tamru, 2021). Urban proximity and improved infrastructure reduce farmers' costs to reach economic centers and thereby lower net costs to modernize management systems and shift from subsistence to commercialized production (Shrestha, 2020; Vandercasteelen, Beyene, Minten, & Swinnen, 2018b). As a result, farms in urban proximity generally show significantly higher levels of modern technology adoption and productivity than those in more remote areas (Damania et al., 2017; Steinhübel & von Cramon-Taubadel, 2021; Vandercasteelen et al., 2018b), i.e., they act on comparative advantage. Considering ongoing high rates of urbanization—for low-income countries, it is expected that the urban population will grow by a factor of 2.5 until 2070 (UN-Habitat, 2022)—this holds a real chance for agricultural and economic development in regions so far reliant on subsistence and extensive agriculture. With the urban spread and growing secondary towns in originally remote areas, more and more farmers will gain better access to urban markets allowing for higher levels of agricultural modernization and commercialization (Dorosh & Thurlow, 2013).

However, such positive outlooks stimulated by urbanization trends might be offset by another global development that has gained momentum in recent years: the rise of violent conflict. While the early 2000s still presented historically low levels of conflict and gave hope for a more peaceful future, during the last decade we have witnessed a new surge in violent escalation affecting all world regions (Davies, Pettersson, & Öberg, 2022; Palik, Obermeier, & Rustad, 2022). Only in 2022 did political violence increase by 27 percent compared to the year before. [1] Furthermore, Palik et al. (2022) report that all types of conflict (state-based, non-state, one-sided) are on the rise, surpassing numbers of affected countries as well as death tolls from the turbulent times directly after the fall of the Soviet Union. This situation is particularly dire for the world's poorest, for which the World Bank (2020) estimates that more than 50 percent will live in fragile or conflicted-affected settings by 2023. Thus, not surprisingly the literature on conflict and its consequences for rural livelihoods has surged in the last years and has become an important strand of research in the fields of agriculture and development economics (Verwimp, Justino, & Brück, 2019). Recent work shows that conflict exposure affects agricultural production through different pathways. There are direct effects due to destruction and violence, but there are also indirect effects due to conflict risk and related uncertainty (Arias, Ibáñez, & Zambrano, 2019).

One other important characteristic of conflict is that it usually comes in non-random spatial patterns (Palik et al., 2022). To challenge authority and establish legitimacy as the ruling party, control over important economic, cultural, or political centers is often critical; that is, conflict events are usually more frequent in urban proximity (George, Adelaja, & Weatherspoon, 2020). In other settings, conflict actors favor more remote areas because they are easier to control (Arias et al., 2019). Considering the potential remoteness gradients in agricultural development based on urban proximity discussed above, the exposure to conflict likely has very different effects on agricultural systems at different spatial locations. Interestingly, even though most authors acknowledge the spatial patterns of conflict, they generally still assume the effect of conflict to be homogeneous (fixed effect) in space when it comes to their (empirical) analyses.

[1] https://acleddata.com/conflict-watchlist-2023/, last accessed May 4, 2023

This is where we contribute to the literature, by analyzing the effect of conflict exposure not only on agricultural production but on the relationship between market access and production. That is, we explore whether the effect of conflict exposure on agricultural development varies in space. For our analysis, we use a unique nationally representative survey data set of 2,292 paddy farmers in Myanmar containing detailed production data for the monsoon season of 2021. After a decade of liberalization, Myanmar witnessed a military coup in February 2021 leading to a surge in conflict events throughout the country. Moreover, paddy is one of the most important staple crops in in Myanmar and Asia more broadly, both in terms of subsistence and commercialized agriculture (MAPSA, 2022) and thus presents a good proxy crop for overall agricultural development in the region. We further supplement our survey data with spatial information on conflict events and road networks to calculate conflict exposure (Conflict Severity Index - CSI) and market access (travel times). Our empirical strategy is based on a generalized additive regression framework that allows us to model spatially dependent and nonlinear conflict effects on agricultural production. We also run several robustness checks and model specifications with instrumental variables (IV) to address potential issues with endogeneity and omission bias regarding our key variables of interest (i.e., travel times and conflict exposure).

Our analysis provides important new empirical evidence for a crop and geographic region that is so far underrepresented in the literature on conflict economics (most studies are on conflict in Africa) and we do find that the effect of conflict varies in space along a remoteness gradient. That is, paddy production by households located in direct proximity of urban centers (i.e., areas with likely high modernization levels) and very remote areas (i.e., areas with likely high poverty and low development levels) suffer disproportionately from conflict.

The rest of the paper is structured as follows: We first develop a brief conceptual framework to guide our empirical analysis (section 2) and provide background information on agriculture and conflict in Myanmar (section 3). In section 4, we present our data including the most important summary statistics and describe our estimation strategy. Afterward, we present and discuss our results (section 5) and summarize our findings in section 6.

2. CONCEPTUAL FRAMEWORK

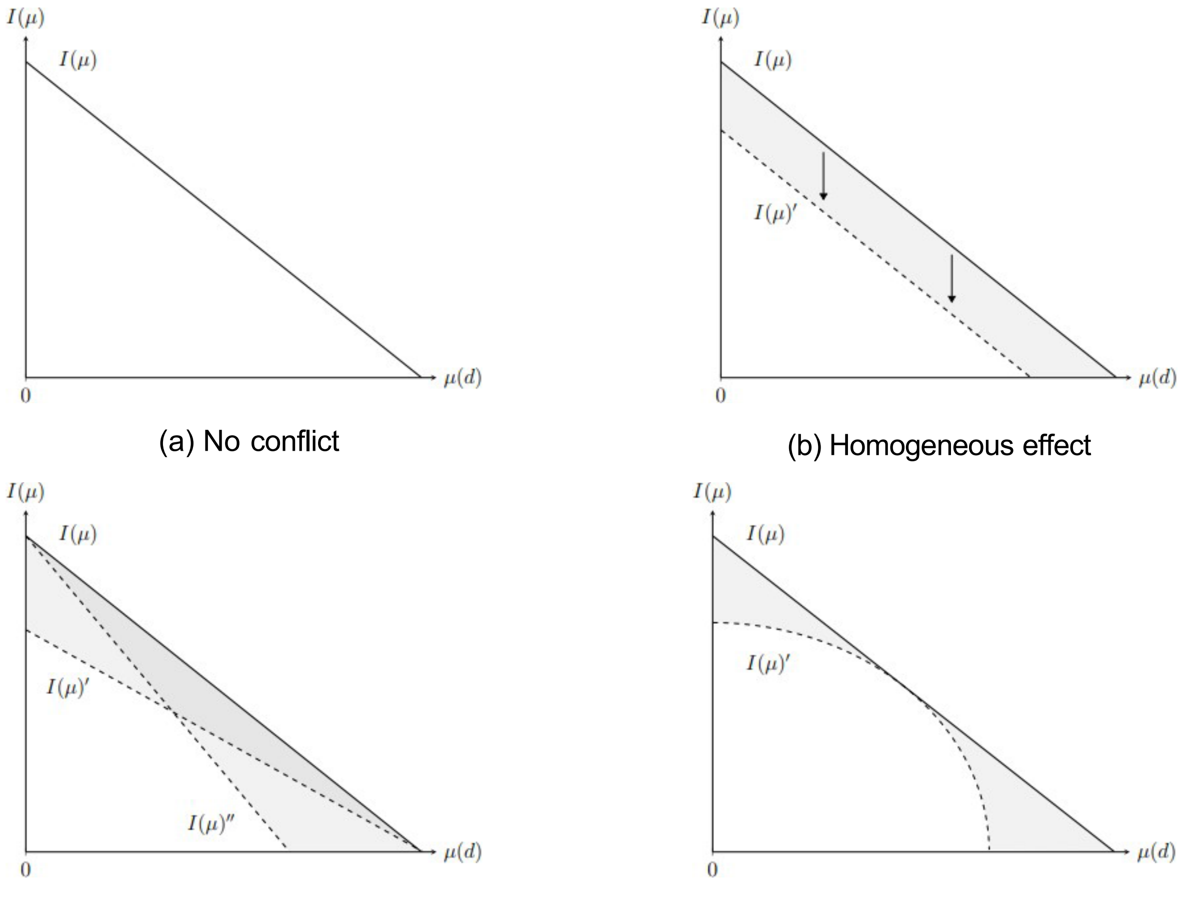
Conceptually, we follow work by Damania et al. (2017) and Vandercasteelen et al. (2018b) and model market access as transportation costs. The general idea is that farmers located closer to a market center face lower costs to access said market and, thus, can realize higher net prices for their agricultural produce and face lower net input prices relative to farmers further away. We, furthermore, assume that farmers facing lower market access costs are more likely to intensify their production systems. We can visualize this relationship by defining an indicator function $I(\mu)$ of agricultural intensification (i.e., input and output quantities, prices) negatively correlated with transportation costs μ (Figure 1a). Transportation costs are defined as function $\mu(d)$, where d is a measure of household distance to the market center.

We then want to understand how the exposure to conflict affects the relationship between agricultural production and transportation costs, i.e., the effect of conflict exposure on $I(\mu)$. We can think about the exposure to conflict as an additional cost that farm households factor in when making decisions about their management systems (i.e., profit maximization) and which has an added negative effect on agricultural intensification levels. Note that in our model this cost is not simply an addition to transportation cost $\mu(d)$ (i.e., a shift to the right on the x-axis). Even though conflict might increase transportation costs by roadblocks and infrastructure destruction, in this paper we are concerned with the effects of conflict exposure; that is household experiencing conflict in the vicinity of their farms. Such incurred costs are not necessarily proportional to d and can go beyond transportation-related issues such as, for example, the destruction of property or erosion of trust in the community. We, therefore, model the effect of conflict exposure as a shift of the entire function $I(\mu)$ instead.

Now, if these costs of conflict exposure do not depend on location *d* and affect agricultural management systems homogeneously in space, we would observe an overall drop in intensification levels depicted as a parallel downward shift of $I(\mu) \rightarrow I(\mu)'$ (Figure 1b). However, if the added cost of conflict depends on location d, more complex patterns arise. Generally, there are two possibilities: (i) a change in the slope of $I(\mu)$ or even (ii) nonlinear patterns in $I(\mu)$ (Figures 1c and 1d, respectively).

If the slope of $I(\mu)$ changes (Figure 1c), this means that the cost of conflict differs between household close to the market and in more remote areas. A steeper slope would indicate a relatively higher cost of conflict exposure in remote areas, while a flatter slope would mean relatively higher costs in urban proximity. Theoretically, some factors could explain either shift. For instance, households in remote areas have to travel longer distances to acquire inputs or sell products in the market, which increases the likelihood of encountering conflict-related issues on the way. In addition, social composition and a strength of social ties might vary between urban and remote areas, likely affecting farmers' ability to cope with adversity when faced with conflict. Moreover, conflict intensity and the presence of conflict parties are normally higher in urban proximity since these locations are of higher strategic value (George, Adelaja, & Awokuse, 2020). In the end, only an empirical analysis will allow us to identify the pattern for the case study at hand. The same holds for potential nonlinear effects. Figure 1d is only one (likely) option, where urban and remote areas are more strongly affected than areas in between.

Figure 1. Conceptual framework



(a) No conflict

(b) Homogeneous effect

(c) Change in slope

(d) Nonlinear pattern

3. BACKGROUND ON AGRICULTURE AND CONFLICT IN MYANMAR

Agriculture in Myanmar Paddy is one of the main staple crops in Myanmar, contributing more than 50 percent of the calories consumed in the country and it factors majorly in the crop portfolio of many farmers, especially during the main growing season (monsoon) (MAPSA, 2022). The agricultural sector in general plays an important role as about half of the country's population is employed in farming directly or businesses offering accompanying services (Cunningham & Muñoz, 2018; Diao, Pauw, Thurlow, & Boughton, in press). Nonetheless, productivity and intensification levels vary substantially in the country. The central region (*Dry Zone*) and the *Delta* in the Southwest are the most important agricultural regions (Belton, Win, Zhang, & Filipski, 2021), while agricultural development in more mountainous regions lags behind. Next to paddy, other major crops cultivated in Myanmar are, for example, oil seeds or pulses; in the northern, cooler parts of the country, also vegetables or tea and coffee are possible (Boughton et al., 2021). Paddy cultivation is particularly common in lowland areas or regions with sufficient access to water for irrigation (Belton et al., 2021). Similar to other sectors, the decade of liberalization beginning with the democratic reforms in 2011 led to rapid growth and transformation of the agricultural sector. Employment opportunities in urban centers attracted many rural migrants resulting in increasing agricultural wages in more remote areas (Belton & Filipski, 2019). The consequence is an increased uptake of mechanization for all sorts of agricultural operations (e.g., land preparation, harvesting, threshing) and thriving rental businesses for machinery (Belton et al., 2021).

