Urban proximity, conflict, and agricultural development: Smallholder paddy production in Myanmar

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Abstract

Paddy plays a crucial role in both subsistence and commercialized agriculture in Asia. Urban proximity is generally associated with improved market access and agricultural intensification, while farming systems in remote areas are characterized by larger shares of subsistence production. Similarly, conflict often shows spatial patterns and consequences for agricultural development are likely location-dependent. Therefore, we investigate how conflict exposure affects the relationship between urban proximity and agricultural intensification, that is, whether the effects of the conflict vary in space. Based on nationally representative data from 2,292 paddy farmers in Myanmar and secondary spatial data on conflict events and road infrastructure, we apply multivariate additive models to estimate nonlinear and interacted effects of travel times and past and present conflict exposure on agricultural management. Conflict exposure is measured by a Conflict Severity Index based on four indicators (deadliness, danger, diffusion, fragmentation) representing relative conflict pressure for households in the Myanmar context. We find that (negative) conflict effects on paddy production are disproportionately pronounced in direct proximity to urban centers and in very remote areas. This has serious implications for smallholder welfare and Myanmar's agricultural sector in general as it suggests that particularly productive areas, on the one side, and the poorest areas of the country, on the other side, are especially affected by the ongoing escalation of violence.

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

1 Introduction

Improved market access is often seen as an important requirement for the modernization and intensification of smallholder production systems in low- and middle-income countries (LMICs). Farms in urban proximity generally show significantly higher levels of modern technology adoption and productivity than those in more remote areas (Vandercasteelen, Beyene, Minten, & Swinnen, 2018b). The lower the transportation and access costs to economic centers, the higher the comparative advantage and the opportunity for economic growth. Even though theoretically straightforward, empirical evidence of the effect of market access on agricultural management systems is still scarce and regionally clustered (e.g., Ethiopia, India) (Steinhübel & von Cramon-Taubadel, 2021; Vandercasteelen et al., 2018b). With ongoing global urbanization trends, it is, however, indispensable to understand how rural and agricultural areas are affected by urban centers to foster the inherent potential for economic growth, mitigate threats of over-exploitation of natural resources, and manage other externalities for communities and the environment.

Another global trend affecting more and more countries in recent years is conflict. According to Conflict Watch List 2023 published by the the Armed Conflict Location Event Data Project (ACLED), only in 2022 did political violence increase by 27 percent.[1] Among others, hotspots of ongoing conflict are countries such as Ukraine, Haiti, Nigeria, or Myanmar. One important characteristic of conflict is that it usually comes in non-random spatial patterns. 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, Ibáñez, & Zambrano, 2019).

Combining these two trends, several questions arise. What will happen to the comparative advantage of being a farmer near a city during times of conflict? And more broadly, is the effect of conflict on agricultural management systems spatially dependent?

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 events affect 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 et al., 2019). However, 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.

We aim to address this gap in the literature by analyzing the effect of conflict on the relationship between

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

market access and paddy production during the monsoon of 2021 in Myanmar. After a decade of liberalization, Myanmar witnessed a military coup in February 2021 leading to a surge in conflict events. Paddy is one of the most important staple crops in Asia, both in terms of subsistence and commercialized agriculture (MAPSA, 2022). For our analysis, we combine primary and nationally representative data of 2,292 farm households with spatial information on conflict events and road networks to calculate conflict exposure (Conflict Severity Index - CSI) and market access (travel times). We furthermore propose a flexible empirical methodology (generalized additive regression) to model spatially dependent and nonlinear conflict effects on agricultural production.

Our analysis provides important 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 of 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 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 location relative to the market center.

We then want to understand how conflict affects the relationship between agricultural production and transportation costs, i.e., the effect of conflict on $I(\mu)$. We model conflict as an additional cost to the location-dependent transportation costs $\mu(d)$, which has an added negative effect on agricultural intensification levels.

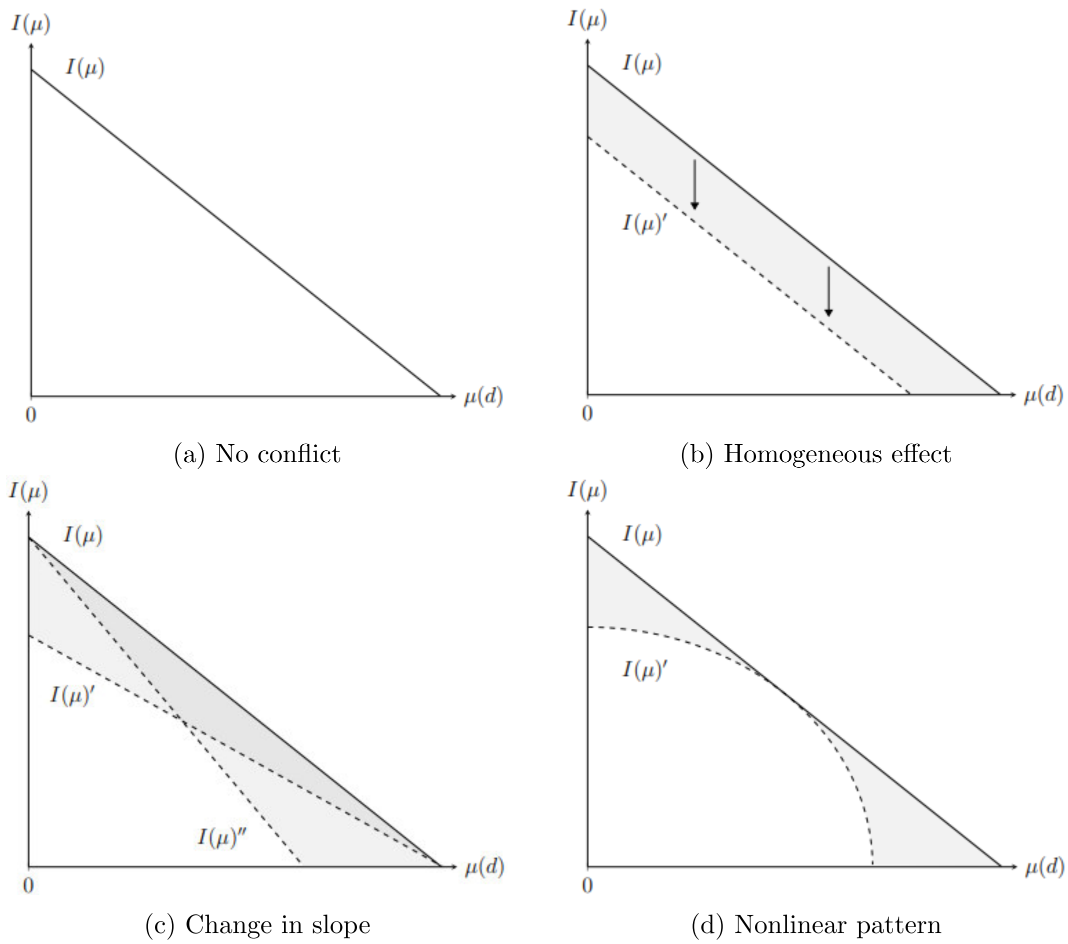


Figure 1: Conceptual framework

Now, if these costs 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 $I(\mu) \longrightarrow I(\mu)'$ (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 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 produce in the market, which increases the likelihood of encountering conflict-related issues on the way. In contrast, 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 also for potential nonlinear effects. Figure 1d is only one (likely) option, where urban and remote areas are more strongly affected than areas in between.

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% of the calories consumed in the country and it factors majorly in the crop portfolio of many farmers, especially during the monsoon season (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). 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 countries, also vegetables or tea and coffee are possible (Boughton et al., 2021). Paddy cultivation is particularly common in lowland areas or in 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 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% (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% 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
Input	Use 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% 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 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 time 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

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	34.863	33.137	0	4	50	150
Price of urea ('000 MMK/50 kg)	2292	0.44	0.23	0.167	0.321	0.478	2.392
Price of urea (log, '000 MMK/50 kg)	2292	-0.911	0.385	-1.787	-1.138	-0.737	0.872
Yield (kg/acre)	2292	1329.135	555.844	146.3	940.5	1672	3448.5
Yield (log, kg/acre)	2292	7.088	0.496	4.986	6.846	7.422	8.146
Input expenditure ('000 MMK/acre)	2292	223.101	144.122	26.25	120	300	1000
Input expenditure (log, '000 MMK/acre)	2292	5.209	0.652	3.268	4.787	5.704	6.908
Paddy/Rice price (MMK/kg)	2292	439.556	230.447	167.464	320.574	478.469	2392.345
Price machinery ('000 MMK/acre)	2292	25.528	13.568	0.333	18	30	300
Price machinery (log, '000 MMK/acre)	2292	3.087	0.645	-1.099	2.89	3.401	5.704
Wage ('000 MMK/day)	2292	5.962	1.773	2.75	5	6.75	23
Wage (log, '000 MMK/day)	2292	1.748	0.266	1.012	1.609	1.91	3.135
Sales (Share)	2292	0.508	0.387	0	0	0.867	1
Travel times to closest city (minutes)	2292	145.292	54.111	21.812	109.975	176.05	375.212
Travel times to closest town (minutes)	2292	88.986	31.496	17.216	69.086	105.344	227.51
CSI (monsoon21)	2292						
... 0	1089	47.5%					
... 1	761	33.2%					
... 2	442	19.3%					
CSI (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%					

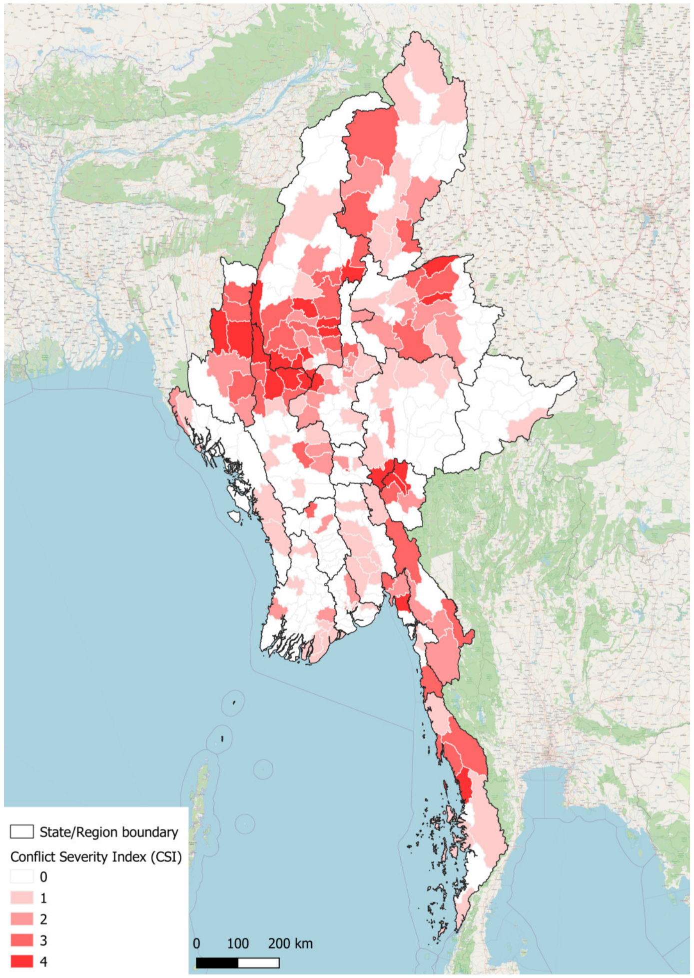
final CSI is the sum of all indicators per township and ranges from no/little conflict (0) to severe conflict (4). Note that the threshold definition makes the CSI a relative measure, which also relies on pre-defined time horizons. To construct the CSI for the monsoon season of 2021, we consider all ACLED events in that time 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.

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. In Table 2 you can find 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 7), 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.

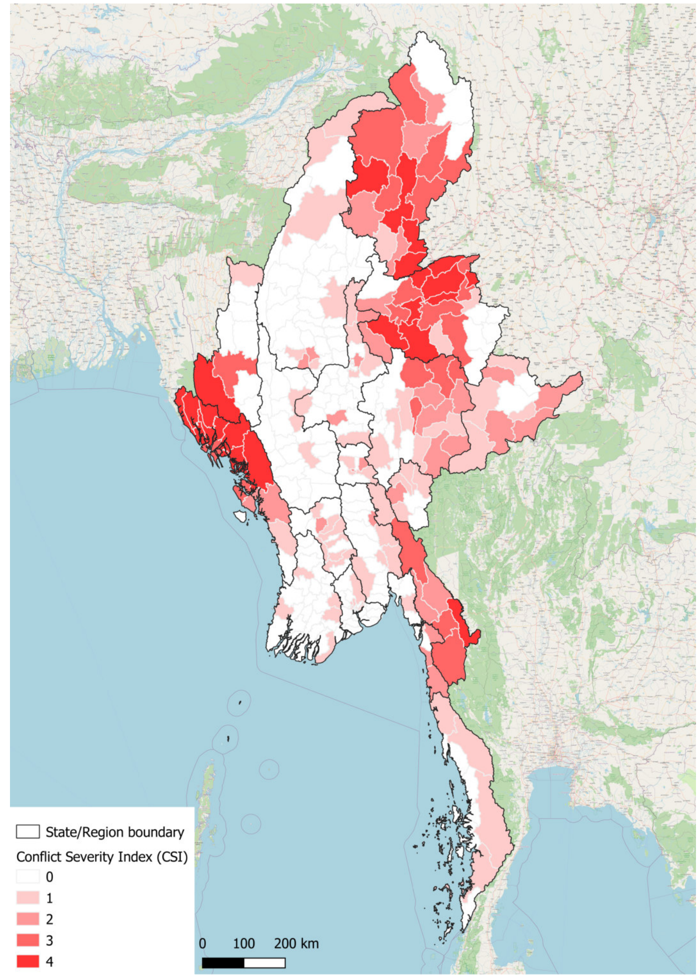
Table 3: Description of indicators to build the adapted Conflict Severity Index (CSI)

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

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



(a) Monsoon season 2021



(b) Before coup (2010-2020)

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

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 Tables 9 and 10 in the appendix.