Conflict and crisis in Myanmar Despite promising economic growth after 2011, any such development came to a halt at the latest with the outbreak of the Covid-19 pandemic in 2020 and the takeover of the government by the military in February 2021. Studies by Headey et al. (2022) and Boughton et al. (2021) show that the pandemic led to significant disruptions in agri-food systems and surges in poverty and income loss. Poverty and food insecurity continued to be an issue in many parts of the country even before 2020, but the pandemic led to a significant deterioration in the situation. The coup in February 2021, thus, happened at a time when households' resources were already strained and the resulting surge in unrest and violent conflict has driven the country further into an economic crisis (MAPSA, 2021). The number of conflict events jumped significantly with the military coup in 2021. Note, however, that even before the coup and during times of rapid economic growth the country already suffered from relatively frequent and violent conflict. Myanmar is one of the most ethnically diverse countries in the world with 135 registered ethnic groups plus minorities such as the Rohingya who are not officially recognized (Bergren & Bailard, 2017). Discrimination and inter-ethnic tensions have unfortunately a long-standing history in the country. The disastrous attacks against the Rohingya in 2017 are probably the internationally most known example of conflict escalation in Myanmar before the military takeover in 2021 (Beyrer & Kamarulzaman, 2017).

4. METHODS

4.1 Data

Our empirical analysis is based on production data from the monsoon season of 2021 provided by 2,292 paddy farmers in Myanmar. The data was collected as part of the first round of the Myanmar Agriculture Performance Survey (MAPS), which was implemented in February and March 2022. MAPS covers a total of 3,891 crop-farming households and is a subsample of households originally interviewed in the nationally representative Myanmar Households Welfare Survey (MHWS, $N = 12,100$) earlier in 2022. The subsample was drawn based on whether households reported any crop production for the last 12 months in the MHWS ($N = 5,465$). Of the selected households about 71 percent (i.e., N = 3, 891) could be re-interviewed for MAPS, of which 2,675 reported paddy production. After removing observations with missing values, we end up with the final sample of 2,292 paddy farmers from 241 townships (out of 330).

Due to the unstable situation in the country caused by the unrest in the aftermath of the coup in February 2021 and the continuing Covid-19 pandemic, MAPS and MHWS were both conducted via phone. Despite the shortcomings of phone-based surveys such as sampling issues, larger shares of attrition, or less comprehensive survey instruments (Gourlay, Kilic, Martuscelli, Wollburg, & Zezza, 2021), in the current situation in Myanmar, they are the only feasible mode of collecting household data. MAPS and MHWS, thus, present a unique source of nationally representative information on households' farming practices and livelihoods during times of conflict (for more information see MAPSA (2022)). Furthermore, MAPS and MHWS contain comparably precise spatial identifiers for surveys conducted in a country experiencing an escalation of violence across its entire territory. That is, for 85 percent of the paddy farms we have information on the village tract (VT), where the household is located. VTs represent the smallest administrative unit in Myanmar apart from actual villages. Having such disaggregated spatial information is a great advantage in our analysis of conflict and market access as it allows us to calculate precise measures of conflict exposure and travel times to urban centers.

Indicators for paddy production Similar to other studies (e.g., Vandercasteelen et al., 2018b), we characterize paddy production systems based on a set of indicators. Five of those indicators are related to agricultural input use, while the remaining three measure production outcome and marketing (Table 1). All indicators are calculated based on production information for the monsoon season of 2021 provided in MAPS. The input indicators are (i) the use of urea (kg/acre), (ii) the price of urea (MMK/50kg) (iii) the price for renting machinery for plowing (MMK/acre) (iv) the average agricultural wages (MMK/day), and (v) input expenditures (MMK/acre). Production outcome is measured by (i) paddy yield (kg/acre), (ii) paddy price (MMK/kg), and (iii) the share of paddy production the household sold in the market. Summary statistics of all indicators are provided in Table 2.

Table 1. Description on the indicator variables (*'dependent variable'*)

Variable	Unit	Description
InputUse of urea	kg/acre	Qty of urea used on largest paddy plot
Price urea	MMK/50kg	Price payed for a 50kg bag of urea
Price machinery	MMK/acre	Price for renting a tractor (plowing, 1 acre/hour) (control: 2-/4-wheeler)
Average agricultural wages	MMK/day	Mean of wages reported for male and female laborers
Input expenditures	MMK/acre	Total input expenditures reported for the largest paddy plot
Outcome Paddy yield	kg/acre	Qty harvested on largest paddy plot
Paddy/Rice price	MMK/kg	Price received for paddy/rice (control: paddy/rice)
Paddy/Rice sales	Share	Share of total paddy production sold in the market

Measuring market access and conflict exposure We calculate travel times to the closest city and town as a proxy for market access (Damania et al., 2017; Vandercasteelen, Beyene, Minten, & Swinnen, 2018a; Vandercasteelen et al., 2018b) and construct an index to measure the severity and exposure to conflict based on four dimensions (danger, deadliness, diffusion, fragmentation)

(Raleigh, Kishi, & Billing, 2023). For both these variables, we supplement the survey data with secondary spatial information. To match the two data sources, our primary spatial reference scale is the village tract (VT), for which we extract centroids (hereafter *VT centroids*). For the 15 percent of households for whom we do not have VT information, we calculate township averages based on the VT-level information and include a dummy variable as a control in the subsequent analysis.

To calculate travel times between VT centroids and urban centers, we use *OpenStreetMap* (OSM) road networks with assigned travel speeds for different road types. Since OSM does not provide travel speeds for all road segments in Myanmar, we build the means of all non-zero values per road type and use them for our travel time calculations. Furthermore, we calculate travel times to cities (OSM definition) and towns (OSM definition). Note that for every VT, a town as per OSM definition is closer than a city. Thus, there is no added value in including travel time to the closest urban center (i.e., city or town) in the analysis as it would be identical to the travel time measure to the closest town. All travel time calculations are run in *QGIS* applying the *Origin-Destination-Matrix* algorithm in the *QNEAT3 - QGIS Network Analysis Toolbox 3* plugin. On average, households are located about 2.5 (145 minutes) and 1.5 (89 minutes) hours away from the next city and town, respectively (Table 2).

As most other studies (e.g., George, Adelaja, & Awokuse, 2020), we rely on data provided by the Armed Conflict Location & Event Data Project (ACLED) (Raleigh, Linke, Hegre, & Karlsen, 2010) to generate measures of conflict exposure. Since we aim to capture the immediate and direct effects of conflict as well as indirect effects due to the long-term experience of conflict (Arias et al., 2019), we build our variables based on different periods. For the direct effects, we consider all events during the monsoon season of 2021, i.e. ACLED events from June to October 2021. The long-term measure of conflict exposure relies on ACLED events from January 2010 (the start of the liberalization period) to January 2021. Other studies investigating conflict effects using ACLED data normally either extract fatalities (George, Adelaja, & Weatherspoon, 2020) or event counts based on classifications such as event type or actors (Adelaja & George, 2019; George, Adelaja, & Awokuse, 2020). In the Myanmar context, such approaches might be of limited use since event types have changed drastically between the period before (mainly battles between local non-governmental actors and the government) and after the coup (increase in violence against civilians). Furthermore, Myanmar is ethnically diverse, and often many different and local actors are involved in violent escalation. We, therefore, decided to create an index based on the newly released Conflict Severity Index (CSI) by ACLED (Raleigh et al., 2023), aiming for a more comparable proxy for conflict exposure in the Myanmar context. The CSI is built based on four indicators (Table 3)–Deadliness, Danger, Diffusion, Fragmentation–and was originally designed to compare countries. We adapt the classification and calculate it for the township level in Myanmar. Thus, for every township, we calculate the respective indicator values (second column in Table 3), and if the value falls above the indicated threshold (third column in Table 3) it scores a 1 for the respective indicator. The final CSI is the sum of all indicators per township and ranges from no/little conflict (0) to severe conflict (4). Note that the threshold definition makes the CSI a relative measure, which also relies on pre-defined time horizons. To construct the CSI for the monsoon season of 2021, we consider all ACLED events in that period. For conflict before the coup, we calculate yearly CSIs (2010-2020) and extract the maximum CSI in any of those years as a measure of past conflict exposure. In Figure 2, we present the spatial distribution of the CSI for the monsoon season of 2021 and the time before the coup.

Table 2. Summary Statistics - Indicator variables and key variables of interest (i.e., travel times and conflict)

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Use of urea (kg/acre)	2292	34.9	33.1	0.0	4.0	50.0	150.0
Price of urea ('000 MMK/50 kg)	2292	62.9	18.8	22	50.0	75.0	162.0
Price of urea (log, '000 MMK/50 kg)	2292	4.1	0.3	3.1	3.9	4.3	5.1
Yield (kg/acre)	2292	1329.1	555.8	146.3	940.5	1672.0	3448.5
Yield (log, kg/acre)	2292	7.1	0.5	5.0	6.9	7.4	8.2
Input expenditure ('000 MMK/acre)	2292	223.1	144.1	26.3	120.0	300.0	1000.0
Input expenditure (log, '000 MMK/acre)	2292	5.2	0.7	3.3	4.8	5.7	6.9
Paddy/Rice price (MMK/kg)	2292	439.6	230.5	167.5	320.6	478.5	2392.4
Price machinery ('000 MMK/acre)	2292	25.5	13.6	0.3	18.0	30.0	300.0
Price machinery (log, '000 MMK/acre)	2292	3.1	0.7	-1.1	2.9	3.4	5.7
Wage ('000 MMK/day)	2292	6.0	1.8	2.8	5.0	6.8	23.0
Wage (log, '000 MMK/day)	2292	1.8	0.3	1.0	1.6	1.9	3.1
Sales (Share)	2292	0.5	0.4	0.0	0.0	0.9	1.0
Travel times to closest city (minutes)	2292	145.3	54.1	21.8	110.0	176.1	375.2
Travel times to closest town (minutes)	2292	89.0	31.5	17.2	69.1	105.3	227.5
CSI[a] (monsoon21)	2292						
... 0	1089	47.5%					
... 1	761	33.2%					
... 2	442	19.3%					
CSI[a] (2010-2020)	2292						
... 0	1464	63.9%					
... 1	611	26.7%					
... 2	217	9.5%					
Indicator – 'Deadliness' (monsoon 2021)	2292						
... 0	1917	83.6%					
... 1	375	16.4%					
Indicator – 'Danger' (monsoon 2021)	2292						
... 0	1629	71.1%					
... 1	663	28.9%					
Indicator – 'Diffusion' (monsoon 2021)	2292						
... 0	1206	52.6%					
... 1	1086	47.4%					
Indicator – 'Fragmentation' (monsoon 2021)	2292						
... 0	1838	80.2%					
... 1	454	19.8%					

Note: [a]CSI (Conflict Severity Index) categories: 0-No/Little conflict, 1-Moderate conflict, 2-Severe conflict

In a final step, we reduce the CSI from four to two severity categories, to ensure that enough observations are in the respective groups for the subsequent estimation of interaction effects. That is, category 1 and 2 of the original CSI become category 1 in the reduced CSI and the original categories 3 and 4 are now aggregated in category 2. Table 2 presents summary statistics for the reduced CSI for the monsoon season 2021 and before the coup, as well as for the separate indicators. When tabulating the indicators against the original CSI (monsoon 2021) (Table A.1), it shows that the first category of the reduced CSI is mainly defined by the indicators 'Danger' and 'Diffusion', whereas category 2 indicates additional 'Deadliness' and 'Fragmentation'. Thus, moderate conflict (category 1) as per the reduced CSI relates to violence against civilians and the spread of conflict events, and severe conflict (category) means an additional high death toll of conflict and high numbers of involved actors.

Control variables in addition to the variables described above, we consider a large set of control variables to capture other factors that likely influence households' management decisions. This includes geophysical variables such as the agroecological zones, elevation, land cover, travel time to the closest border, a factor variable indicating the closest border, and precipitation during the monsoon season of 2021. A second group of controls refers to paddy/agricultural management specifically; that is, the experience of any pest or weather shocks, whether other crops were grown on the farm, the size of the largest paddy plot, the number of rice plots, whether the household owns any land, the rice variety planted, whether the households sold rice or paddy, whether the household received extension services, and if machinery prices are reported for 2- or 4-wheel tractors. The last group of variables captures household characteristics including whether the household reported effects of the Covid-19 pandemic on its agricultural production, gender, age, and education of the agricultural decision-maker, the number of household members, whether the household had access/owns motorized transportation, whether the most important income source was farm or off-farm employment, whether any household member earned income in a non-agricultural sector, and whether the household received any remittances. Summary statistics for all control variables can be found in Table A.3 and Table A.4 in the appendix.

Table 3. Description of indicators to build the adapted Conflict Severity Index (CSI)

Indicator	Description	Threshold
Deadliness	All fatalities (count) from all events in a given time period	Mean
Danger	Count of all events categorized as "Violence against civilians" standardized by population density (2020) in a given time period	Median
Diffusion	Share of village tracts (VTs) with high average weekly event counts in a given time period	1.5 weekly average
Fragmentation	Number of actors in a given time period, excluding unidentified groups and civilians	>80 percentile

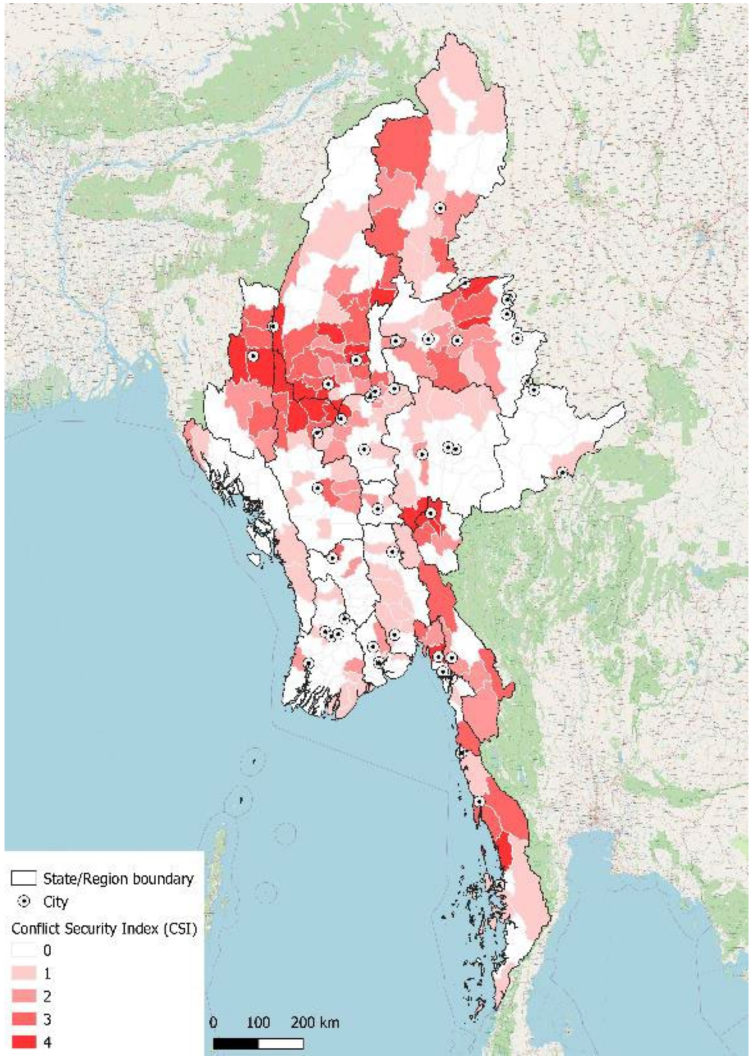
4.2 Estimation strategy

We assume that quantity and price indicators of paddy production are correlated and, therefore, we apply a multivariate regression framework to estimate the effects of travel times and conflict on farmers' management decisions. That means we estimate equations for the eight indicators simultaneously with the model allowing for error term correlation. Moreover, we estimate two different model specifications. The first specification (Eq.1) considers the effects of travel times (i.e., market access) and conflict as independent and represents the specification generally used in the literature. It also coincides with panel (b) in Figure 1 in the conceptual framework (section 2).

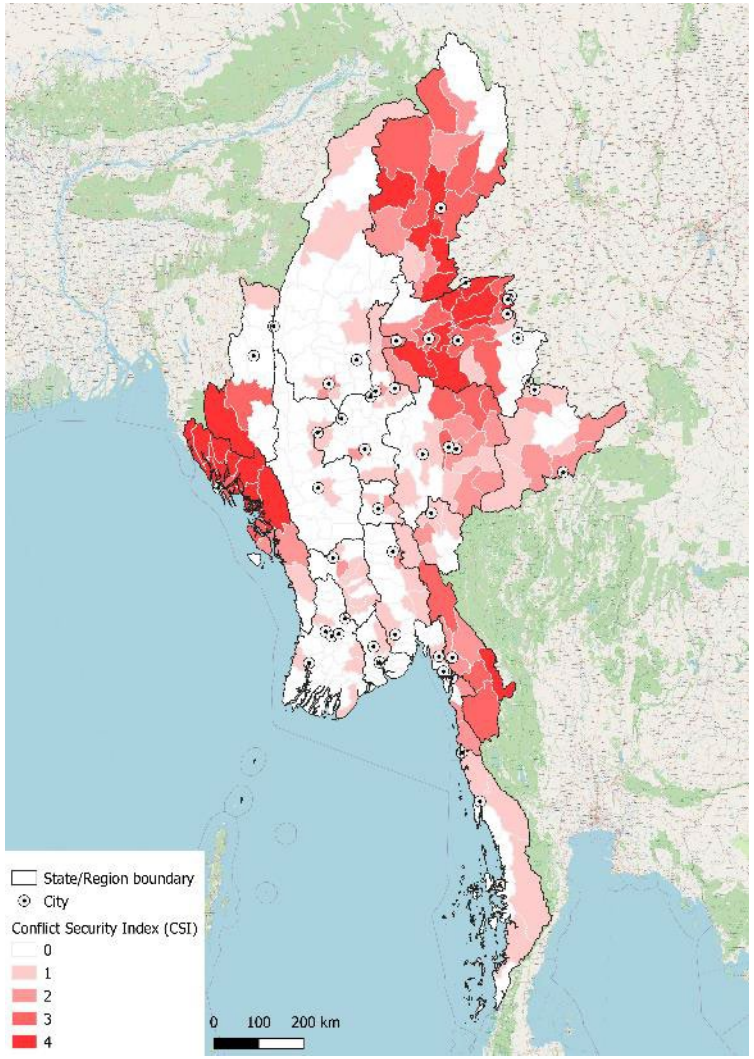
$$Y_i = \alpha + X_i\beta + \gamma_a conflict_{ai} + \gamma_b conflict_{bi} + f\left(tt_{ji}\right) + \nu_s + \nu_d + \nu_r + \varepsilon_i \qquad (1)$$

where Y_i is the vector of the eight indicators of paddy production for household i, X_i is a set of geophysical, production, and household controls, $conflict_{ai}$ and $conflict_{bi}$ are the measures of conflict exposure after (a) and before (b) the coup, and $f\left(tt_{ji}\right)$ is a smooth function of the travel time to urban center j with $j = (city, town)$ (hereafter 'city' and 'town' specification). The parameters α, β, γ_a, γ_b, and function $f\left(tt_{ji}\right)$ are to be estimated. The latter is estimated as penalized splines ($k = 10$ dimension of the basis) to allow for potentially nonlinear effects of travel times, a pattern previously shown in studies by Vandercasteelen et al. (2018a) and Steinhübel and von Cramon-Taubadel (2021). Therefore, instead of estimating a standard generalized linear model (GLM), we rely on a semi-parametric extension of GLMs, a generalized additive model (GAM) (Wood, 2017). Our inference strategy relies on Restricted Maximum Likelihood (REML). Apart from being able to estimate nonlinear effect functions, another advantage of a GAM set-up is the easy inclusion of random effects to build a hierarchical model controlling for different spatial/nested scales in the data. Therefore, ν_s, ν_d, ν_r are random intercepts at the township, district, and state/region levels. ε_i is a stochastic error term.

Figure 2. Conflict Severity Index (CSI) calculated on township level for the monsoon season 2021 and the period between 2010 and 2020



(a) Monsoon season 2021



(b) Before coup (2010-2020)

In the second model specification (Eq.2), we extend Eq.1 by including interaction terms.

$$\begin{aligned} Y_i = \alpha + X_i\beta + \gamma_a conflict_{ai} + \gamma_b conflict_{bi} + \\ f_0(tt_{ji}) + conflict_{ai} \times f_a(tt_{ji}) + conflict_{bi} \times f_b(tt_{ji}) + \\ \nu_s + \nu_d + \nu_r + \varepsilon_i \end{aligned} \quad (2)$$

In addition to the parameters above, we now also estimate functions $f_a(tt_{ji})$, and $f_b(tt_{ji})$; that is, the effect of travel times conditional on households experiencing conflict (defined as CSI categories) before (b) and after (a) the coup respectively (compare panels 1c and 1d in section 2). The function $f_0(tt_{ji})$ captures the main effect of travel times, i.e., without any conflict exposure.

Robustness checks and identification strategy[2] We run several robustness checks to test the suitability of the reduced CSI to measure conflict exposure. Thus, we estimate both models (Eq.1 and 2) replacing the CSI with the separate indicators. This makes our analysis also comparable with other studies using, for example, fatalities as a proxy for conflict (i.e., closely related to our 'Deadliness' indicators). Estimation results of all other variables are robust and model-fit-criteria suggest preferring the CSI specification above a particular indicator (see Table A.5).

Another issue that might arise for both our key variables of interest (conflict and market access) is reverse causality. That is, conflict might be more likely in poorer regions with lower agricultural development, (Arias et al., 2019; George, Adelaja, & Weatherspoon, 2020) and roads (and, thus, travel times) might be of better quality in richer and more developed areas. Concerning the conflict measure, some studies make the case that this is only an issue for aggregated analysis (George, Adelaja, & Weatherspoon, 2020). Since we use household-level data, we are therefore confident that conflict exposure can be assumed largely exogenous to management decisions. As for the travel times, we re-run the analysis applying an IV approach using instruments—a natural path variable and Euclidean distance—tested and established in previous studies (Damania et al., 2017; Vandercasteelen et al., 2018b, 2021). Since estimates are quite robust to the inclusion of the instruments, we proceed with the analysis using the model estimates as described above.

5. RESULTS AND DISCUSSION

Travel times In Figure 3, we present the estimated splines for the effect of travel times to the closest city on the eight paddy production indicators based on the model specification without interaction terms (Eq.1). For five out of eight of the indicators, we observe statistically significant and negative effects of travel times to the closest city.[3]

On the input side, we find statistically significant gradients for the use of urea and input expenditure, but none of the input prices (urea, machinery, or wages; Figures 3b-3d). Everything else equal, paddy farms located closer to cities use about 30 kg of urea more per acre than farms located furthest away and spend about 7 percent more on input on their largest paddy plot (Figure 3e). This hints towards higher intensification levels in urban proximity, i.e., higher expenditures result from higher levels of applied inputs and not from higher input prices. The outcome indicators show all

[2] For the sake of brevity, the estimation results are not included in the appendix but are available on request.

[3] Note that for the GAM to be identifiable, the smooth functions have to have zero means over the covariate (i.e., travel time) values (see horizontal lines at zero in the plot). That means, the splines have to be seen relative to the sample mean (i.e., Intercept) or in the case of the interaction terms the main effect (Panel (a)). For more information refer to Wood (2017).

statistically significant gradients with travel times. For paddy yields the difference between urban and remote farms lies around a small 1-2 percent (Figure 3f), whereas paddy/rice prices vary strongly. That is a farm close to a city receives about 80 MMK/kg more than a remote household (Figure 3g), which amounts to about 18 percent of the average price households receive in our sample (440 MMK/kg, Table 2). Also, urban households sell about 20-30 percent more of their harvest compared with remote households (Figure 3h).

All in all, this suggests that households in urban proximity invest larger amounts in their paddy production and reach higher intensification levels. They also receive higher prices and are more likely to sell paddy/rice in the market, ceteris paribus. These findings match the results in previous studies, where authors identify similar patterns for teff production and livestock in Ethiopia (Vandercasteelen et al., 2018b; Vandercasteelen et al., 2021) or the adoption of irrigation technology in India (Steinhübel, Weg-mann, & Mußhoff, 2020). Therefore, it appears that the theory of comparative advantage for smallholder households in urban proximity also holds for paddy farms in Myanmar. Note, however, that this pattern is more pronounced for travel times to the closest city. Estimated splines for travel time to the closest town are only statistically significant for the use of urea, agricultural wages, paddy/rice price, and sales (see Figure A.6 in the appendix) and gradients are flatter. Therefore, the subsequent discussion of results mainly focuses on the 'city' specification and, for brevity, we only provide estimation results for 'town' specification on request.