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.

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

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 $f(tt_{ji})$ 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 $f(tt_{ji})$ are to be estimated. The latter are 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 & 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.

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

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

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. 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 11).

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; Vandercasteelen, Minten, & Tamru, 2021). Since estimates are quite robust to the inclusion of the instruments, we proceed the analysis with the model estimates as described above.

[2] For the sake of brevity, the estimation results are not included in the appendix but are available on request and will be provided alongside the paper as online supplementary material of the published paper.

5 Results and Discussion

5.1 Travel times and conflict - Separate

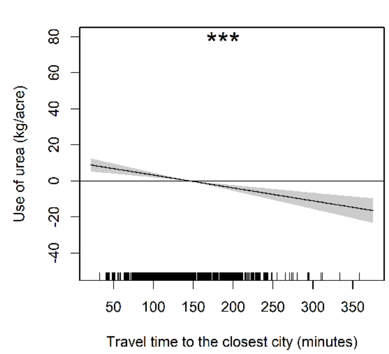
Travel times In Figure 3, we present the estimated splines for the effect of travel times to the closest city on the eight paddy production indicators based on the model specification without interaction terms (Eq.1). For six out of eight of the indicators, we observe statistically significant and negative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

Everything else equal, paddy farms located closer to cities use about 30 kg of urea more per acre than farms located furthest away (Figure 3a), but they also pay about 3 percent more on average (Figure 3b). In contrast, we do not observe any statistically significant gradients in prices for machinery and agricultural wages (Figure 3c and Figure 3d). For overall input expenditures on the largest paddy plot, Figure 3e shows a difference of about 7 percent between farms located close to the city and farms in the most remote areas. The gradient for paddy/rice yields is statistically significant but flat (a difference of 2-3 percent between urban and remote farms) (Figure 3f), whereas paddy/rice prices vary strongly. That is a farm close to a city receives about 75 MMK/kg more than a remote household (Figure 3g), which amounts to about 17 percent of the average price households receive in our sample (440 MMK/kg, Table 2). Also, urban households sell about 20 percent more of their harvest compared with remote households (Figure 3h).

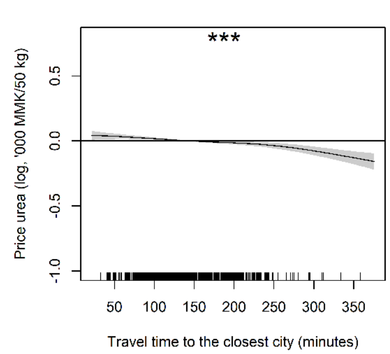
All in all, this suggests that households in urban proximity invest larger amounts in their paddy production, receive higher prices, and are more likely to sell paddy/rice in the market, ceteris paribus. These findings match the results in previous studies, where authors identify similar patterns for teff production and livestock in Ethiopia (Vandercasteelen et al., 2018b; Vandercasteelen et al., 2021) or the adoption of irrigation technology in India (Steinhübel, Wegmann, & 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 and price of urea, agricultural wages, paddy/rice price, and sales (see Figure 7 in the appendix). The gradients are also flatter.

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. Therefore, we present only results for the 'city' specification (Table 4 and results for the 'town' specification can be found in the appendix Table 12).

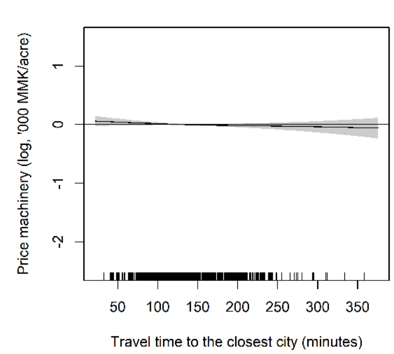
[3] Note that for the GAM to be identifiable, the smooth functions have to have zero-means over the covariate (i.e., travel time) values (see horizontal lines at zero in the plot). That means, the splines have to be seen relative to the sample mean (i.e., Intercept) or in the case of the interaction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



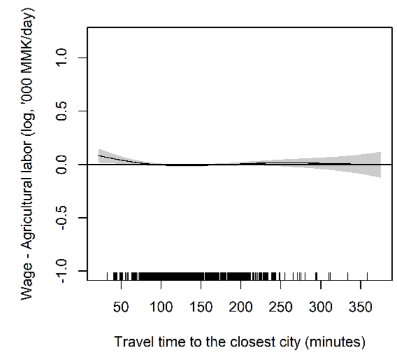
(a) Use of urea



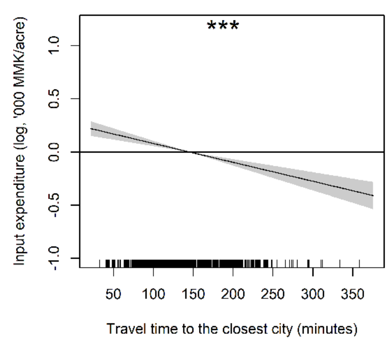
(b) Price of urea



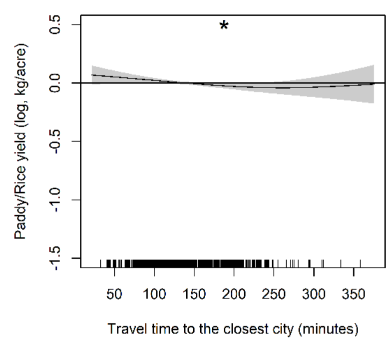
(c) Price machinery



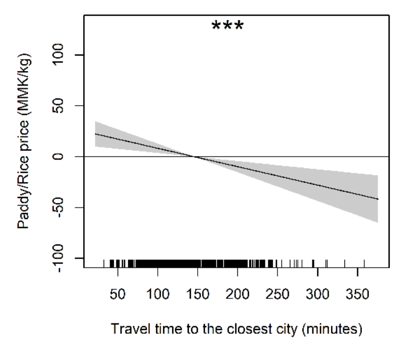
(d) Wage



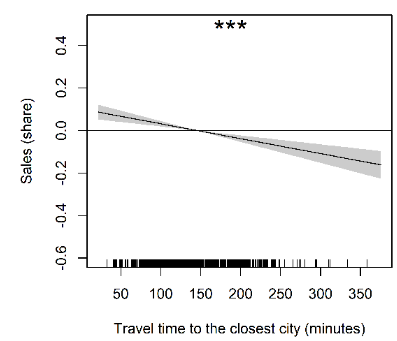
(e) Input expenditure



(f) Paddy/Rice yield



(g) Paddy/Rice price



(h) Sales

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; *p<0.1; **p<0.05; ***p<0.01.

Table 4: Regression results for conflict variables - Eq.1, 'City' specification

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea (log, '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	48.227***	-1.283***	2.736***	1.738***	5.483***	7.453***	270.873***	0.568***
	(9.589)	(0.061)	(0.170)	(0.072)	(0.184)	(0.140)	(33.415)	(0.094)
CSI - Category 1 (monsoon 2021)	-1.798	0.018*	0.007	0.020*	0.050	0.002	4.863	0.024
	(1.603)	(0.010)	(0.028)	(0.012)	(0.031)	(0.023)	(5.600)	(0.016)
CSI - Category 2 (monsoon 2021)	0.270	-0.016	0.025	0.033*	0.152***	0.035	-12.698*	0.113***
	(2.228)	(0.014)	(0.039)	(0.017)	(0.043)	(0.032)	(7.539)	(0.022)
CSI - Category 1 (2010-2020)	2.147	-0.017	-0.033	-0.023*	-0.006	0.033	-8.250	-0.009
	(1.689)	(0.011)	(0.030)	(0.013)	(0.033)	(0.025)	(5.919)	(0.016)
CSI - Category 2 (2010-2020)	2.483	-0.029	0.084	0.026	0.006	-0.012	-19.685	0.005
	(3.576)	(0.023)	(0.063)	(0.027)	(0.069)	(0.052)	(12.508)	(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

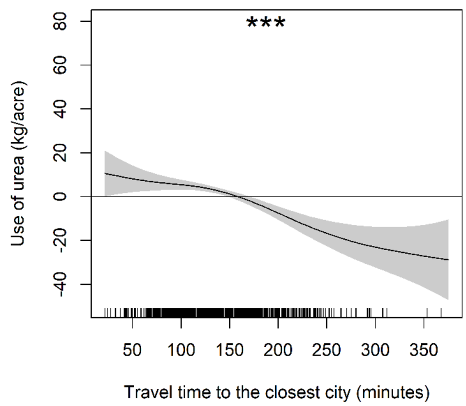
Standard errors in parentheses, [a] see Table 9 and 10 for a full list of all control variables.

Table 4 indicates that not all indicators are affected by conflict in the same way. The use of urea, price for machinery, and paddy/rice 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 (15.2 percent), lower paddy/rice prices (-12.7 MMK/kg), and higher sales shares (11.3 percent), whereas exposure to moderate conflict (monsoon 2021) is associated with higher prices for urea (1.8 percent) and higher wages (2 percent). For past conflict, there is only one statistically significant coefficient for the wage indicator and moderate conflict indicating 2.3-percent lower wages.

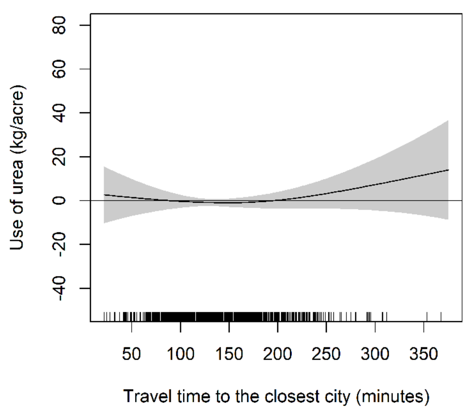
5.2 Travel times and conflict - With interaction

In the previous section, we assumed the effects of travel times and conflict to be independent. Estimating the model specified in Eq.2 we test whether this is an appropriate assumption or whether the relationship between the production indicators and travel times changes conditional on conflict exposure. Except for one indicator (paddy/rice price with city travel times, see **Pattern 3** in Table 5), we find statistically significant interaction terms for all indicators independent of the specification of travel times (city vs. town) and the Akaike information criterion (AIC) significantly improves for model estimations including interaction effects of travel times and CSI categories (Table 11). A first important result of our analysis is therefore that the effect of conflict indeed varies in space along a remoteness gradient. Consequently, independent consideration of remoteness and conflict effects as presented in the section above, and other studies run the risk to be biased.

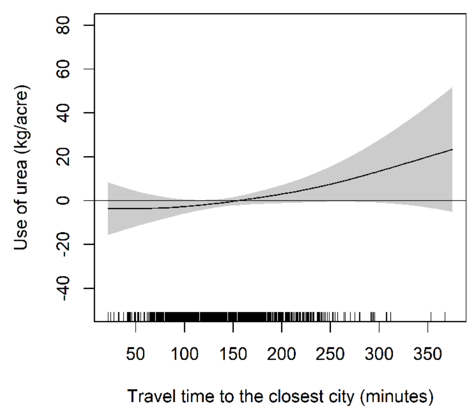
Moreover, we identify linear as well as nonlinear patterns in the interaction terms estimated based on the model specification in Eq.2; we summarize them in Table 5. For the sake of brevity, we present results for some selected but representative production indicators (in bold in Table 5, Figures 4, 5, and 6) and figures for the remaining indicators can be found in the appendix (Figures 8-20). Every figure consists of five panels, of which the first one (a) presents the main effect of travel times on the respective indicator, i.e., the effect of travel times without any conflict exposure. 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).



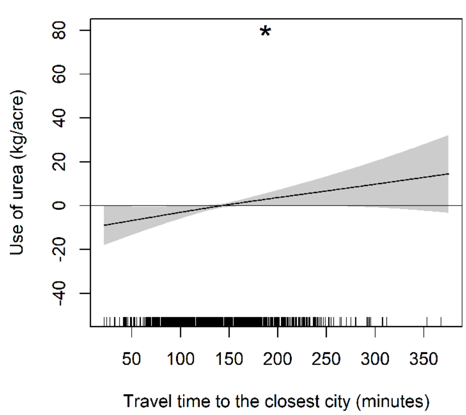
(a) TT base: $\widehat{f_0(tt)}$



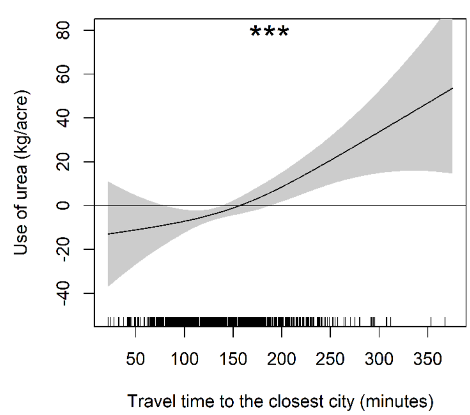
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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



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



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

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 (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 13) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.

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	
			Sales	
Nonlinear				
2.1	Travel times	linear*/−		**Price of urea**, Figure 5
	Travel times × conflict	nonlinear* → *local*		Input expenditures
				Paddy/Rice price
				Sales
2.2	Travel times	linear*/−	Paddy/Rice yield	Wage
	Travel times × conflict	nonlinear* → *U-shape*	**Wage**, Figure 6	
2.3	Travel times	linear*/−	Price of urea	Price machinery
	Travel times × conflict	nonlinear* → *mix*	Price machinery	Paddy/Rice yield
No interaction				
3	Travel times	linear*	Paddy/Rice price	
	Travel times × conflict	not significant		

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. As example of this pattern, we present the results for the use of urea ('city' specification) in 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 panels (d) and (e) are statistically significant. As for an interpretation, this means that conflict exposure reduces the comparative advantage for farms in urban proximity. Furthermore, the effect is stronger for severe conflict (Figure 4e. This effect is similar for urea usage in the specification with travel times to the closest town (Figure 14), whereas results for input expenditures and sales shares ('city' specification) show positive interaction effects for past conflict exposure and negative interaction effects for conflict exposure during the monsoon season of 2021 (Figures 10) and 13). The latter means that recent conflict exposure increases the gradient in input expenditures between urban and remote farms by another 2-3 percent and the gradient in paddy/rice sales by up to 4 percent (the effect is stronger for severe conflict, Figure 13c).

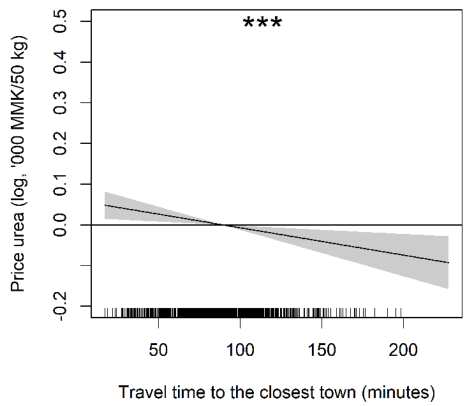
Nonlinear Pattern - 2 While the main effect of travel times is either linear or statistically insignificant, we identify three types of nonlinear interaction terms in the second pattern.

The first type (2.1) is similar to pattern 1 with the difference that the interaction effect is limited to a subset of travel time values (i.e., 'local'). As an example, we present results for the price of urea ('town' specification) in Figure 5. Note that the interaction effect for past severe conflict (Figure 5e) follows pattern 1, but the positive interaction effect for severe conflict during the monsoon season of 2021 (Figure 5c) is limited to travel times larger than two hours (120 minutes). Interaction effects for the other indicators in this type (Figures 17, 19, and 20) are similar, which means that conflict disproportionately increases urea prices (up to 20 percent, recent conflict), input expenditures (up to 100 percent, past conflict), and paddy/rice prices (100-200 MMK/kg, past and recent conflict) and sales (up to 20 percent, past conflict) in remote areas.

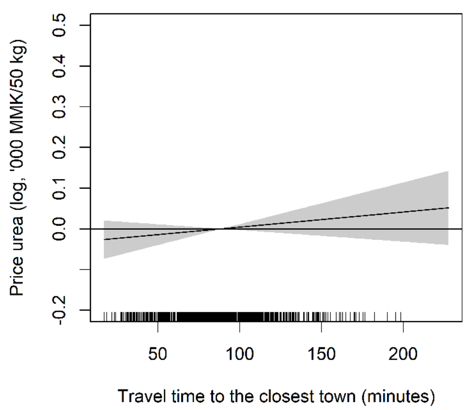
The second type (2.2) of nonlinear interaction terms presents a 'U-shape' coinciding with the fourth panel in our conceptual framework (Figure 1d) indicating a disproportional effect of conflict in urban and very remote areas. We find this pattern for the indicator of agricultural wages ('city' and 'town' specification, Figures 6 and 16) and paddy/rice yields ('city' specification, Figure 11). For example, 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. When we use travel times to the closest town, we find a similar but not as strong effect for recent exposure to severe conflict (Figure 6c). An explanation might be migration and increasing prices for machinery. That is, with the surge of conflict after the coup, household members employed in the non-agricultural sector might have left cities for safety reasons to return home to family farms creating a labor shortage close to urban centers and leading to an increase in wages. In remote areas, conflict might make access to machinery difficult, thus, increasing the importance of labor. The effect for paddy/rice yield (Figure 11) is the opposite with yields being up to 50 percent lower in urban and remote areas when households faced severe conflict in the past.

The third type (2.3) presents a mix of types 2.1 and 2.2, often with local U-shaped patterns, and contains results for the price of machinery ('city' and 'town' specification, Figures 9 and 15), price of urea ('city' specification, Figure 8), and paddy/rice yields ('town' specification, Figure 18)

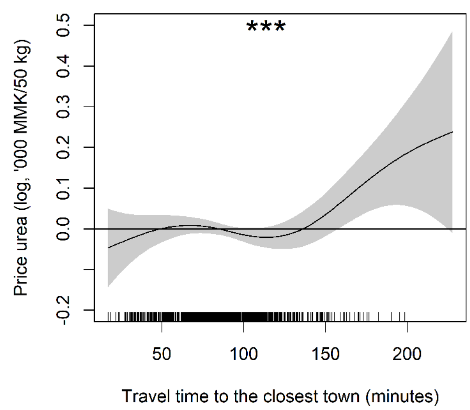
There are several general findings we can draw from these identified patterns. First, the most remote households seem to suffer disproportionately under the effects of conflict. Travel times to the closest towns present a good proxy to identify the most remote areas as every household is located closer to a town (OSM definition) than a city; thus, long travel times to a town also indicate long travel times to a city. Considering



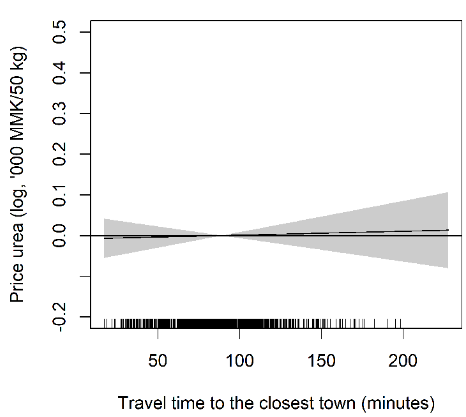
(a) TT base: $\widehat{f_0(tt)}$



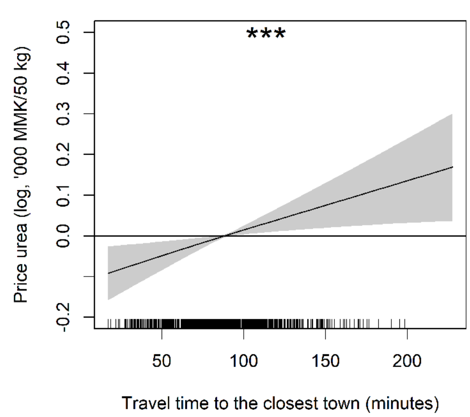
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

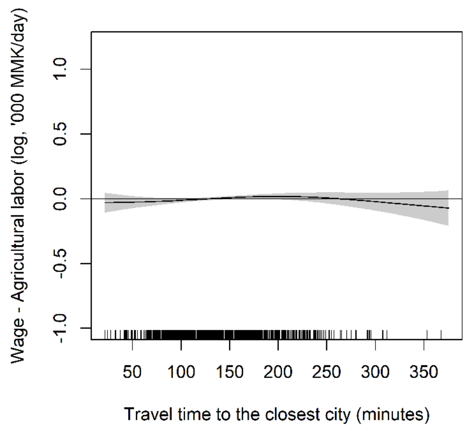


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

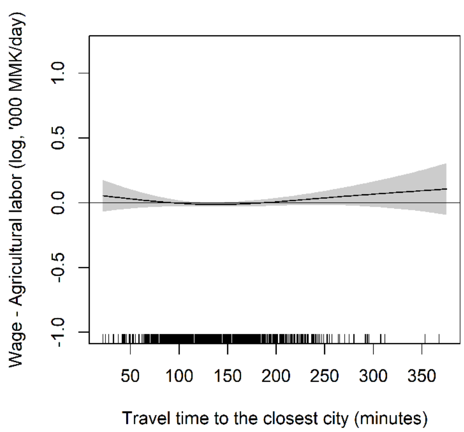


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

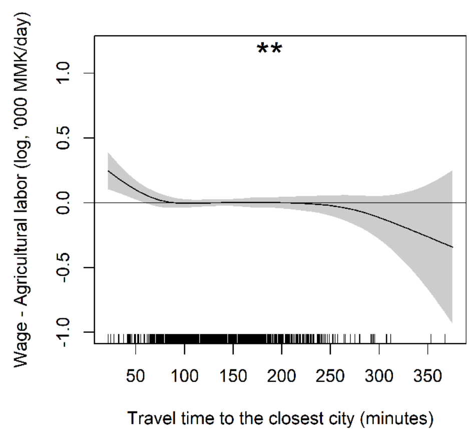
Figure 5: Effect of travel time to the closest town (minutes) on the price of urea, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline: *p<0.1; **p<0.05; ***p<0.01.



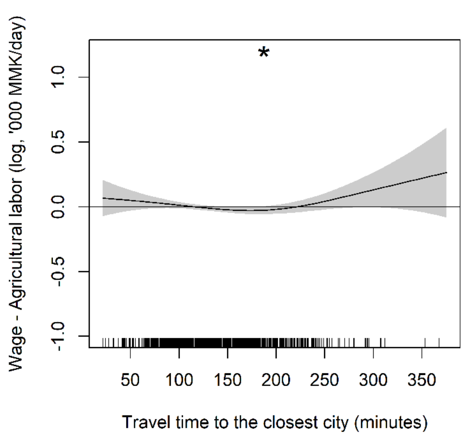
(a) TT base: $\widehat{f_0(tt)}$



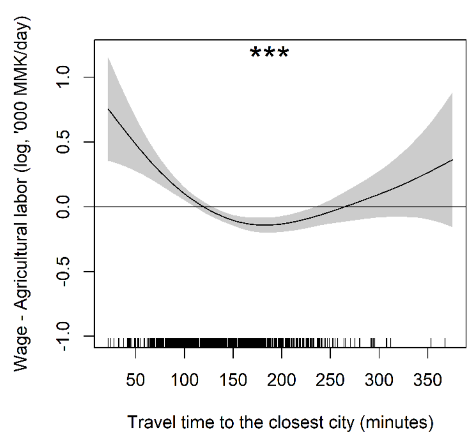
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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



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



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

Figure 6: Effect of travel time to the closest city (minutes) on agricultural wages, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 13)) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.

our results for pattern 2.1 (Table 5), this means that the most remote households face disproportionately higher prices and expenditures for agricultural inputs (e.g., urea) due to conflict exposure and agricultural production might be hit harder compared with management systems closer to urban centers.

Second, despite the effects identified for remote households, there are also signs that conflict dampens some of the comparative advantage of urban proximity for agricultural development (at least for some indicators). This is most pronounced for results in pattern 1 (Table 5), where past conflict exposure significantly reduces investment in management systems (i.e., input expenditures) and sales. Furthermore, even though recent conflict seems to be associated with an increase in input expenditures and sales, in the context of the decreased use of agricultural input in urban proximity (e.g., urea - Figure 4) these are likely only short-term adjustments to deal with increased input prices. Differences in short- and long-term responses to conflict exposure are also in line with the literature (Arias et al., 2019). Note that also the 'quality' of conflict has changed substantially between the periods before and after the coup in 2021 in terms of frequency, actors, and spatial distribution (Figure 2). Thus, It is essential to track developments in the coming years to evaluate the long-term effect of the current surge in conflict on paddy production.

Taken together, there are some strong indications that the overall effect of conflict on the relationship between market access and paddy production follows a nonlinear pattern as outlined in the conceptual framework (Figure 1d).