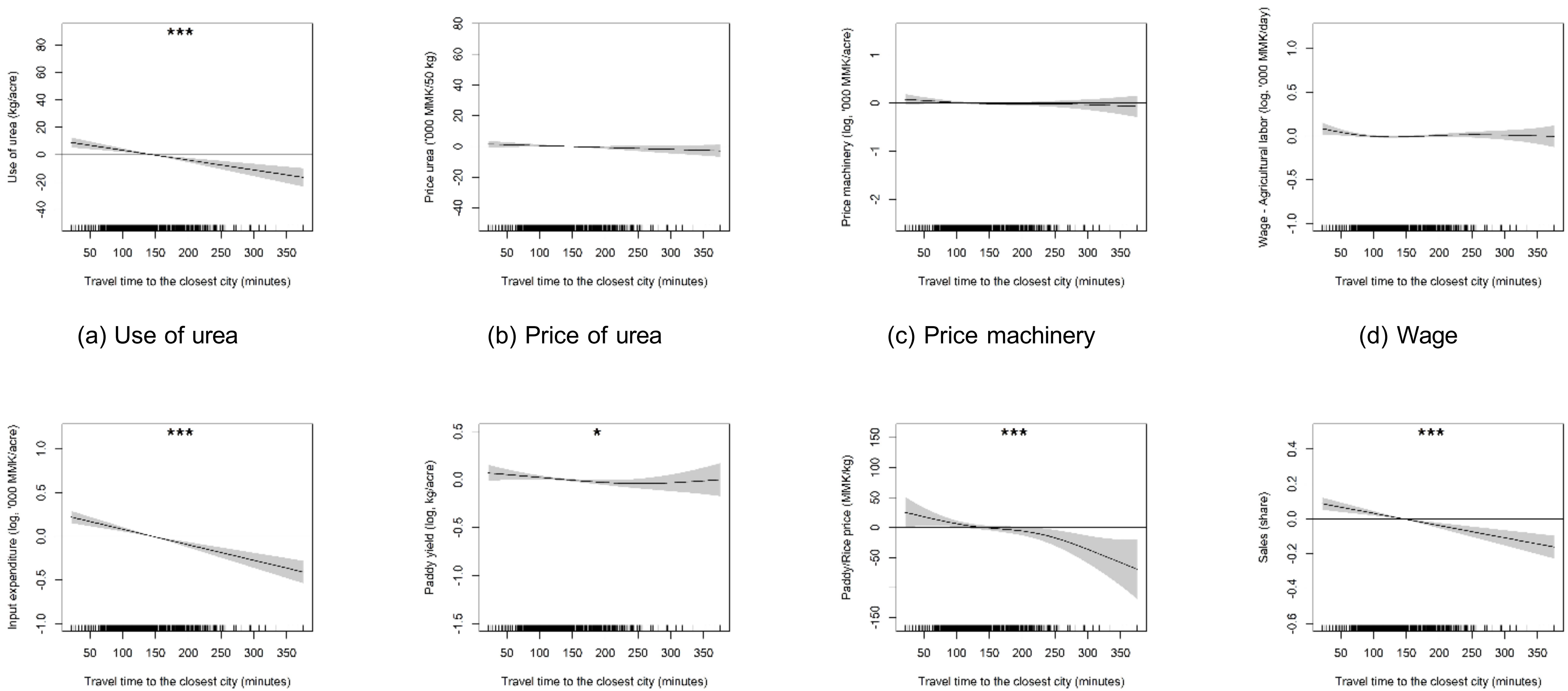
Conflict The estimated effect of conflict on paddy management systems is robust to whether travel times to the closest city or town are included in Eq. 1. Table 4 indicates that not all indicators are affected by conflict in the same way. The use of urea, price for machinery, and paddy yields do not show any statistically significant coefficients, independent of past or recent conflict exposure. Patterns for the other indicators are diverse but recent and, in particular, severe conflict (CSI category: 2) more often yields statistically significant coefficients. Everything else equal, exposure to severe conflict during the monsoon season of 2021, is associated with higher agricultural wages (3.3 percent), higher input expenditures (15.3 percent), and higher sales shares (11.3 percent). Exposure to moderate conflict (monsoon 2021) is only associated with higher wages (2 percent).

For past moderate conflict, we find higher prices for urea (1,659 MMK per bag (50 kg)) and lower wages (- 2.3 percent). Past exposure to severe conflict only yields statistically significant coefficients for paddy/rice prices with farmers earning about 22 MMK less per kg, everything else equal.

So far, we have assumed that the effects of remoteness and conflict are independent (Eq.1). As shown in section 2, this might be an oversimplification leading to biased estimation results. Therefore, by estimating the model specified in Eq.2, we test whether the relationship between the production indicators and travel times changes conditional on conflict exposure. Since the estimation output of this model specification is rather bulky, we group the production indicators into three groups based on displayed effect patterns (Table 5), i.e., linear, nonlinear, and no-interaction patterns. [4] Except for one indicator (paddy/rice price in the 'city' specification, see Pattern 3), we find statistically significant interaction terms for all indicators independent of the specification of travel times. In addition, the model fit criteria such as the Akaike information criterion (AIC) improve substantially when including interaction effects of travel times and CSI categories (Table A.5). Thus, the first important result of our analysis is that the effect of conflict does indeed vary along the remoteness gradient and the assumption of independent effects is inappropriate.

[4] Note that some production indicators show linear as well as nonlinear interaction terms. In these cases, we rely on the interaction effect with the highest level of significance for the assignment to a pattern in Table 5.

Figure 3. Effect of travel time to the closest city (minutes) estimated as penalized spline. Asterisks in the plots indicate overall significance of the estimated spline.



(a) Use of urea (b) Price of urea (c) Price machinery (d) Wage

(e) Input expenditure (f) Paddy yield (g) Paddy/Rice price (h) Sales

Note: Asterisks in the plots indicate overall significance of the estimated spline; ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

Now that we know that the effects of conflict do vary spatially, the next step is to understand how they vary and what this means for agricultural development. First, we provide a more detailed description of the patterns presented in Table 5 and discuss the role of location in conflict effects. Afterward, we elaborate on the effects observed regarding the timing and intensity of conflict and implications for the agricultural management system in general. Finally, we will present and discuss the results for some other factors influencing paddy production in Myanmar.

Table 4. Regression results for conflict variables[b] - Eq.1, 'City' specification

	Use of urea (kg/acre)	Price of urea ('000 MMK/50 kg)	Price machinery (log, '000 MMK/acre)	Wage (log, '000 MMK/day)	Input expenditure (log, '000 MMK/acre)	Yield (log, kg/acre)	Paddy/Rice price (MMK/kg)	Sales (Share)
Intercept	48.471***	70.264***	2.735***	1.738***	5.481***	7.453***	267.811***	0.568***
	(9.598)	(5.565)	(0.170)	(0.072)	(0.184)	(0.140)	(33.594)	(0.094)
CSI - Category 1 (monsoon 2021)	-1.793	-1.009	0.007	0.020*	0.051	0.002	5.019	0.024
	(1.603)	(0.933)	(0.028)	(0.012)	(0.031)	(0.023)	(5.607)	(0.016)
CSI - Category 2 (monsoon 2021)	0.247	-0.915	0.022	0.033*	0.153***	0.035	-11.515	0.113***
	(2.228)	(1.256)	(0.040)	(0.017)	(0.043)	(0.032)	(7.754)	(0.022)
CSI - Category 1 (2010-2020)	2.157	1.659*	-0.034	-0.023*	-0.006	0.033	-8.478	-0.009
	(1.689)	(0.986)	(0.030)	(0.013)	(0.033)	(0.025)	(5.915)	(0.016)
CSI - Category 2 (2010-2020)	2.482	1.049	0.084	0.026	0.006	-0.011	-21.853*	0.005
	(3.575)	(2.083)	(0.063)	(0.027)	(0.069)	(0.052)	(12.536)	(0.035)
Full set of controls[a]	Yes							
Splines: Travel time	Yes							
Interaction	No							
RE	Yes							
Observations	2,292							
AIC	24264.38							
Deviance explained	0.407							

Note: ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01
Standard errors in parentheses, [a]see Table A.3 and Table A.4 for a full list of all control variables.
[b]CSI (Conflict Severity Index) categories: 0-No/Little conflict (reference), 1-Moderate conflict, 2-Severe conflict.

5.1 The role of location in conflict effects

The estimated interaction effects based on Eq.2 are presented as figures with five panels (Figures 4-Figure A.5). The first panel (a) always presents the main effect of travel times on the respective indicator, i.e., the effect of travel times without any conflict exposure, past or present. The remaining four panels (b)-(e) present the interaction effects. As with standard linear interaction effects, they must be interpreted with reference to the main effect, that is panel (a). The panels in the second row present interaction effects based on recent (monsoon 2021) exposure to moderate (CSI=1, (b)) and severe conflict (CSI=2, (c)), while panels (d) and (e) do the same for past conflict exposure (2010-2020).

For brevity, we only include the figures for three production indicators in the main text (Figures 4-6, bold in Table 5). They present good examples for the different effect patterns in Table 5 and the more general results presented in the next section (5.2). All remaining figures for the 'city' specification can be found in the appendix (Figures A.1-Figure A.5).

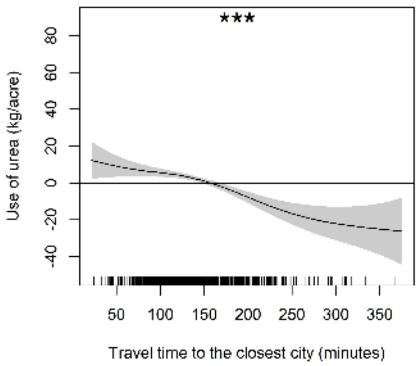
Table 5. Description of effect patterns, model specification Eq.2

Pattern	Description	Effect is:	Travel times to *j* j = City	 j = Town
Linear - 1	Travel times	linear*	**Use of urea** (Figure 4)	Use of urea
	Travel times × conflict	linear*	Input expenditures	Price of urea
			Sales (Figure 5)	
Nonlinear - 2				
2.1	Travel times	linear$^{*}/^{-}$	**Wage** (Figure 6)	Wage
	Travel times × conflict	nonlinear* → *U-shape*	Paddy yield	Sales
			Price machinery	
2.2	Travel times	linear$^{*}/^{-}$	Price of urea	Price machinery
	Travel times × conflict	nonlinear* → *local*		Input expenditures
				Paddy yield
				Paddy/Rice price
No interaction - 3	Travel times	linear*	Paddy/Rice price	
	Travel times × conflict	not significant		

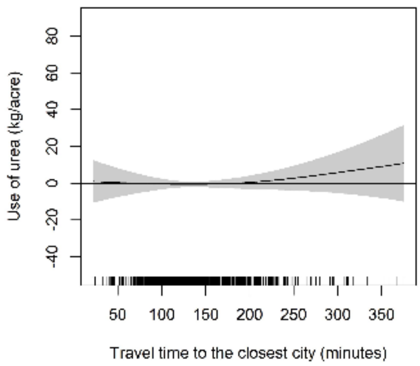
Note: If indicator shows several effect patterns, we assign based on the highest significance level.

Linear Pattern - 1 The first pattern shows statistically significant effects for travel times without conflict (i.e., the main effect $f_0(tt_{ji})$) as well as for at least one interaction term. Both the main and the interaction effects are linear. Let us take the use of urea ('city' specification) as an example (Figure 4). The effect without conflict (Figure 4a) is negative and the gradient is steeper than in the estimation results for Eq.1 (Figure 3a). That means without conflict, the difference in urea usage per acre between urban and remote farms increases to about 40kg compared to 30kg in the specification without interaction terms (Figure 3a). It, thus, makes sense that all four interaction terms show positive slopes (Figure 4b- 4e), although only three are statistically significant. As for an interpretation, this means that conflict exposure reduces the comparative advantage for farms in urban proximity.

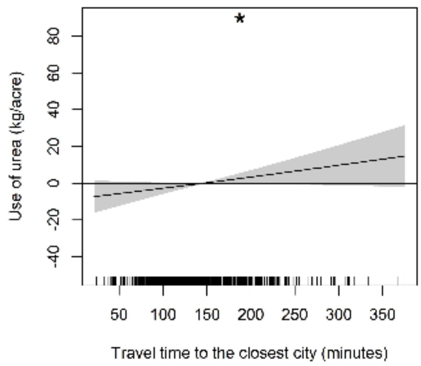
Figure 4. Effect of travel time to the closest city (minutes) on the use of urea (largest paddy plot), (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq. 2.