5.3 Other factors

Even though mainly introduced as control variables, there are several other factors that are significantly linked to paddy production and should be mentioned here (Table 6, for the 'town' specification see Table 15 in the appendix). 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

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

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea (log, '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	45.722***	-1.295***	2.801***	1.818***	5.523***	7.396***	251.344***	0.580***
	(9.238)	(0.059)	(0.163)	(0.070)	(0.178)	(0.136)	(32.403)	(0.091)
Precipitation (monsoon 2021, mm)	-0.014**	-0.000	-0.000***	0.000***	-0.000***	-0.000***	-0.010	-0.000***
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.000)
Shock - pest/disease (dummy)	4.780**	0.002	0.010	0.007	0.092**	-0.048*	3.389	-0.021
	(1.953)	(0.012)	(0.035)	(0.015)	(0.038)	(0.029)	(6.884)	(0.019)
Shock - timing rain (dummy)	-2.855	-0.003	0.033	-0.022	0.003	-0.100**	-11.265	-0.029
	(2.861)	(0.018)	(0.051)	(0.021)	(0.055)	(0.042)	(10.072)	(0.028)
Shock - drought (dummy)	-2.970	0.017	-0.014	-0.011	-0.097	-0.164***	7.065	-0.008
	(3.253)	(0.021)	(0.058)	(0.024)	(0.063)	(0.048)	(11.444)	(0.032)
Shock - floods (dummy)	-1.300	0.045**	-0.062	-0.004	-0.061	-0.137***	18.995*	-0.001
	(3.227)	(0.021)	(0.057)	(0.024)	(0.062)	(0.047)	(11.371)	(0.032)
Travel times to closest border (minutes)	-0.012**	-0.000	-0.000	-0.000***	-0.000**	-0.000*	-0.021	-0.000
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.000)
Closest border - China	4.950	0.033	-0.059	-0.047	0.100	-0.007	11.999	0.138***
	(3.944)	(0.025)	(0.071)	(0.030)	(0.075)	(0.058)	(13.631)	(0.038)
Closest border - India	-1.033	0.129***	-0.088	-0.097***	0.025	-0.147**	47.211***	-0.033
	(4.020)	(0.025)	(0.072)	(0.030)	(0.077)	(0.059)	(13.909)	(0.039)
Closest border - Laos	17.752*	0.095	-0.380**	0.066	-0.018	-0.075	37.872	0.131
	(10.564)	(0.066)	(0.186)	(0.080)	(0.202)	(0.153)	(36.674)	(0.102)
Closest border - Thailand	0.802	0.025	-0.109*	-0.038	-0.055	-0.049	1.573	0.106***
	(3.408)	(0.021)	(0.061)	(0.026)	(0.064)	(0.049)	(11.713)	(0.033)
Other crops (dummy)	-0.256	-0.007	-0.051**	-0.048***	-0.040	-0.011	-6.130	-0.066***
	(1.466)	(0.009)	(0.026)	(0.011)	(0.028)	(0.021)	(5.161)	(0.014)
Plot size (acres)	-1.703***	-0.007**	-0.011	0.005	-0.072***	-0.057***	-3.164*	0.014***
	(0.501)	(0.003)	(0.009)	(0.004)	(0.010)	(0.007)	(1.765)	(0.005)
Number of rice plots (count)	0.009	0.000	-0.001*	0.000	0.000	0.002***	0.107	0.002***
	(0.039)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.137)	(0.000)
Land ownership (dummy)	2.718	0.035*	0.095*	-0.065***	-0.039	-0.023	21.191*	-0.018
	(3.219)	(0.020)	(0.057)	(0.024)	(0.062)	(0.047)	(11.295)	(0.031)
Extension (dummy)	0.714	0.011	-0.016	-0.002	-0.013	0.072***	11.952**	0.023
	(1.431)	(0.009)	(0.025)	(0.011)	(0.028)	(0.021)	(5.036)	(0.014)
Gender - male (dummy)	-0.423	-0.023**	-0.062**	0.035***	-0.021	0.071***	-11.840**	0.020
	(1.438)	(0.009)	(0.025)	(0.011)	(0.028)	(0.021)	(5.068)	(0.014)
Age (years)	0.036	0.001***	-0.000	0.001***	0.001	0.000	0.560***	-0.001**
	(0.056)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.197)	(0.001)
Number of household members (count)	0.077	-0.002	0.002	0.009***	-0.002	0.002	-0.736	-0.015***
	(0.385)	(0.002)	(0.007)	(0.003)	(0.007)	(0.006)	(1.358)	(0.004)
Motorized transportation (dummy)	1.878	0.008	0.013	0.022	0.098**	0.063**	0.020	0.031
	(1.998)	(0.013)	(0.035)	(0.015)	(0.039)	(0.029)	(7.036)	(0.020)
Covid-19 (dummy)	2.930*	-0.010	0.057**	0.013	0.078**	-0.030	-3.690	0.010
	(1.647)	(0.010)	(0.029)	(0.012)	(0.032)	(0.024)	(5.800)	(0.016)
Most important income - off-farm (dummy)	-1.336	-0.025**	-0.013	-0.001	-0.021	-0.042*	-6.455	-0.021
	(1.712)	(0.011)	(0.030)	(0.013)	(0.033)	(0.025)	(6.032)	(0.017)
Non-agricultural income (dummy)	4.087***	0.020**	0.020	0.015	0.090***	0.051**	6.922	0.008
	(1.452)	(0.009)	(0.026)	(0.011)	(0.028)	(0.021)	(5.109)	(0.014)
Remittances (dummy)	-3.941	0.004	-0.041	0.005	-0.053	0.009	-7.033	-0.043*
	(2.564)	(0.016)	(0.045)	(0.019)	(0.050)	(0.037)	(9.029)	(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 9 and 10 for a full list of all control variables and reference groups for categorical variables.

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/rice 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.

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 market access. Furthermore, instead of using dummy or count variables of conflict events, we construct a conflict severity index representing 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 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 literally 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 in 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, it is crucial that location is considered when evaluating how conflict affects a household's livelihood. In addition, these insights also 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 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 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

Table 7: Crosstable of CSI indicators (dummies) and CSI categories (0-4)

	0		1		2		3		4	
Indicator	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent
Deadliness (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100%	437	99.1%	286	89.4%	105	38.7%	0	0%
... 1	0	0%	4	0.9%	34	10.6%	166	61.3%	171	100%
Danger (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100%	378	85.7%	144	45%	18	6.6%	0	0%
... 1	0	0%	63	14.3%	176	55%	253	93.4%	171	100%
Diffusion (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100%	104	23.6%	13	4.1%	0	0%	0	0%
... 1	0	0%	337	76.4%	307	95.9%	271	100%	171	100%
Fragmentation (Monsoon 2021)	1089		441		320		271		171	
... 0	1089	100%	404	91.6%	197	61.6%	148	54.6%	0	0%
... 1	0	0%	37	8.4%	123	38.4%	123	45.4%	171	100%

Table 8: 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	143.496	51.347	761	149.928	53.313	442	141.736	61.239	F= 4.36**
TT - town (min)	1089	87.654	30.908	761	89.268	29.322	442	91.78	36.092	F= 2.748*
Before coup (2010-2020)										
TT - city (min)	1464	141.554	53.782	611	142.975	53.144	217	177.033	48.644	F= 42.902***
TT - town (min)	1464	89.795	32.049	611	85.706	28.822	217	92.76	34.196	F= 5.375***

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 9: Summary Statistics - GIS control variables

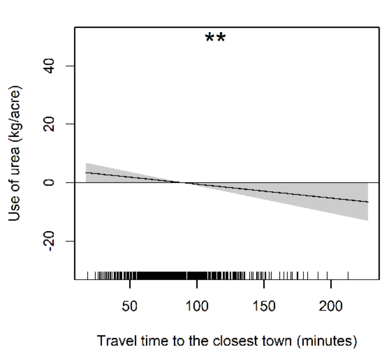
Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
No VT information (dummy)	2292	0.1					
Agroecological zone	2292						
... Coastal	148	0.065					
... Delta	880	0.384					
... Dry	856	0.373					
... Hills	408	0.178					
Elevation (m)	2292	204.507	346.628	-3.841	11.186	160.473	1564.392
Precipitation (monsoon 2021, mm)	2292	368.63	205.402	110.921	207.53	488.435	1036.308
Land cover - water (percent)	2292	2.977	7.35	0	0	1	73
Land cover - cultivated (percent)	2292	47.797	26.744	0	24.329	70.647	89.43
Land cover - forrest (percent)	2292	20.761	22.575	0	2.184	34.99	79.734
Soil nutrient availability	2292						
... No limitations	1391	0.607					
... Moderate limitations	435	0.19					
... Severe limitations	405	0.177					
... Very severe limitations	10	0.004					
... Mainly non-soil	51	0.022					
Travel times to closest border (minutes)	2292	430.223	176.2	29.758	329.128	524.849	1039.846
Closest border	2292						
... Bangladesh	242	0.106					
... China	373	0.163					
... India	487	0.212					
... Laos	11	0.005					
... Thailand	1179	0.514					

Table 10: Summary Statistics - Household/Production control variables

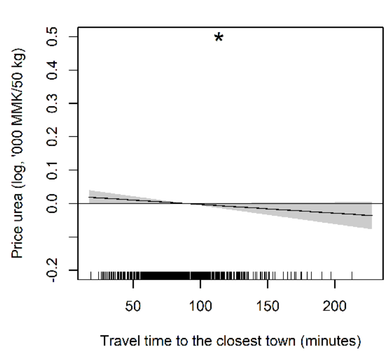
Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
Paddy vs. Rice	2292						
... Paddy	2088	0.911					
... Rice	204	0.089					
2-wheeler vs. 4-wheeler	2292						
... 2-wheeler	895	0.39					
... 4-wheeler	1397	0.61					
Shock - pest/disease (dummy)	2292	0.138					
Shock - timing rain (dummy)	2292	0.058					
Shock - drought (dummy)	2292	0.045					
Shock - floods (dummy)	2292	0.044					
Other crops (dummy)	2292	0.483					
Plot size (acres)	2292	1.301	1.347	0.02	0.6	1.5	20
Rice variety	2292						
... Emata	1197	0.522					
... Letywesin	700	0.305					
... Meedon/Pawsan	339	0.148					
... Ngasein	38	0.017					
... Sticky Rice	18	0.008					
Number of rice plots (count)	2292	14.601	17.846	1	4	18	150
Land ownership (dummy)	2292	0.954					
Extension (dummy)	2292	0.324					
Gender	2292						
... Female	755	0.329					
... Male	1537	0.671					
Age	2292	42.407	12.104	18	33	51	74
Number of household members (count)	2292	4.844	1.75	1	4	6	14
Motorized transportation (dummy)	2292	0.857					
Covid-19 (dummy)	2292	0.205					
Most important income	2292						
... farm	1737	75.8%					
... off-farm	555	24.2%					
Non-agricultural income (dummy)	2292	0.474	0.499	0	0	1	1
Remittances (dummy)	2292	0.073					

Table 11: Model comparison

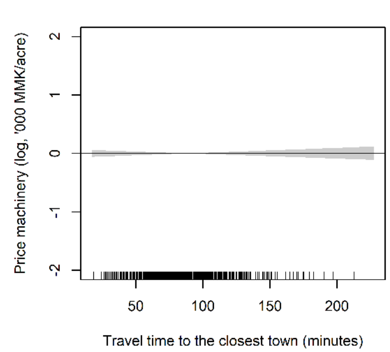
Model	AIC	Dev. expl.
City		
No interaction	24264.38	0.407
Interaction - CSI	24138.83	0.413
Indicators separately		
Interaction - Danger	24145.54	0.411
Interaction - Deadliness	24164.93	0.411
Interaction - Diffusion	24196.64	0.41
Interaction - Fragmentation	24177.24	0.411
Town		
No interaction	24323.98	0.405
Interaction - CSI	24255.88	0.411
Indicators separately		
Interaction - Danger	24257.42	0.409
Interaction - Deadliness	24256.12	0.41
Interaction - Diffusion	24286.3	0.409
Interaction - Fragmentation	24293.93	0.408



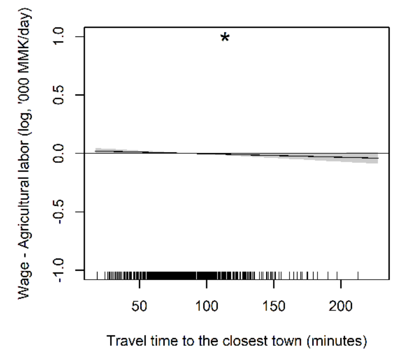
(a) Use of urea



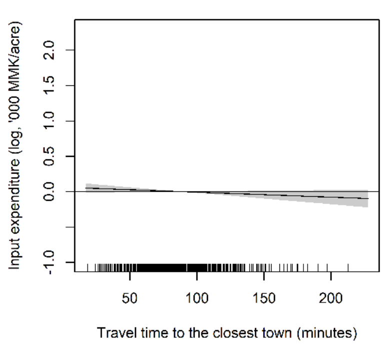
(b) Price of urea



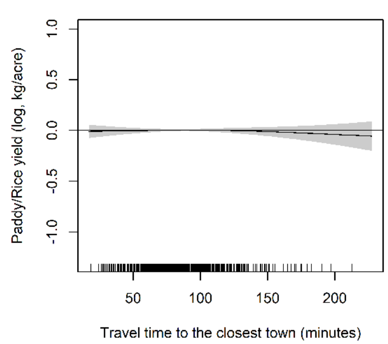
(c) Price machinery



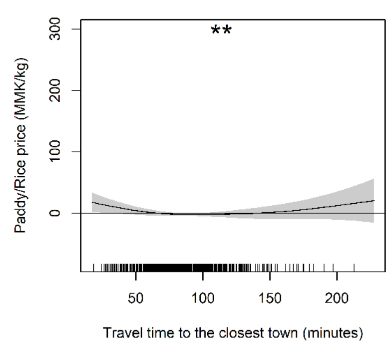
(d) Wage



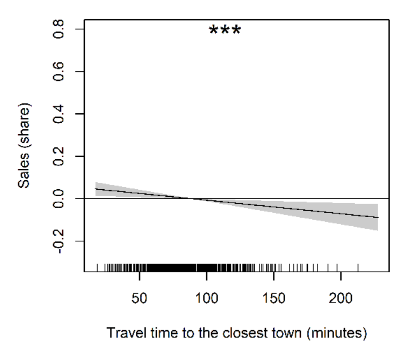
(e) Input expenditure



(f) Paddy/Rice yield

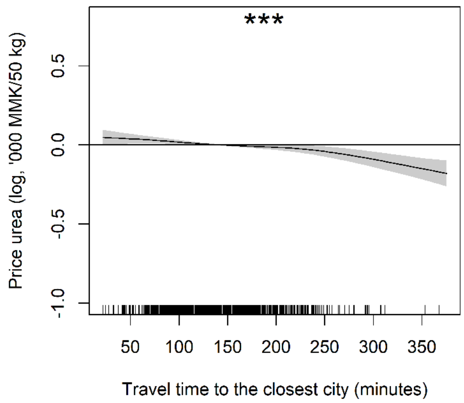


(g) Paddy/Rice price

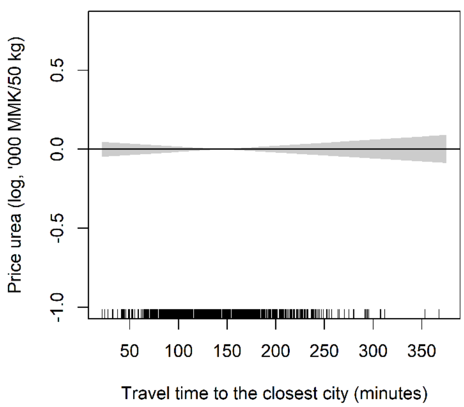


(h) Sales

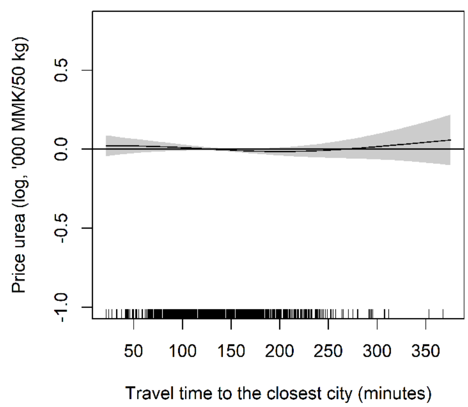
Figure 7: Effect of travel time to the closest town (minutes) estimated as penalized spline. Asterisks in the plots indicate overall significance of the estimated spline; *p<0.1; **p<0.05; ***p<0.01.



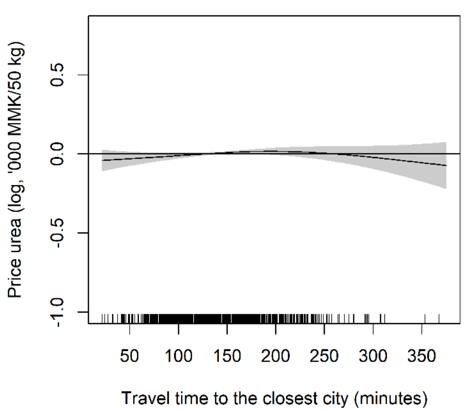
(a) TT base: $\widehat{f_0(tt)}$



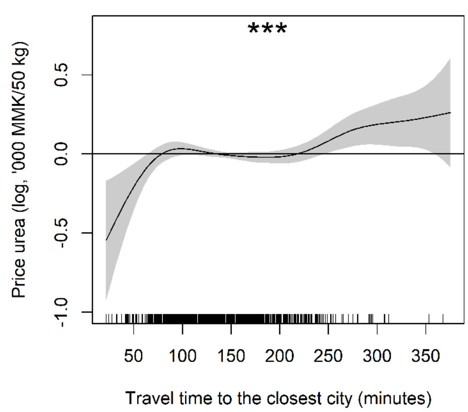
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

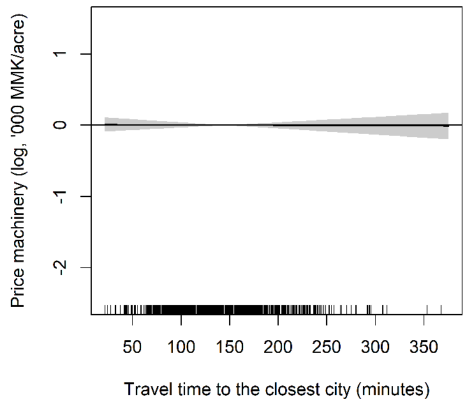


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

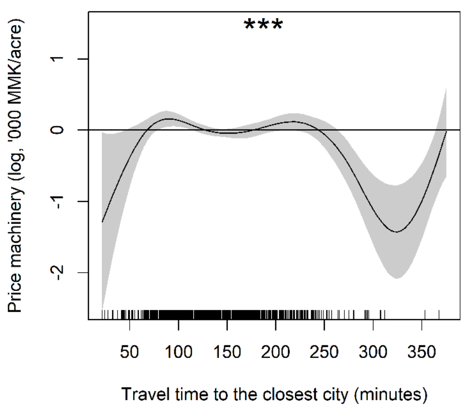


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

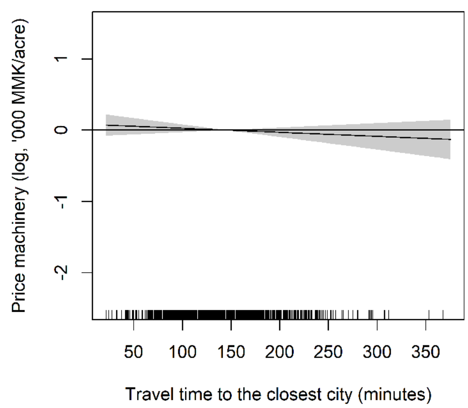
Figure 8: Effect of travel time to the closest city (minutes) on the price of urea, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 13)) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



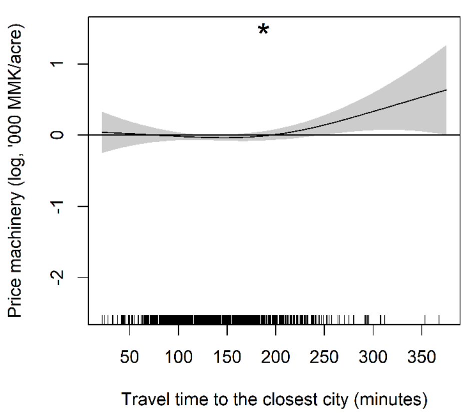
(a) TT base: $\widehat{f_0(tt)}$



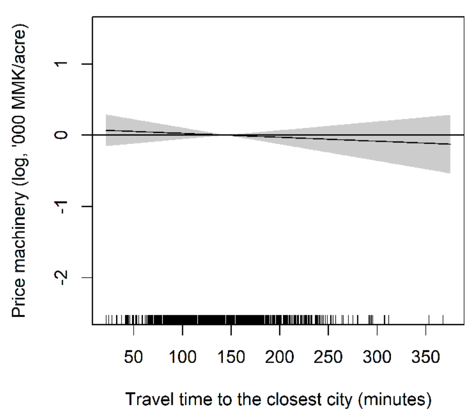
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

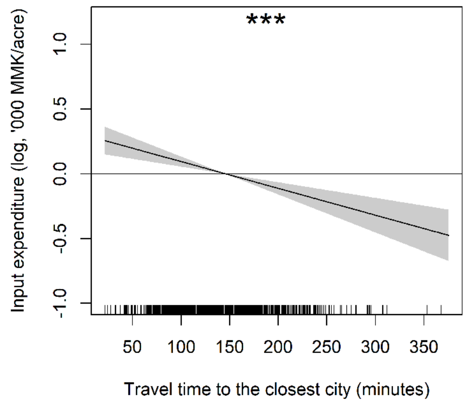


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

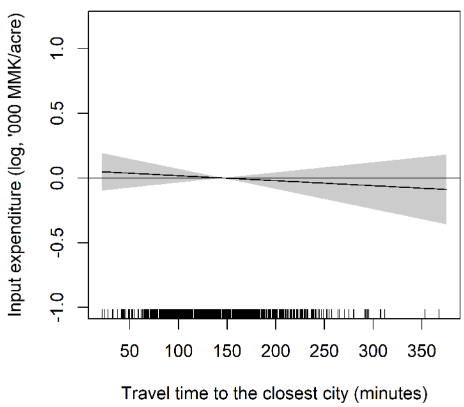


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

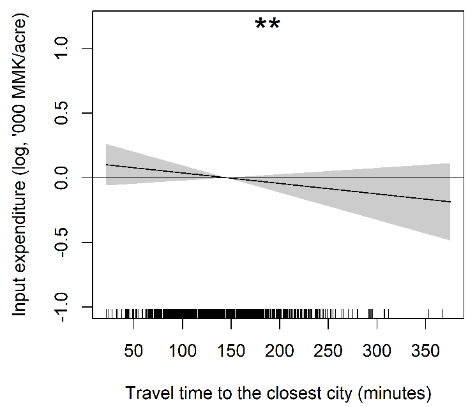
Figure 9: Effect of travel time to the closest city (minutes) on the price of machinery, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma_a}$ and $\hat{\gamma_b}$, can be found in 13)) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



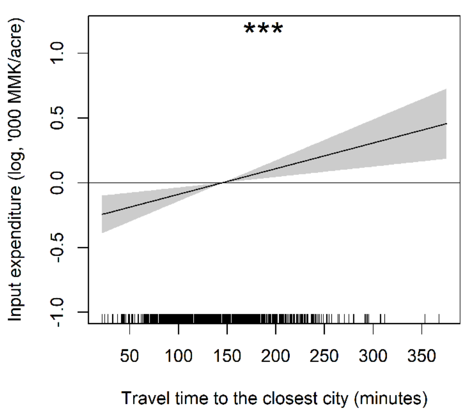
(a) TT base: $\widehat{f_0(tt)}$



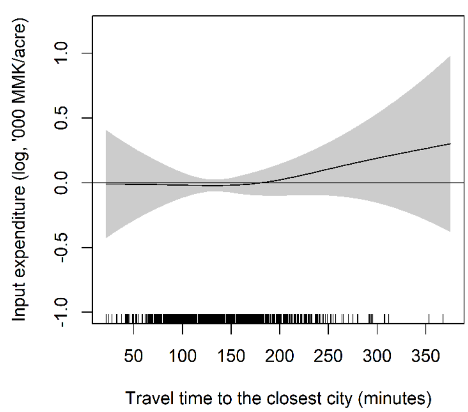
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

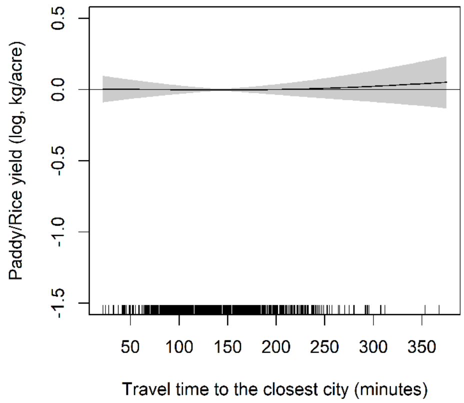


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

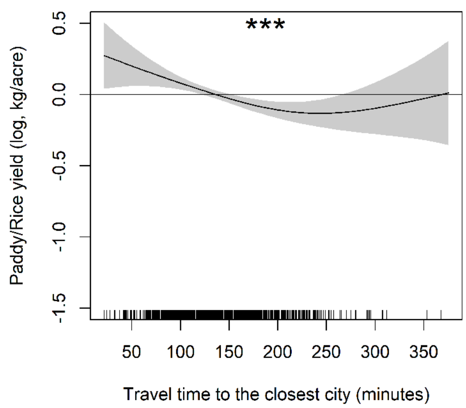


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

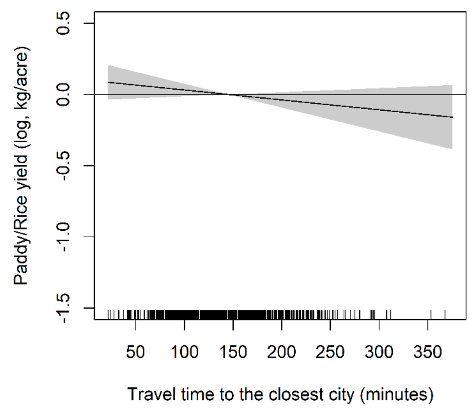
Figure 10: Effect of travel time to the closest city (minutes) on input expenditures (largest paddy plot), (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 13)) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



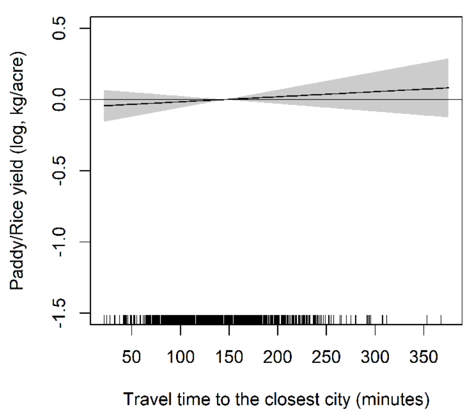
(a) TT base: $\widehat{f_0(tt)}$



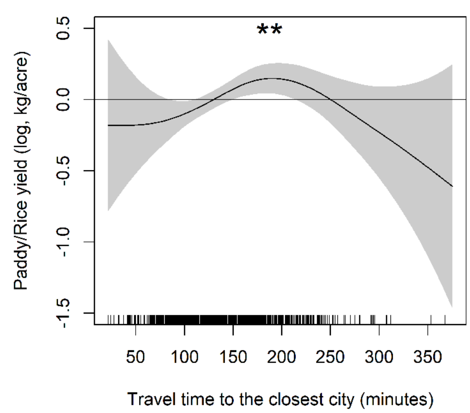
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