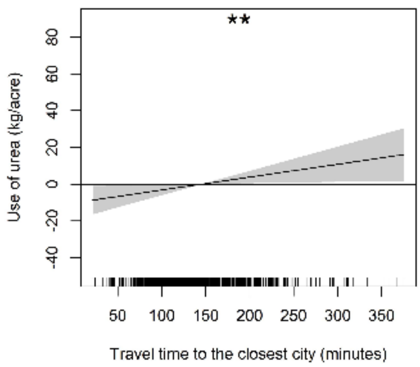
(a) TT base: $f_0(tt)$



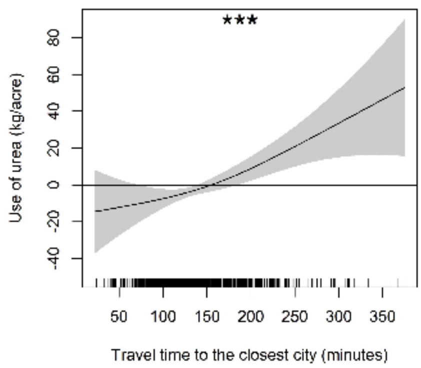
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



(d) $\mathrm{conflict}_{b(CSI=1)} \times \widehat{f_b(tt)}$



(e) $\mathrm{conflict}_{b(CSI=2)} \times \widehat{f_b(tt)}$

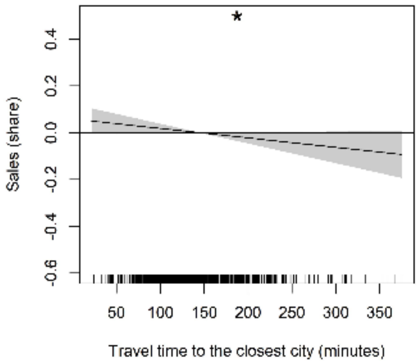
Note: Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; $*$p<0.1; $**$p<0.05; $***$p<0.01.

Nonlinear Pattern - 2 While the main effect of travel times is either linear or statistically insignificant, we identify two types of nonlinear interaction terms in the second pattern.

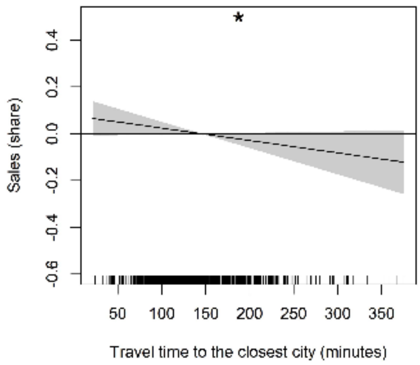
The first type of nonlinear interaction effects (2.1) presents a ’U-shape’ coinciding with the fourth panel in our conceptual framework (Figure 1d) indicating a disproportional effect of conflict in urban and very remote areas. We find this pattern for the indicator of agricultural wages, the price for machinery (’city’ specification, Figure A.2), paddy yields (’city’ specification, Figure A.4), and sales (’town’ specification). Most pronounced is the effect for wages as presented in Figure 6. For households who experienced conflict in the past and live within two hours of a city, agricultural wages can be more than 75 percent higher compared to households located within travel times between 2 and 4 hours (Figure 6e). Beyond 4 hours wages again increase up to 40 percent, everything else equal. This indicates a relative labor shortage in urban as well as remote areas. In the Myanmar context, especially two explanations come to mind—off-farm labor markets/migration and mechanization. Even before the coup, Myanmar had a large share of people moving from remote areas to cities for better income opportunities (Belton & Filipski, 2019; Cunningham & Muñoz, 2018; MAPSA, 2023). As a results agricultural labor in rural areas has become scarce and migrants to cities normally do not work in the agricultural sector. Similarly, people already living in urban proximity might choose off-farm employment over agricultural wage labor. To some extent, machinery can substitute for agricultural labor and this is a trend that has been recently observed in many regions of Myanmar along with substantial growth in rental services (Belton et al., 2021). Nonetheless, high prices for machinery determine to which extent farmers can realize such a substitution. Difficult access to remote areas and higher demand in areas with intensified agriculture (often in urban proximity) likely increase prices for machinery, which again increases the importance of agricultural labor leading to higher wages in those regions. Such patterns in prices for machinery are exactly what we observe in Figure d. Note that we find these patterns only for past conflict exposure. Patterns for conflict after the coup are much more diffuse and may be linked to short-term dynamics. For a more detailed discussion on the timing of conflict and consequences for agricultural development see section 5.2.

The second type of nonlinear effects (2.2) can be best described as either half a U-shape or a local linear interaction effect. That is, the interaction effect is limited to a subset of travel time values (i.e., ’local’). Note that this is the dominating interaction effect for the ’town’ specification (Table 5, four out of eight production indicators), and in all cases (’city’ and ’town’ specification) it is observed for more remote households and particularly for price-related indicators. That is remote households report relatively higher increases in prices and input expenditures due to conflict. For example, moderate conflict (past and present) at locations more than six hours away from the next city is associated with a relative increase of urea prices by 30,000-40,000 MMK per bag (Figure A.1).

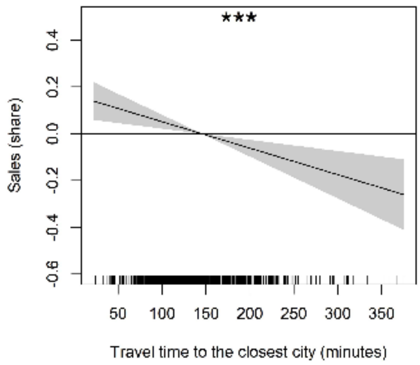
Figure 5. Effect of travel time to the closest city (minutes) on the share of paddy/rice sales, (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq. 2.



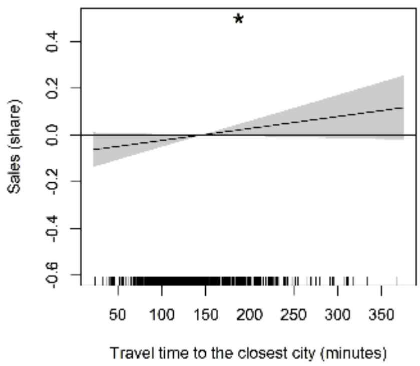
(a) TT base:$f_0(tt)$



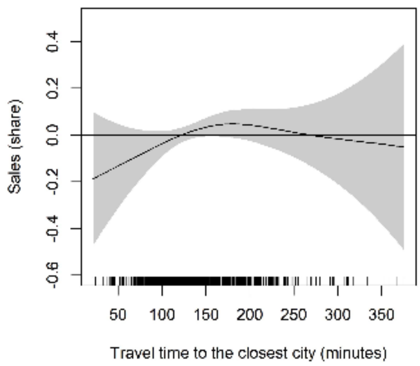
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



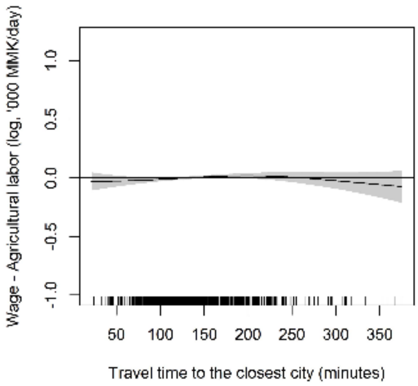
(d) $\mathrm{conflict}_{b(CSI=1)} \times \widehat{f_b(tt)}$



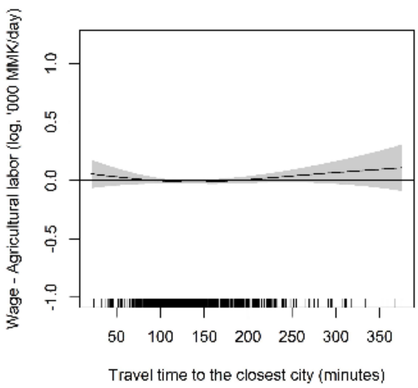
(e) $\mathrm{conflict}_{b(CSI=2)} \times \widehat{f_b(tt)}$

Note*:* Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; $*$p<0.1; $**$p<0.05; $***$p<0.01.

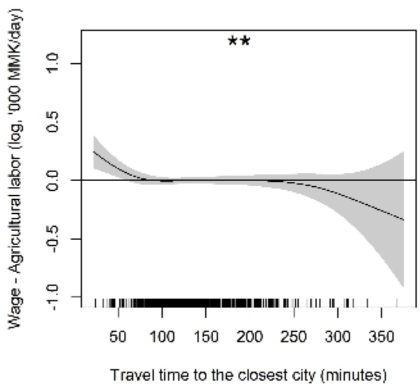
Figure 6. Effect of travel time to the closest city (minutes) on agricultural wages, (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq.2.



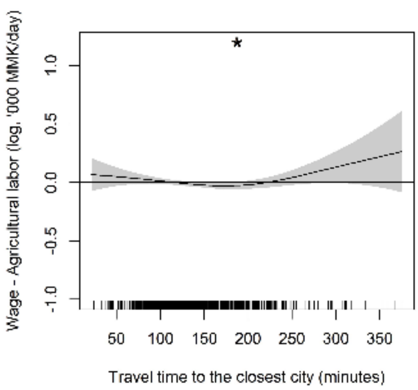
(a) TT base:$f_0(tt)$



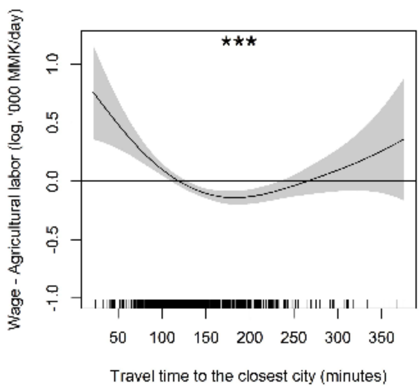
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



(d) $\mathrm{conflict}_{b(CSI=1)} \times \widehat{f_b(tt)}$



(e) $\mathrm{conflict}_{b(CSI=2)} \times \widehat{f_b(tt)}$

Note: Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; $*$p<0.1; $**$p<0.05; $***$p<0.01.

5.2 The role of intensity and timing in conflict effects

Next to general spatial patterns of conflict effects on paddy production, the intensity of the conflict experienced by households also plays an important role in agricultural development. For three out of the eight production indicators ('city' specification), we observe the same effect for CSI categories 1 and 2, but the effect is stronger for a higher CSI. That means, for the use of urea (Figure 4), agricultural wages (Figure 6), and paddy sales (Figure 5), the escalation of conflict amplifies the location-dependent conflict effects discussed in the section before (5.1).

For the remaining production indicators and in particular, the prices for urea and machinery as well as input expenditure, the interaction effects of conflict and travel times are dominated by moderate conflict (i.e., CSI category 1). As discussed in the data section (4), this conflict category is mainly determined by violence against civilians and the spread of conflict events. That means these two dimensions of conflict appear to be especially important in determining agricultural input prices. This is in contrast to other studies that find that it is especially fatalities (i.e., 'deadliness' in CSI terms) that drive conflict effects on agricultural systems (Adelaja & George, 2019). Considering the very different regional contexts of these studies, this highlights the necessity of location-specific empirical evidence to assess the effect of conflict on agriculture.

We argue in favor of using an index measure such as the CSI to capture conflict effects in our study because conflict in Myanmar is inherently complex. Several regions in the country have a long history of escalation. The great diversity of ethnicities, religions, and cultural traditions means that conflict is often driven by local interests. Then, with the coup in 2021 a completely new scale of violence rolled over the country also affecting so far rather stable states such as Sagaing or Magwe. Looking at our results, it appears that the CSI is indeed a suitable measure to extract and harmonize the underlying dimensions of different and complex conflict settings that affect agricultural decision-making. That is, effect patterns for conflict before the coup and during the monsoon season of 2021 generally show the same pattern for most production indicators. The only noteworthy exceptions are the price for machinery, paddy yields, and sales. While past exposure to conflict is associated with higher prices close to cities and in remote areas, we observe the exact opposite with prices dropping by over 100 percent in these regions exposed to conflict during the monsoon season of 2021, everything else equal (Figure A.2). As for yields, households in urban proximity and remote areas exposed to severe conflict in the past reported up to 50 percent lower yields relative to households with intermediate travel times (Figure A.4e). After the coup, the effect pattern is inverse and only observed for moderate conflict (Figure A.4b). These results might be explained by the regional shift in conflict patterns as presented in Figure 2. During the monsoon season of 2021, we can observe conflict in many townships in central Myanmar (Figure 2a) that were stable in the past and are considered the most agriculturally productive area in the country (MAPSA, 2022). Thus, the effects in Figure A.4b might be also driven by some remnants related to conflict clusters in productive and originally conflict-free agricultural areas. Monitoring of the situation in the country and particularly in these relatively productive areas is essential to assess the long-term consequences of the current escalation on agricultural development and the food system in Myanmar. Finally, we also see a change in marketing decisions between exposure to conflict before and after the coup. While exposure to conflict before the coup rather flattens the gradient of sales shares, exposure to conflict during the monsoon season in 2021 leads to a relative increase in sales in urban proximity. Generally, one would expect households to retain more of the paddy produce, since it is a durable staple crop. Due to an increase in looting after the coup, however, farmers might decide to sell higher shares of their harvest to avoid losing any crop. Welfare implications of this strategy will largely depend on the development of food prices, i.e., do farmers have to pay more to buy back the rice when they need it for home consumption? From our results on paddy/rice prices (Figure A.5), it seems that households close to cities can realize relatively higher prices. Nonetheless, additional analysis of food prices also spanning longer periods will be necessary to make a final statement on how food security and other welfare indicators will be affected.