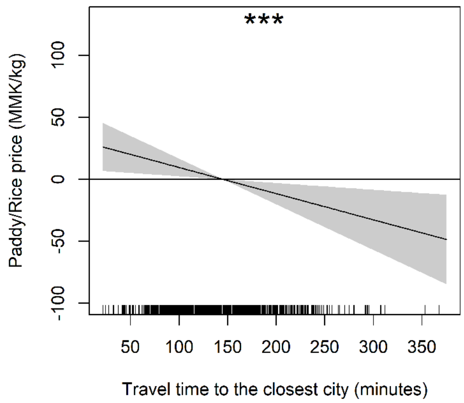


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

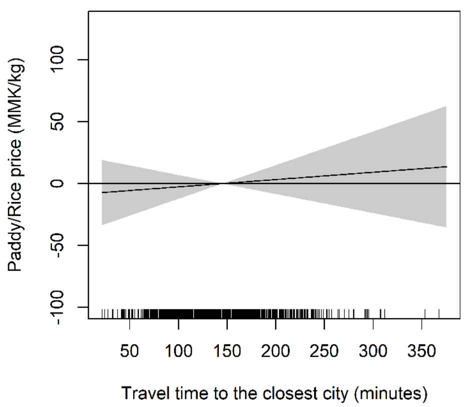


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

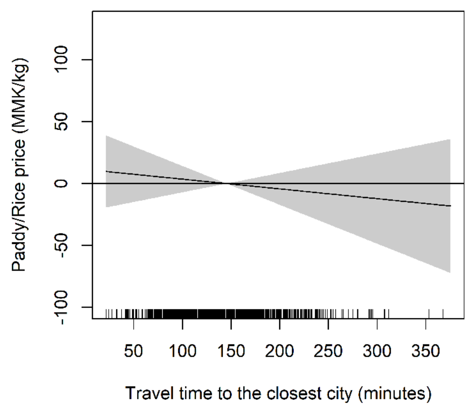
Figure 11: Effect of travel time to the closest city (minutes) on the paddy/rice yields (largest paddy plot), (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 13)) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



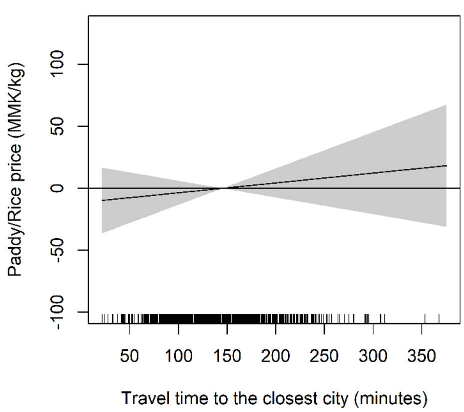
(a) TT base: $\widehat{f_0(tt)}$



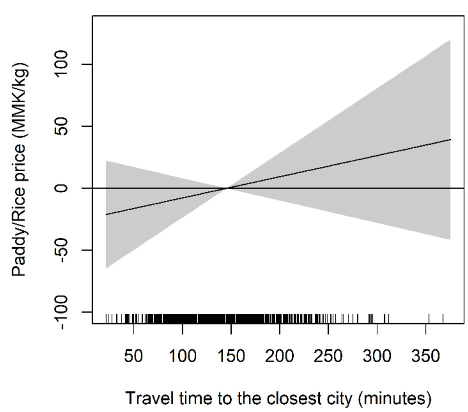
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

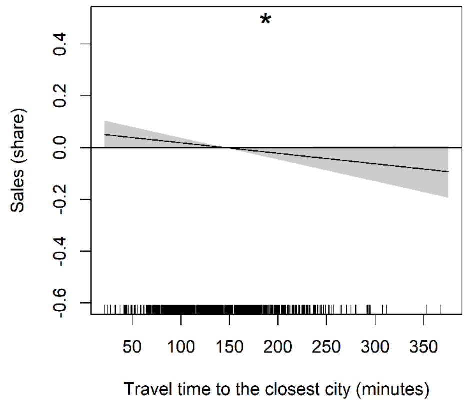


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

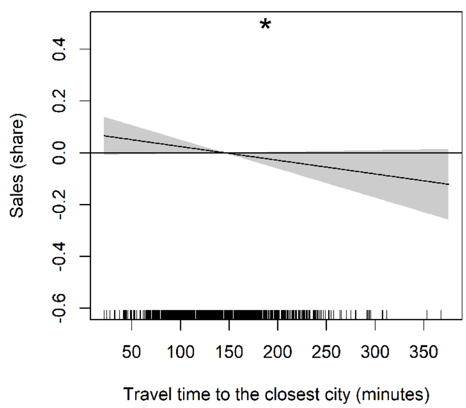


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

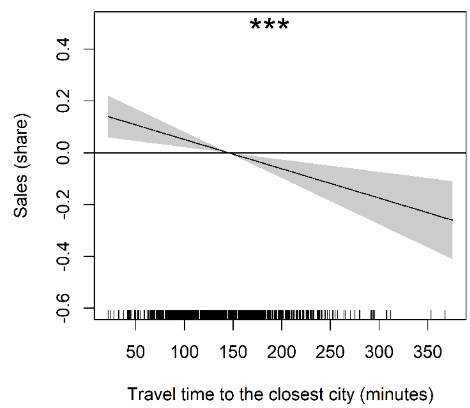
Figure 12: Effect of travel time to the closest city (minutes) on paddy/rice prices, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 13)) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



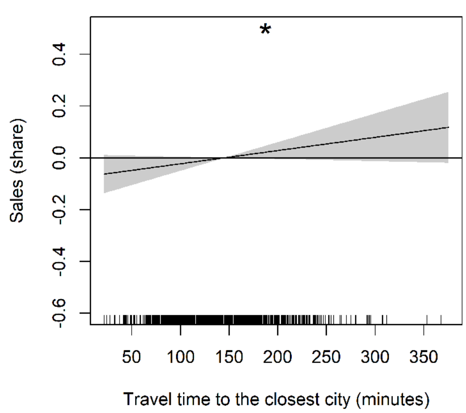
(a) TT base: $\widehat{f_0(tt)}$



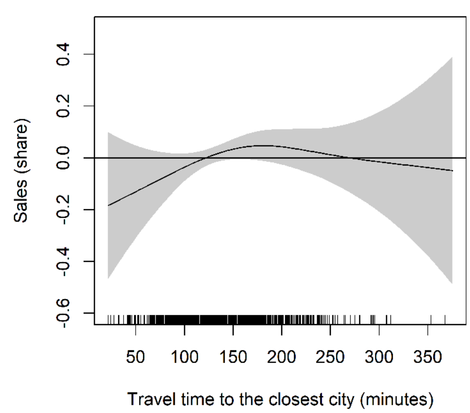
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

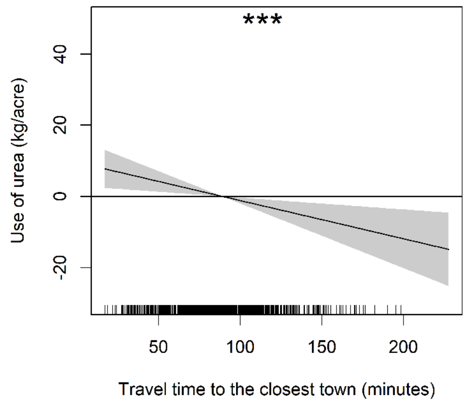


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

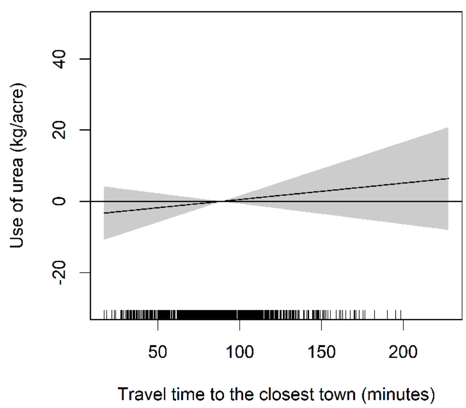


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

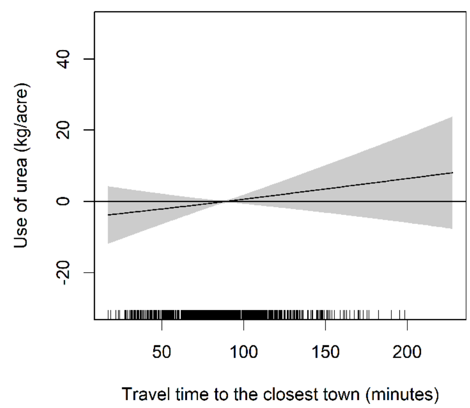
Figure 13: Effect of travel time to the closest city (minutes) on the share of paddy/rice sales, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 13)) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



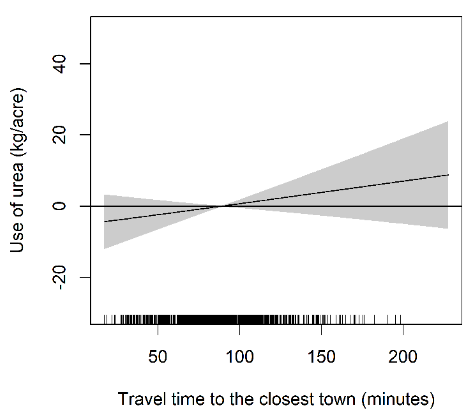
(a) TT base: $\widehat{f_0(tt)}$



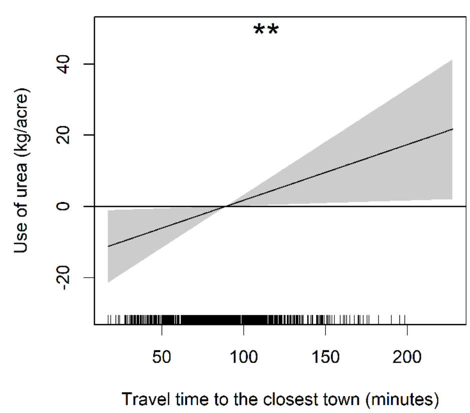
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

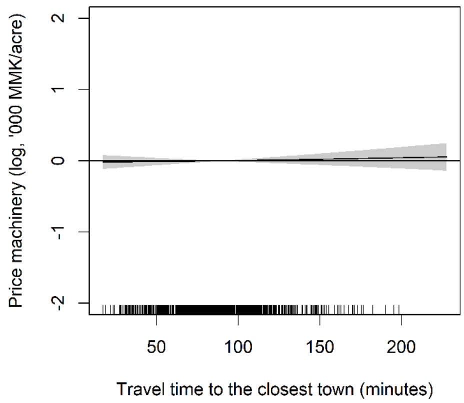


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

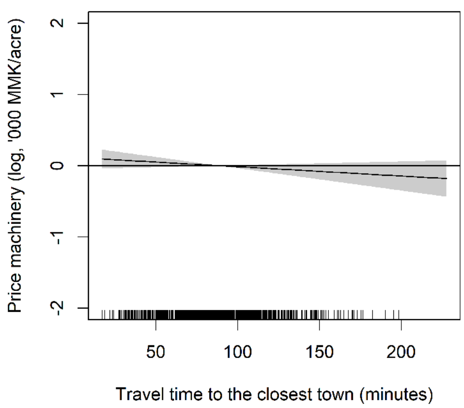


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

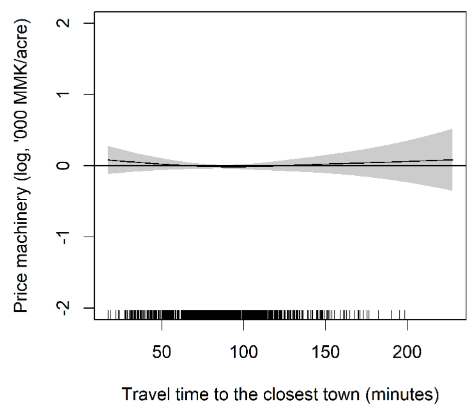
Figure 14: Effect of travel time to the closest town (minutes) on the use of urea (largest paddy plot), (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline: *p<0.1; **p<0.05; ***p<0.01.