5.3 Other factors

Even though mainly introduced as control variables, several other factors are significantly linked to paddy production and should be mentioned here (Table 6). Travel times to the closest border show a statistically significant and negative association with four of the production indicators. We can, thus, assume that borders and markets in neighboring countries have similar effects to the markets in cities in Myanmar. However, it appears that it is not only the proximity to the border but also the neighboring country that is closest that plays a role. Relative to Bangladesh and everything else equal, households located close to China and Thailand report 13.8 and 10.6 percent higher shares of paddy/rice sales, respectively. This fits reports highlighting the importance of cross-border trade (MAPSA, 2021). In contrast, farms located close to the Indian border report, for example, 14.7 percent lower yields but significantly higher prices (+47.2 MMK/kg). Concerning input prices, urea prices are 12.9 percent higher and wages 9.7 percent lower close to the Indian border, while machinery is 38 and 10.9 percent cheaper close to the border of Laos and Thailand, respectively.

Paddy farms also growing other crops reported significantly lower input expenditures for their largest paddy plot and lower shares of paddy sales, i.e., larger shares are likely kept for home consumption. When households own land they achieve paddy/rice prices 21.2 MMK/kg higher than the sample mean, ceteris paribus, while extension leads to a price increase of almost 12 MMK/kg and a yield increase of almost 7.2 percent, on average.

Another important factor seems to be whether households faced any issues in their farming operation due to the Covid-19 pandemic. Everything else equal, households indicating problems use more urea and report significantly higher input expenditures and prices to rent machinery. In addition, all four pest and weather shocks significantly reduce paddy yields between 5 and 16 percent. Nonetheless, only pests are associated with higher input use (urea) and input expenditures.

Households with at least one member being employed in the non-agricultural sector use significantly more urea on their largest paddy plot and report significantly higher input expenditures, ceteris paribus. Furthermore, on average they achieve about 5 percent higher paddy yields than the sample mean. Households receiving remittances sell 4.3 percent less of their harvest, on average and everything else equal.

Table 6. Regression results for selected control variables - Eq.2, 'City' specification

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea ('000 MMK/50 kg)	Price machinery (log, '000 MMK/acre)	Wage (log, '000 MMK/day)	Input expenditure (log, '000 MMK/acre)	Yield (log, kg/acre)	Paddy/Rice price (MMK/kg)	Sales (Share)
Intercept	45.740***	68.750***	2.801***	1.817***	5.521***	7.392***	249.742***	0.580***
	(9.233)	(5.338)	(0.163)	(0.070)	(0.178)	(0.136)	(32.443)	(0.091)
Precipitation (monsoon 2021, mm)	-0.014**	-0.010**	-0.000***	0.000***	-0.000***	-0.000***	-0.011	-0.000***
	(0.007)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.000)
Shock - pest/disease (dummy)	4.789**	-0.515	0.010	0.007	0.092**	-0.048*	3.094	-0.021
	(1.954)	(1.136)	(0.035)	(0.015)	(0.038)	(0.029)	(6.870)	(0.019)
Shock - timing rain (dummy)	-2.861	-0.554	0.032	-0.022	0.003	-0.101**	-10.862	-0.029
	(2.862)	(1.663)	(0.051)	(0.021)	(0.055)	(0.042)	(10.059)	(0.028)
Shock - drought (dummy)	-2.922	0.924	-0.014	-0.011	-0.098	-0.165***	7.395	-0.008
	(3.250)	(1.889)	(0.058)	(0.024)	(0.063)	(0.048)	(11.443)	(0.032)
Shock - floods (dummy)	-1.288	-1.623	-0.061	-0.004	-0.061	-0.136***	18.162	-0.001
	(3.227)	(1.877)	(0.057)	(0.024)	(0.062)	(0.047)	(11.350)	(0.032)
Travel times to closest border (hours)	-0.709**	-0.202	-0.003	-0.021***	-0.012**	-0.009*	-1.428	-0.004
	(0.005)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.000)
Closest border - China	4.837	-3.253	-0.059	-0.047	0.101	-0.007	15.775	0.138***
	(3.940)	(2.331)	(0.071)	(0.030)	(0.075)	(0.058)	(13.865)	(0.038)
Closest border - India	-1.111	-1.913	-0.089	-0.097***	0.028	-0.146**	50.125***	-0.033
	(4.014)	(2.356)	(0.072)	(0.030)	(0.077)	(0.059)	(14.111)	(0.039)
Closest border - Laos	17.171	-11.078*	-0.381**	0.067	-0.010	-0.073	49.244	0.131
	(10.509)	(6.115)	(0.186)	(0.080)	(0.202)	(0.153)	(37.127)	(0.102)
Closest border - Thailand	0.649	-3.219	-0.110*	-0.037	-0.053	-0.049	5.027	0.107***
	(3.402)	(2.007)	(0.061)	(0.026)	(0.064)	(0.050)	(11.976)	(0.033)
Other crops (dummy)	-0.253	0.181	-0.051**	-0.048***	-0.040	-0.011	-6.155	-0.066***
	(1.466)	(0.851)	(0.026)	(0.011)	(0.028)	(0.021)	(5.151)	(0.014)
Plot size (acres)	-1.707***	-0.002	-0.011	0.005	-0.072***	-0.057***	-3.300*	0.014***
	(0.501)	(0.291)	(0.009)	(0.004)	(0.010)	(0.007)	(1.762)	(0.005)
Number of rice plots (count)	0.009	0.029	-0.001*	0.000	0.000	0.002***	0.125	0.002***
	(0.039)	(0.023)	(0.001)	(0.000)	(0.001)	(0.001)	(0.136)	(0.000)
Land ownership (dummy)	2.594	-0.466	0.095*	-0.065***	-0.040	-0.024	22.988**	-0.018
	(3.218)	(1.875)	(0.057)	(0.024)	(0.062)	(0.047)	(11.327)	(0.031)
Extension (dummy)	0.728	-1.408*	-0.016	-0.002	-0.014	0.072***	11.716**	0.023
	(1.431)	(0.830)	(0.025)	(0.011)	(0.028)	(0.021)	(5.031)	(0.014)
Gender - male (dummy)	-0.414	-0.295	-0.062**	0.035***	-0.022	0.071***	-12.183**	0.020
	(1.438)	(0.836)	(0.025)	(0.011)	(0.028)	(0.021)	(5.057)	(0.014)
Age (years)	0.037	0.022	-0.000	0.001***	0.001	0.000	0.548***	-0.001**
	(0.056)	(0.032)	(0.001)	(0.000)	(0.001)	(0.001)	(0.196)	(0.001)
Number of household members (count)	0.078	0.012	0.002	0.009***	-0.002	0.002	-0.760	-0.015***
	(0.385)	(0.224)	(0.007)	(0.003)	(0.007)	(0.006)	(1.355)	(0.004)
Motorized transportation (dummy)	1.870	0.086	0.013	0.022	0.099**	0.063**	0.604	0.031
	(1.999)	(1.160)	(0.035)	(0.015)	(0.039)	(0.029)	(7.023)	(0.020)
Covid-19 (dummy)	2.922*	1.444	0.057*	0.013	0.079**	-0.030	-3.681	0.010
	(1.647)	(0.956)	(0.029)	(0.012)	(0.032)	(0.024)	(5.787)	(0.016)
Most important income - off-farm (dummy)	-1.339	-0.964	-0.013	-0.001	-0.020	-0.042*	-6.386	-0.021
	(1.712)	(0.995)	(0.030)	(0.013)	(0.033)	(0.025)	(6.018)	(0.017)
Non-agricultural income (dummy)	4.074***	-0.840	0.020	0.015	0.088***	0.051**	6.797	0.008
	(1.452)	(0.842)	(0.026)	(0.011)	(0.028)	(0.021)	(5.096)	(0.014)
Remittances (dummy)	-3.928	0.557	-0.041	0.005	-0.053	0.009	-6.910	-0.043*
	(2.564)	(1.491)	(0.045)	(0.019)	(0.050)	(0.037)	(9.019)	(0.025)
Full set of controls[a]	Yes							
Splines: Travel time	Yes							
Interaction	Yes							
RE	Yes							
Observations	2,292							
AIC	24138.83							
Deviance explained	0.413							

Note: *p<0.1; **p<0.05; ***p<0.01 Standard errors in parentheses, [a] see Table A.3 and A.4 for a full list of all control variables and reference groups for categorical variables.

6. CONCLUSION

In our study, we analyze the effect of conflict exposure on the relationship between market access and agricultural development based on primary data collected from more than 2,000 paddy farmers in Myanmar for the monsoon season of 2021. We combine this data set with secondary spatial data of conflict events (2010-2021) and calculate travel times as proxies for market access. Furthermore, instead of using dummy or count variables of conflict events, we construct a conflict severity index representing four dimensions of conflict (danger, deadliness, diffusion, fragmentation) and, thus, explicitly account for the complexity of past and recent conflict in Myanmar. In our empirical analysis, we apply a flexible empirical framework (additive regression) that allows us to capture nonlinear effects in the interaction of conflict exposure and market access and control for multiple spatial scales. Furthermore, we run several robustness checks including instruments for travel times (i.e., natural path and Euclidean distance) to control for potential endogeneity concerns.

Comparable to other studies, we find that urban proximity is positively associated with agricultural development, i.e., higher intensification and commercialization levels in urban proximity compared to remote areas. Furthermore, our study shows that the effect of conflict on agricultural production indeed varies in space along said remoteness gradient (measured by travel times to the closest city or town). In most cases, these interaction effects of conflict exposure and travel times are nonlinear, displaying either local or/and U-shape patterns. Putting together the results for all indicators, two overall effect patterns emerge regarding the effect of conflict on the relationship between market access and paddy production systems. First, the most remote farmers pay the highest price for conflict, facing disproportionately higher urea prices and input expenditures, for example. Second, conflict also appears to reduce the comparative advantage of being located close to an urban center. We find, for example, that households in urban proximity reduce their use of urea more strongly relative to remote households when experiencing conflict. All in all, it appears that conflict is especially harmful to agricultural management systems in direct urban proximity and very remote areas.

To our knowledge, we are among the first to examine spatially varying effects of conflict on agricultural production systems and further monitoring of the development in Myanmar and analysis of other conflict settings is necessary to verify our results. Nonetheless, based on the results of this study, location must be considered when evaluating how conflict affects a household's livelihood. In addition, these insights help to understand how a conflict will affect a country's agricultural sector in general. Assuming that farms with good access to markets and towns normally reach higher levels of modernization and, thus, contribute significantly to agricultural development, a disproportionately negative effect of conflict exposure in these regions can have lasting effects on the country's overall agricultural performance. On the other end, remote smallholders often belong to the most vulnerable and poorest groups in low- and middle-income countries. Especially severe effects of conflict in these regions could amplify already existing problems around food insecurity, poverty, and welfare in general.

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APPENDIX TABLES

Table A.1 Crosstable of CSI indicators (dummies) and CSI categories (0-4)[a]

	0		1		2		3		4	
Indicator	N	%	N	%	N	%	N	%	N	%
Deadliness (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100.0	437	99.1	286	89.4	105	38.7	0	0.0
... 1	0	0.0	4	0.9	34	10.6	166	61.3	171	100.0
Danger (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100.0	378	85.7	144	45.0	18	6.6	0	0.0
... 1	0	0.0	63	14.3	176	55.0	253	93.4	171	100.0
Diffusion (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100.0	104	23.6	13	4.1	0	0.0	0	0.0
... 1	0	0.0	337	76.4	307	95.9	271	100.0	171	100.0
Fragmentation (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100.0	404	91.6	197	61.6	148	54.6	0	0.0
... 1	0	0.0	37	8.4	123	38.4	123	45.4	171	100.0

Note: [a]CSI (Conflict Severity Index) categories: 0-No/Little conflict, 1-Moderate conflict, 2-Severe conflict.