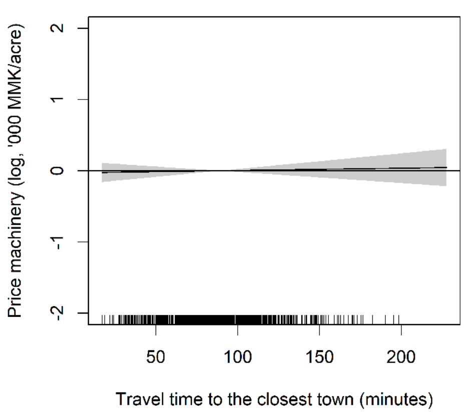
(a) TT base: $\widehat{f_0(tt)}$



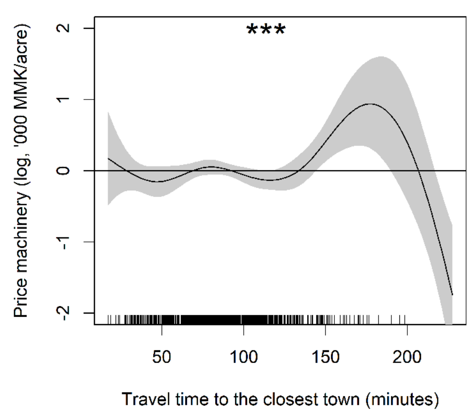
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

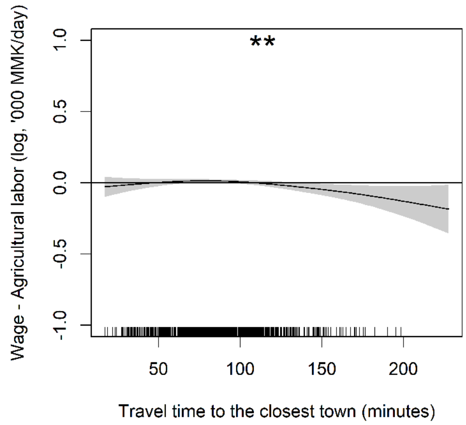


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

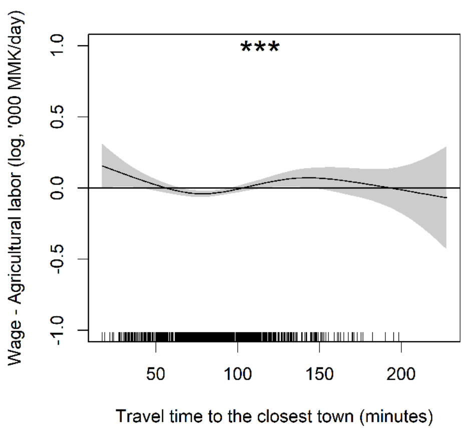


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

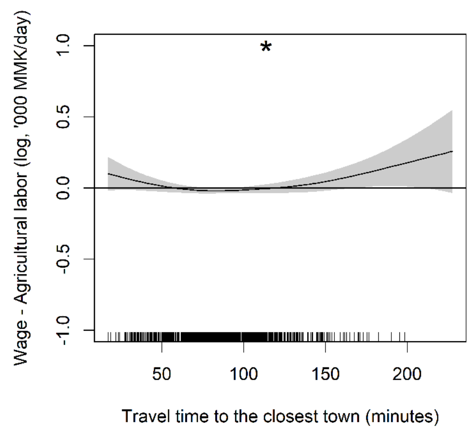
Figure 15: Effect of travel time to the closest town (minutes) on the price of machinery, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline: *p<0.1; **p<0.05; ***p<0.01.



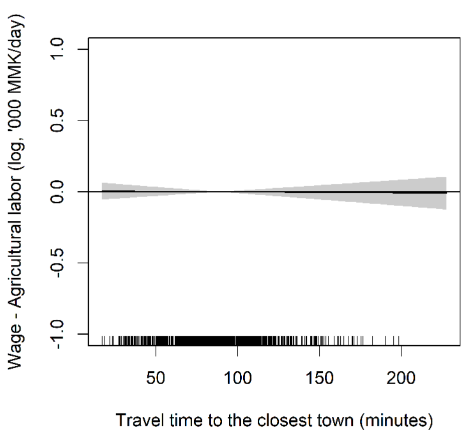
(a) TT base: $\widehat{f_0(tt)}$



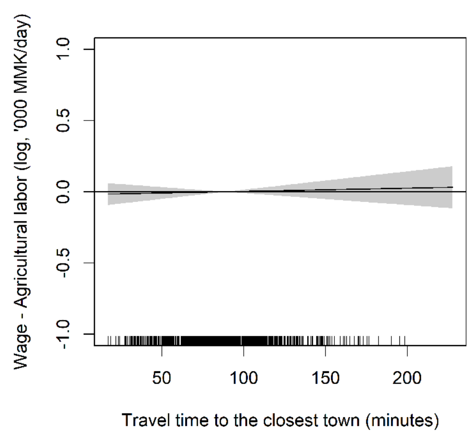
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

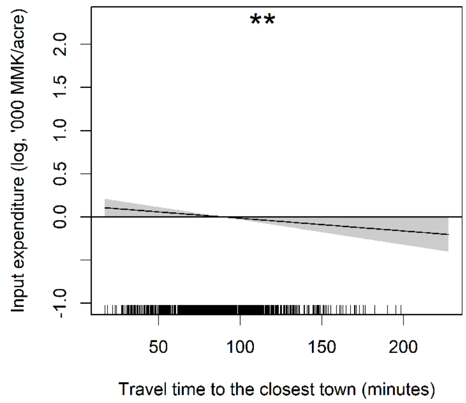


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

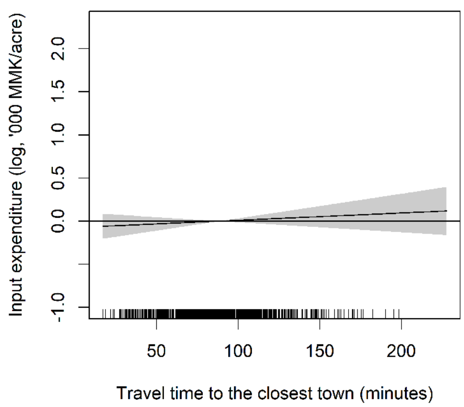


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

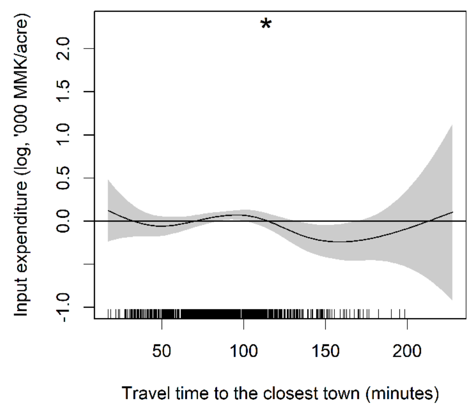
Figure 16: Effect of travel time to the closest town (minutes) on agricultural wages, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline: *p<0.1; **p<0.05; ***p<0.01.



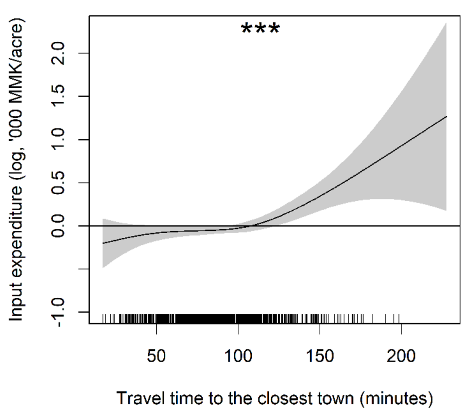
(a) TT base: $\widehat{f_0(tt)}$



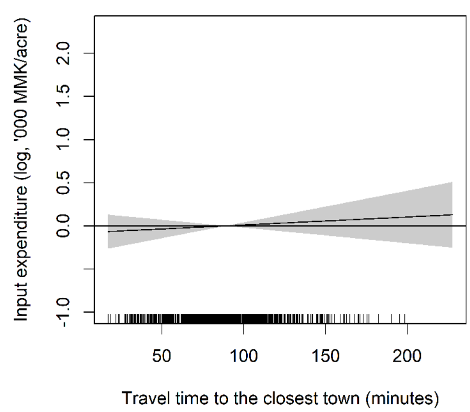
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

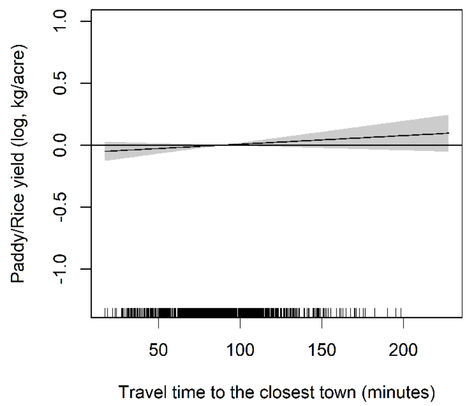


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

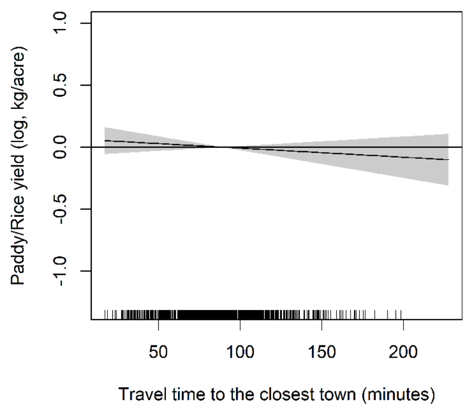


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

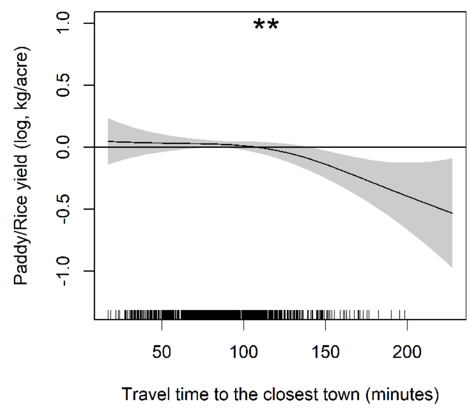
Figure 17: Effect of travel time to the closest town (minutes) on input expenditures (largest paddy plot), (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline: *p<0.1; **p<0.05; ***p<0.01.



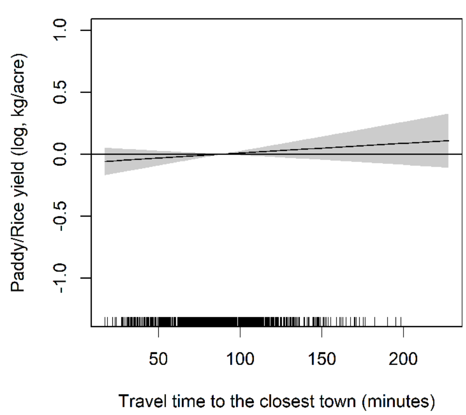
(a) TT base: $\widehat{f_0(tt)}$



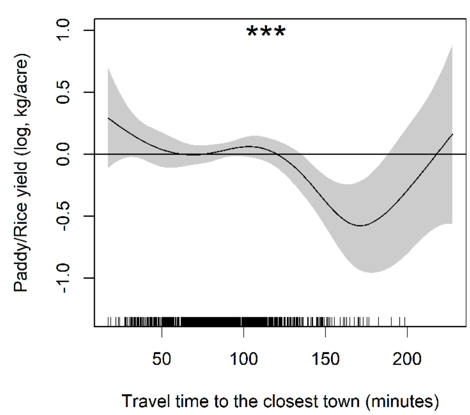
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

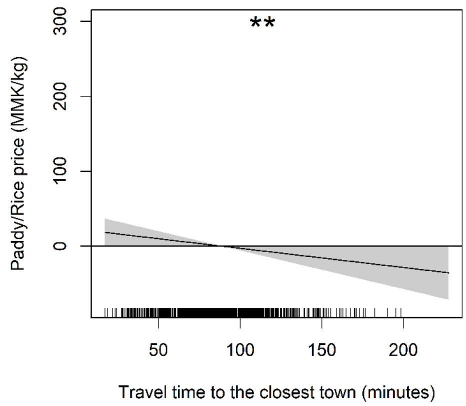


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

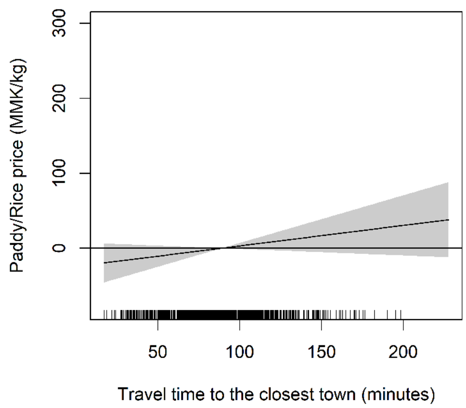


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

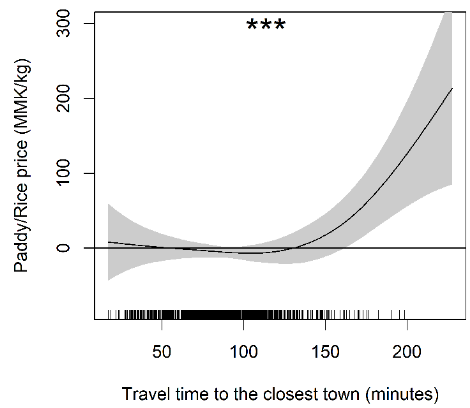
Figure 18: Effect of travel time to the closest town (minutes) on the paddy/rice yields (largest paddy plot), (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