Table A.2 Travel times (TT) by CSI categories[a] calculated for the monsoon season 2021 vs. the period between 2010 and 2020 (‘*before the coup*’)

		0			1			2		
Variable	N	Mean	SD	N	Mean	SD	N	Mean	SD	Test
Monsoon 2021 TT - city (min)	1089	143.5	51.4	761	149.9	53.3	442	141.7	61.2	F=4.4**
TT - town (min)	1089	87.7	30.9	761	89.3	29.3	442	91.8	36.1	F=2.8*
Before coup (2010 - 2020) TT - city (min)	1464	141.6	53.8	611	143.0	53.1	217	177.0	48.6	F=42.9***
TT - town (min)	1464	89.8	32.1	611	85.7	28.8	217	92.8	34.2	F=5.4***

Note: Statistical significance markers: * p<0.1; ** p<0.05; *** p<0.01
[a]CSI (Conflict Severity Index) categories: 0-No/Little conflict, 1-Moderate conflict, 2-Severe conflict

Table A.3 Summary Statistics - GIS control variables

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
No VT information (dummy)	2292	0.1					
Agroecological zone	2292						
... Coastal	148	0.1					
... Delta	880	0.4					
... Dry	856	0.4					
... Hills	408	0.2					
Elevation (m)	2292	204.5	346.6	-3.8	11.2	160.5	1564.4
Precipitation (monsoon 2021, mm)	2292	368.6	205.4	110.9	207.5	488.4	1036.3
Land cover - water (percent)	2292	3.0	7.4	0.0	0.0	1.0	73.0
Land cover - cultivated (percent)	2292	47.8	26.7	0.0	24.3	70.7	89.4
Land cover - forrest (percent)	2292	20.8	22.6	0.0	2.2	35.0	79.7
Soil nutrient availability	2292						
... No limitations	1391	0.6					
... Moderate limitations	435	0.2					
... Severe limitations	405	0.2					
... Very severe limitations	10	0.004					
... Mainly non-soil	51	0.02					
Travel times to closest border (minutes)	2292	430.2	176.2	29.8	329.1	524.9	1039.9
Closest border	2292						
... Bangladesh	242	0.1					
... China	373	0.2					
... India	487	0.2					
... Laos	11	0.01					
... Thailand	1179	0.5					

Table A.4 Summary Statistics - Household/Production control variables

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Paddy vs. Rice	2292						
... Paddy	2088	0.9					
... Rice	204	0.1					
2-wheeler vs. 4-wheeler	2292						
... 2-wheeler	895	0.4					
... 4-wheeler	1397	0.6					
Shock - pest/disease (dummy)	2292	0.1					
Shock - timing rain (dummy)	2292	0.1					
Shock - drought (dummy)	2292	0.1					
Shock - floods (dummy)	2292	0.04					
Other crops (dummy)	2292	0.5					
Plot size (acres)	2292	1.3	1.4	0.02	0.6	1.5	20.0
Rice variety	2292						
... Emata	1197	0.5					
... Letywesin	700	0.3					
... Meedon/Pawsan	339	0.2					
... Ngasein	38	0.02					
... Sticky Rice	18	0.01					
Number of rice plots (count)	2292	14.6	17.9	1.0	4.0	18.0	150.0
Land ownership (dummy)	2292	0.95					
Extension (dummy)	2292	0.3					
Gender	2292						
... Female	755	0.3					
... Male	1537	0.7					
Age	2292	42.4	12.1	18.0	33.0	51.0	74.0
Number of household members (count)	2292	4.8	1.8	1.0	4.0	6.0	14.0
Motorized transportation (dummy)	2292	0.9					
Covid-19 (dummy)	2292	0.2					
Most important income	2292						
... farm	1737	0.8					
... off-farm	555	0.2					
Non-agricultural income (dummy)	2292	0.5					
Remittances (dummy)	2292	0.1					

Table A.5 Model comparison

Model	AIC	Dev. expl.
City No interaction	48417.85	0.396
Interaction - CSI	48278.17	0.404
Indicators separately Interaction - Danger	48295.03	0.401
Interaction - Deadliness	48315.43	0.401
Interaction - Diffusion	48334.06	0.401
Interaction - Fragmentation	48323.90	0.401
Town No interaction	48480.28	0.395
Interaction - CSI	48411.69	0.401
Indicators separately Interaction - Danger	48418.20	0.398
Interaction - Deadliness	48413.76	0.400
Interaction - Diffusion	48451.43	0.398
Interaction - Fragmentation	48459.38	0.397

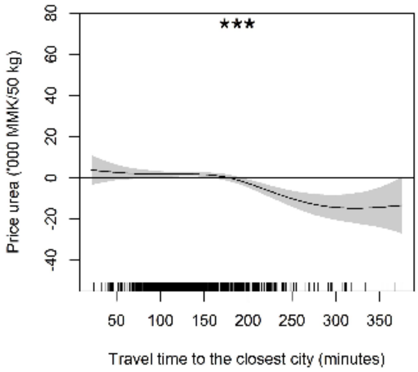
Table A.6 Regression results for conflict variables[b] - Eq.2, 'City' specification

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea ('000 MMK/50 kg)	Price machinery (log, '000 MMK/acre)	Wage (log, '000 MMK/day)	Input expenditure (log, '000 MMK/acre)	Yield (log, kg/acre)	Paddy/Rice price (MMK/kg)	Sales (Share)
Intercept	45.740***	68.750***	2.801***	1.817***	5.521***	7.392***	249.742***	0.580***
	(9.233)	(5.338)	(0.163)	(0.070)	(0.178)	(0.136)	(32.443)	(0.091)
CSI - Category 1 (monsoon 2021)	0.690	-0.728	0.008	0.014	0.108***	0.035	-8.743	0.083***
	(1.593)	(0.902)	(0.028)	(0.012)	(0.030)	(0.023)	(5.533)	(0.015)
CSI - Category 2 (monsoon 2021)	1.519	0.238	0.019	-0.003	0.017	0.008	-9.719**	0.025**
	(1.283)	(0.754)	(0.023)	(0.010)	(0.025)	(0.019)	(4.521)	(0.012)
CSI - Category 1 (2010-2020)	-0.252	0.347	0.084*	0.058***	0.018	-0.035	-18.477*	-0.006
	(2.754)	(1.591)	(0.048)	(0.021)	(0.053)	(0.041)	(9.610)	(0.027)
CSI - Category 2 (2010-2020)	-2.313	-1.432	0.079**	0.051***	0.008	-0.044*	-3.207	0.005
	(1.776)	(1.032)	(0.031)	(0.013)	(0.034)	(0.026)	(6.226)	(0.017)
Full set of controls[a]	Yes							
Splines: Travel time	Yes							
Interaction	Yes							
RE	Yes							
Observations	2,292							
AIC	24138.83							
Deviance explained	0.413							

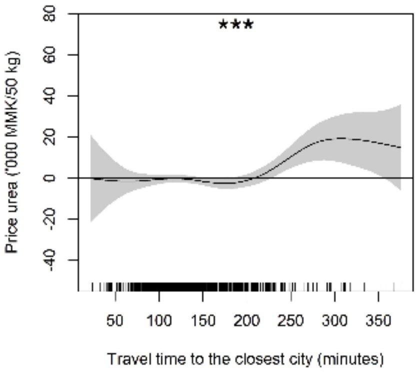
Note: *p<0.1; **p<0.05; ***p<0.01
Standard errors in parentheses, [a]see Table A.3 and A.4 for a full list of all control variables.
[b]CSI (Conflict Severity Index) categories: 0-No/Little conflict (reference), 1-Moderate conflict, 2-Severe conflict.

APPENDIX FIGURES

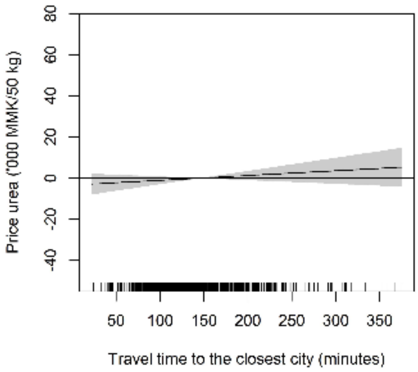
Figure A.1. Effect of travel time to the closest city (minutes) on the price of urea, (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq. 2.



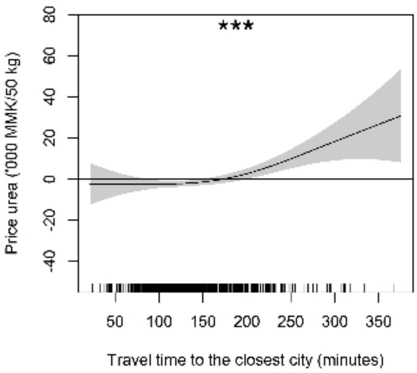
(a) TT base:$f_0(tt)$



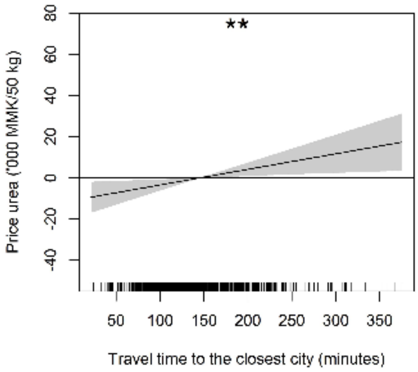
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



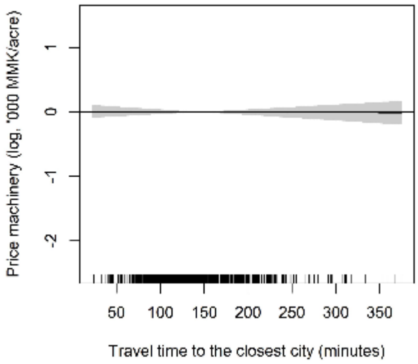
(d) $conflict_{b(CSI=1)} \times \widehat{f_b(tt)}$



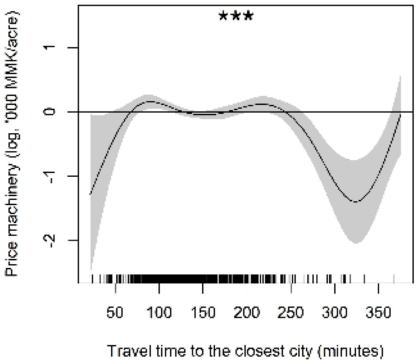
(e) $conflict_{b(CSI=2)} \times \widehat{f_b(tt)}$

Note: Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; $*$p<0.1; $**$p<0.05; $***$p<0.01.

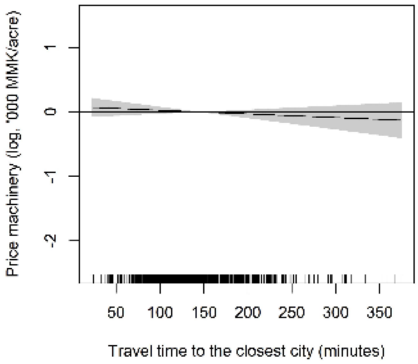
Figure A.2. Effect of travel time to the closest city (minutes) on the price of machinery, (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq. 2.



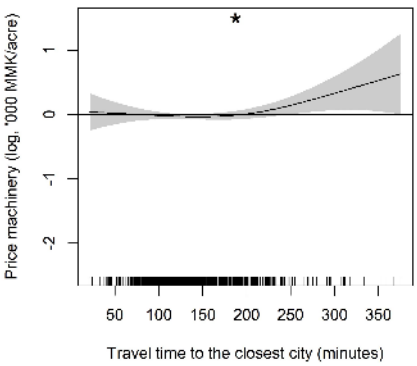
(a) TT base: $f_0(tt)$



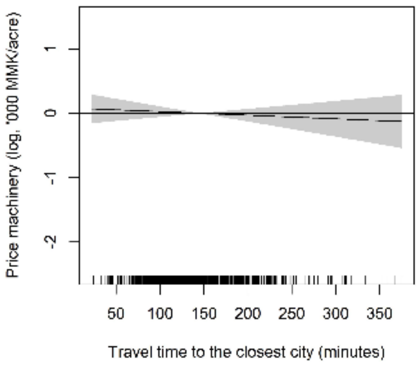
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



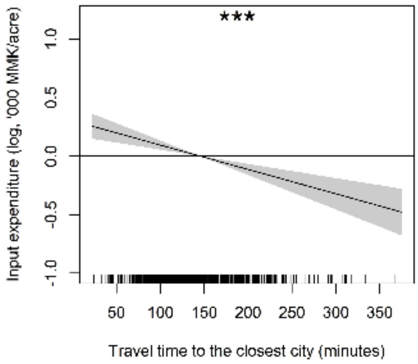
(d) $conflict_{b(CSI=1)} \times \widehat{f_b(tt)}$



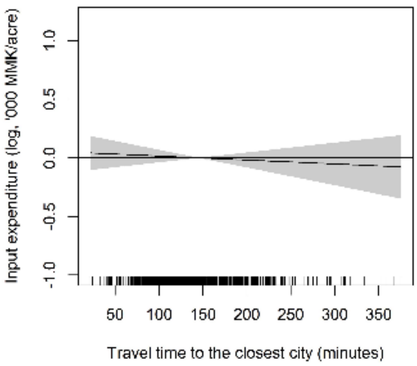
(e) $conflict_{b(CSI=2)} \times \widehat{f_b(tt)}$

Note*:* Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; $*$p<0.1; $**$p<0.05; $***$p<0.01.

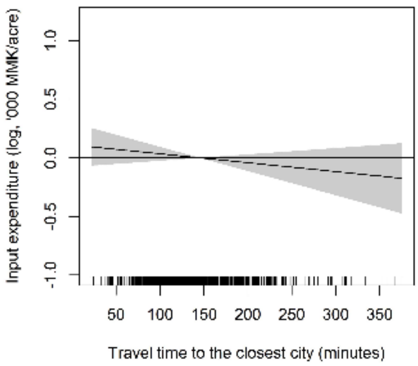
Figure A.3. Effect of travel time to the closest city (minutes) on input expenditures (largest paddy plot), (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq. 2.



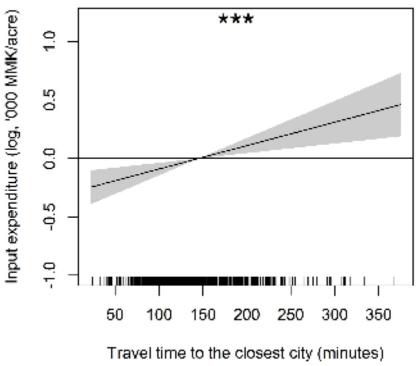
(a) TT base: $f_0(tt)$



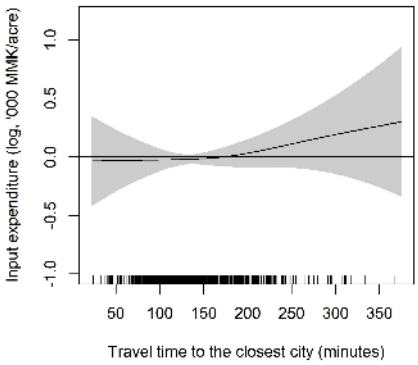
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



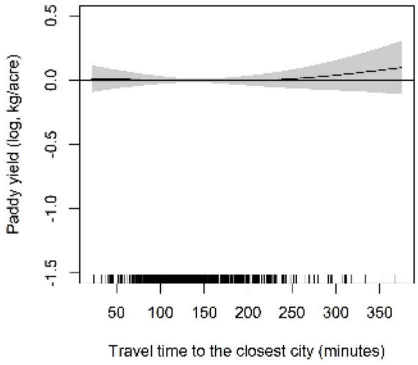
(d) $conflict_{b(CSI=1)} \times \widehat{f_b(tt)}$



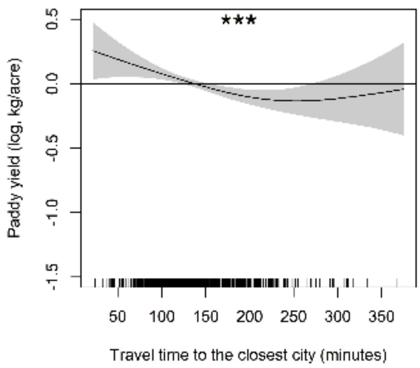
(e) $conflict_{b(CSI=2)} \times \widehat{f_b(tt)}$

Note: Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; $*$p<0.1; $**$p<0.05; $***$p<0.01.

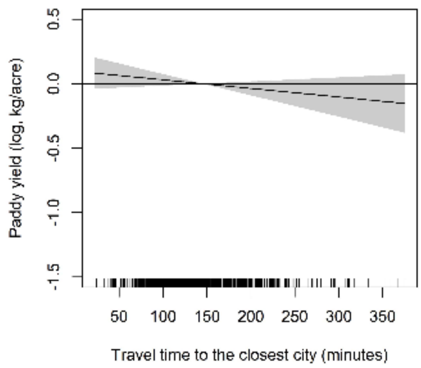
Figure A.4. Effect of travel time to the closest city (minutes) on the paddy yields (largest paddy plot), (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq. 2.



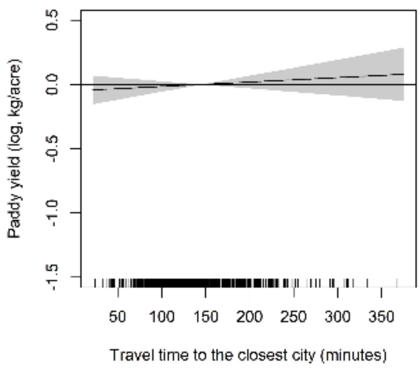
(a) TT base: $f_0(tt)$



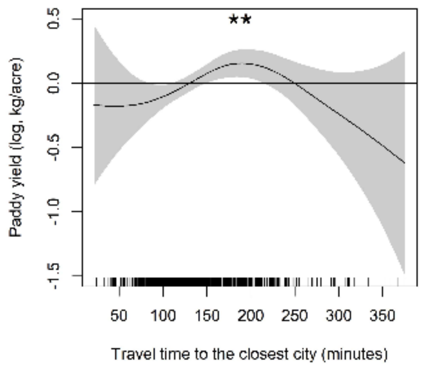
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



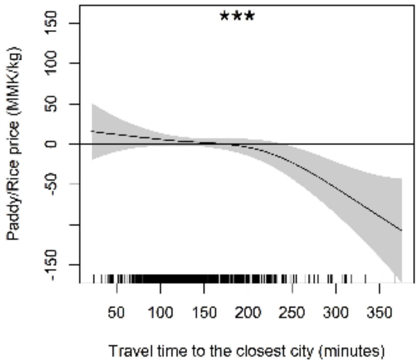
(d) $conflict_{b(CSI=1)} \times \widehat{f_b(tt)}$



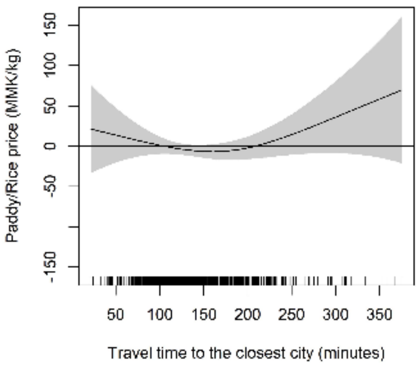
(e) $conflict_{b(CSI=2)} \times \widehat{f_b(tt)}$

Note: Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

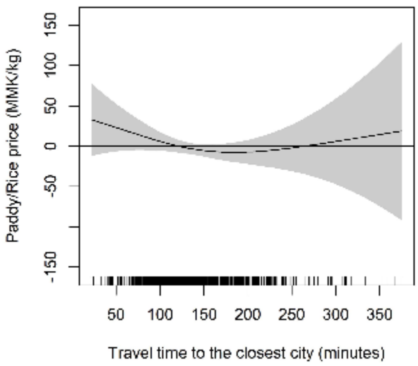
Figure A.5. Effect of travel time to the closest city (minutes) on paddy/rice prices, (a) shows the estimated main effect of travel times and (b)-(e) the estimated interacted effect functions ($f_a(tt)$, $f_b(tt)$) in Eq.2.



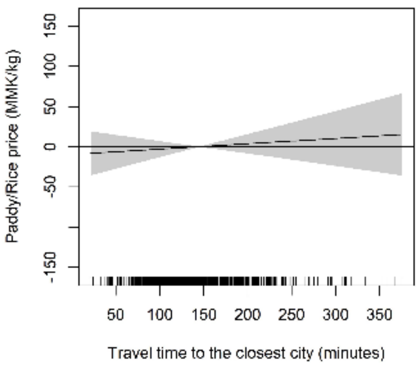
(a) TT base:$f_0(tt)$



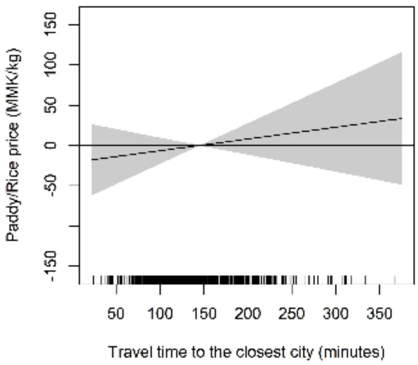
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



(c) $conflict_{a(CSI=2)} \times \widehat{f_a(tt)}$



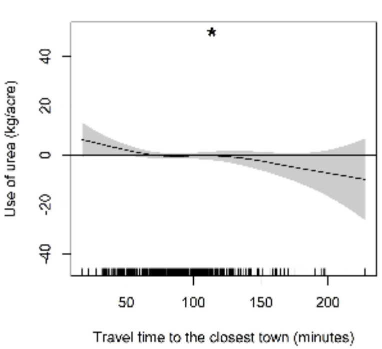
(d) $conflict_{b(CSI=1)} \times \widehat{f_b(tt)}$



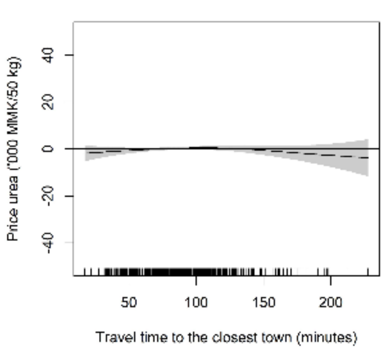
(e) $conflict_{b(CSI=2)} \times \widehat{f_b(tt)}$

Note: Main effects for conflict, γ_a and γ_b, can be found in Table A.6; Asterisks in the plots indicate overall significance of the estimated spline; ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

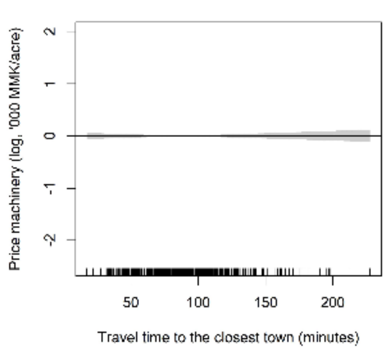
Figure A.6. Effect of travel time to the closest town (minutes) estimated as penalized spline. Asterisks in the plots indicate overall significance of the estimated spline.



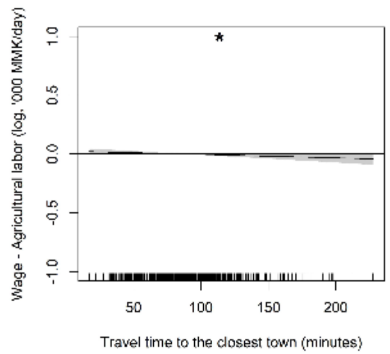
(a) Use of urea



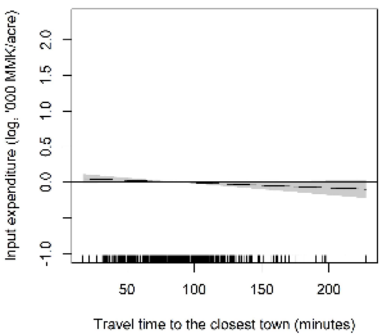
(b) Price of urea



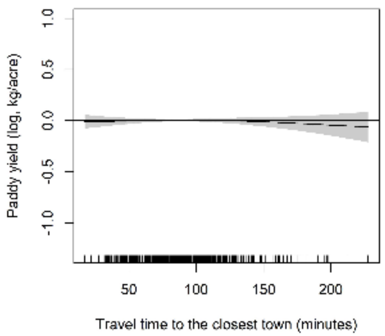
(c) Price machinery



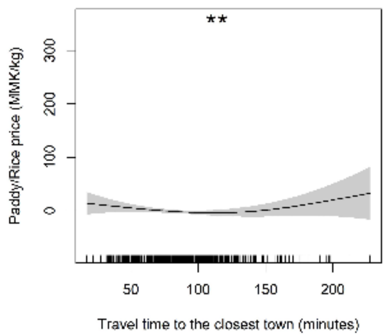
(d) Wage



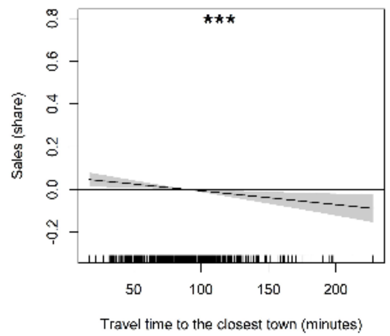
(e) Input expenditure



(f) Paddy yield



(g) Paddy/Rice price



(h) Sales

Note: Asterisks in the plots indicate overall significance of the estimated spline; ∗p<0.1; ∗∗p<0.05; ∗∗∗p<0.01.

ACKNOWLEGEMENTS

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