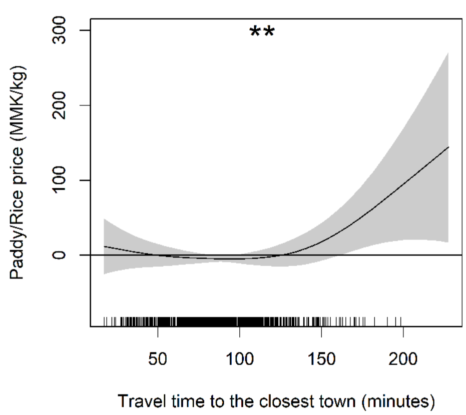
(a) TT base: $\widehat{f_0(tt)}$



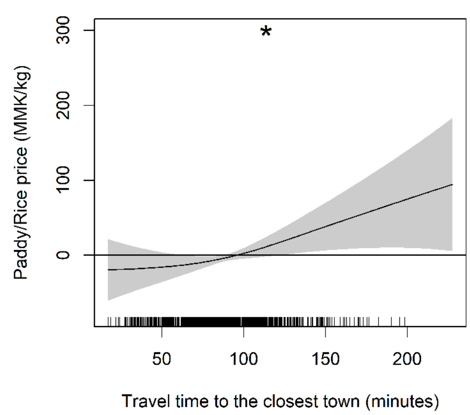
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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

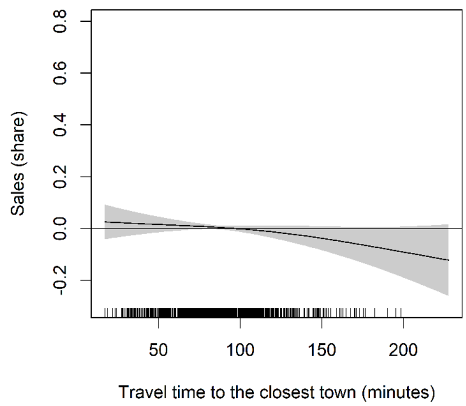


(d) $conflict_{b(CSI=1)} \times \widehat{f_a(tt)}$

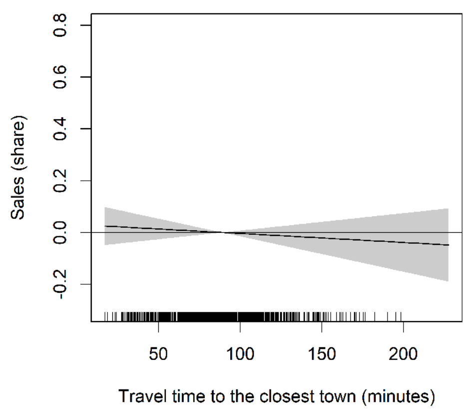


(e) $conflict_{b(CSI=2)} \times \widehat{f_a(tt)}$

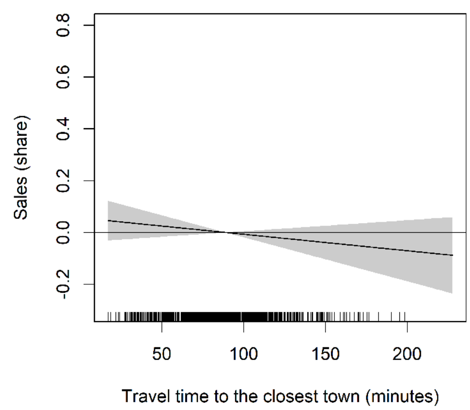
Figure 19: Effect of travel time to the closest town (minutes) on paddy/rice prices, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma}_a$ and $\hat{\gamma}_b$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq. 2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.



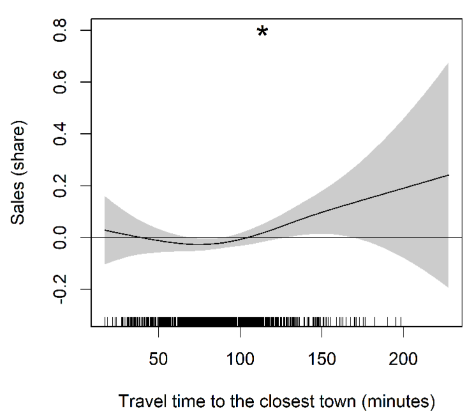
(a) TT base: $\widehat{f_0(tt)}$



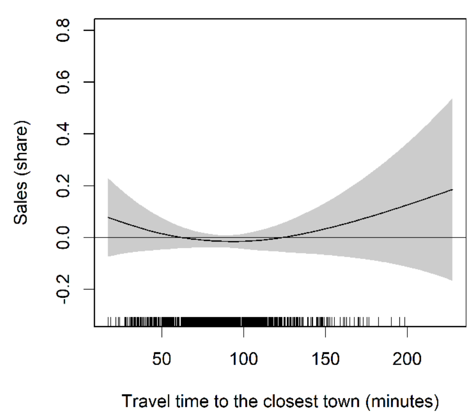
(b) $conflict_{a(CSI=1)} \times \widehat{f_a(tt)}$



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



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



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

Figure 20: Effect of travel time to the closest town (minutes) on the share of paddy/rice sales, (a) shows the estimated main effect of travel times (main effects for conflict, $\hat{\gamma_a}$ and $\hat{\gamma_b}$, can be found in Table 14) and (b)-(e) the estimated interacted effect functions ($\widehat{f_a(tt)}$, $\widehat{f_b(tt)}$) in Eq.2. Asterisks in the plots indicate overall significance of the estimated spline; **p<0.05; ***p<0.01.

Table 12: Regression results for conflict variables - Eq.1, 'Town' specification

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea (log, '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	48.293***	-1.296***	2.744***	1.736***	5.502***	7.474***	264.321***	0.566***
	(9.602)	(0.061)	(0.170)	(0.072)	(0.186)	(0.140)	(33.676)	(0.094)
CSI - Category 1 (monsoon 2021)	-2.257	0.018*	0.005	0.021*	0.039	-0.002	4.315	0.020
	(1.607)	(0.010)	(0.028)	(0.012)	(0.031)	(0.023)	(5.605)	(0.016)
CSI - Category 2 (monsoon 2021)	0.948	-0.008	0.028	0.040**	0.171***	0.037	-9.549	0.120***
	(2.237)	(0.014)	(0.039)	(0.017)	(0.043)	(0.032)	(7.722)	(0.022)
CSI - Category 1 (2010-2020)	2.249	-0.017	-0.031	-0.024*	0.000	0.034	-7.845	-0.009
	(1.699)	(0.011)	(0.030)	(0.013)	(0.033)	(0.025)	(5.936)	(0.017)
CSI - Category 2 (2010-2020)	2.509	-0.028	0.086	0.022	0.015	-0.015	-18.684	0.001
	(3.608)	(0.023)	(0.064)	(0.027)	(0.070)	(0.052)	(12.586)	(0.035)
Full set of controls[a]	Yes							
Splines: Travel time	Yes							
Interaction	No							
RE	Yes							
Observations	2,292							
AIC	24323.98							
Deviance explained	0.405							

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses, [a] see Table 9 and 10 for a full list of all control variables.

Table 13: Regression results for conflict variables - Eq.2, 'City' specification

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea (log, '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	45.722***	-1.295***	2.801***	1.818***	5.523***	7.396***	251.344***	0.580***
	(9.238)	(0.059)	(0.163)	(0.070)	(0.178)	(0.136)	(32.403)	(0.091)
CSI - Category 1 (monsoon 2021)	0.594	-0.011	0.008	0.013	0.105***	0.034	-7.848	0.082***
	(1.595)	(0.010)	(0.028)	(0.012)	(0.030)	(0.023)	(5.447)	(0.015)
CSI - Category 2 (monsoon 2021)	1.445	-0.022***	0.019	-0.003	0.017	0.008	-8.860**	0.025**
	(1.284)	(0.008)	(0.023)	(0.010)	(0.025)	(0.019)	(4.489)	(0.012)
CSI - Category 1 (2010-2020)	-0.215	-0.026	0.084*	0.058***	0.018	-0.036	-17.124*	-0.005
	(2.758)	(0.017)	(0.048)	(0.021)	(0.053)	(0.041)	(9.566)	(0.027)
CSI - Category 2 (2010-2020)	-2.193	-0.000	0.079**	0.051***	0.009	-0.044*	-3.296	0.005
	(1.780)	(0.011)	(0.031)	(0.013)	(0.034)	(0.026)	(6.184)	(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 9 and 10 for a full list of all control variables.

Table 14: Regression results for control variables - Eq.2, 'Town' specification

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea (log, '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	49.075***	-1.317***	2.708***	1.775***	5.548***	7.522***	251.002***	0.600***
	(9.223)	(0.058)	(0.164)	(0.069)	(0.179)	(0.135)	(32.223)	(0.090)
CSI - Category 1 (monsoon 2021)	0.276	-0.007	0.014	0.024**	0.125***	0.035	-7.841	0.086***
	(1.597)	(0.010)	(0.028)	(0.012)	(0.031)	(0.023)	(5.530)	(0.015)
CSI - Category 2 (monsoon 2021)	2.172*	-0.018**	0.006	-0.007	0.043*	0.023	-8.206*	0.033***
	(1.281)	(0.008)	(0.023)	(0.010)	(0.025)	(0.019)	(4.480)	(0.013)
CSI - Category 1 (2010-2020)	1.235	-0.024	0.090*	0.012	0.021	-0.012	-14.270	0.004
	(2.572)	(0.016)	(0.046)	(0.019)	(0.050)	(0.038)	(8.960)	(0.025)
CSI - Category 2 (2010-2020)	-1.209	-0.000	0.075**	0.027**	-0.000	-0.038	-3.012	0.007
	(1.690)	(0.011)	(0.030)	(0.013)	(0.033)	(0.025)	(5.898)	(0.017)
Full set of controls[a]	Yes							
Splines: Travel time	Yes							
Interaction	Yes							
RE	Yes							
Observations	2,292							
AIC	24255.88							
Deviance explained	0.411							

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses, [a] see Table 9 and 10 for a full list of all control variables.

Table 15: Regression results for selected control variables - Eq.2, 'Town' specification

	Dependent variable:							
	Use of urea (kg/acre)	Price of urea (log, '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	49.075***	-1.317***	2.708***	1.775***	5.548***	7.522***	251.002***	0.600***
	(9.223)	(0.058)	(0.164)	(0.069)	(0.179)	(0.135)	(32.223)	(0.090)
Precipitation (monsoon 2021, mm)	-0.014**	-0.000	-0.000***	0.000***	-0.000***	-0.000***	-0.011	-0.000***
	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.023)	(0.000)
Shock - pest/disease (dummy)	4.583**	0.001	0.020	0.009	0.090**	-0.052*	3.259	-0.020
	(1.964)	(0.012)	(0.035)	(0.015)	(0.038)	(0.028)	(6.839)	(0.019)
Shock - timing rain (dummy)	-2.752	-0.005	0.026	-0.023	0.007	-0.097**	-9.985	-0.027
	(2.880)	(0.018)	(0.051)	(0.021)	(0.056)	(0.042)	(10.025)	(0.028)
Shock - drought (dummy)	-2.965	0.015	-0.010	-0.007	-0.094	-0.163***	5.095	-0.013
	(3.273)	(0.021)	(0.058)	(0.024)	(0.063)	(0.047)	(11.404)	(0.032)
Shock - floods (dummy)	-2.233	0.042**	-0.052	-0.004	-0.066	-0.136***	17.762	-0.003
	(3.255)	(0.021)	(0.057)	(0.024)	(0.063)	(0.047)	(11.334)	(0.032)
Travel times to closest border (minutes)	-0.014***	0.000	-0.000	-0.000***	-0.000***	-0.000***	-0.022	-0.000*
	(0.005)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.018)	(0.000)
Closest border - China	5.067	0.021	-0.060	-0.058*	0.075	-0.022	9.791	0.102***
	(3.873)	(0.025)	(0.068)	(0.030)	(0.075)	(0.056)	(13.514)	(0.038)
Closest border - India	1.768	0.133***	-0.086	-0.119***	0.068	-0.143**	49.893***	-0.037
	(3.978)	(0.025)	(0.070)	(0.031)	(0.077)	(0.058)	(13.845)	(0.039)
Closest border - Laos	22.425**	0.118*	-0.424**	0.017	-0.023	-0.095	56.780	0.134
	(10.538)	(0.067)	(0.186)	(0.079)	(0.206)	(0.153)	(36.953)	(0.103)
Closest border - Thailand	4.330	0.025	-0.112*	-0.070***	-0.030	-0.043	4.064	0.097***
	(3.306)	(0.021)	(0.058)	(0.026)	(0.064)	(0.048)	(11.523)	(0.032)
Other crops (dummy)	0.150	-0.006	-0.053**	-0.046***	-0.037	-0.012	-6.520	-0.065***
	(1.483)	(0.009)	(0.026)	(0.011)	(0.029)	(0.021)	(5.160)	(0.014)
Plot size (acres)	-1.756***	-0.007**	-0.012	0.006*	-0.075***	-0.059***	-3.185*	0.013***
	(0.505)	(0.003)	(0.009)	(0.004)	(0.010)	(0.007)	(1.758)	(0.005)
Number of rice plots (count)	0.013	0.000	-0.001*	-0.000	0.000	0.002***	0.068	0.002***
	(0.039)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.136)	(0.000)
Land ownership (dummy)	3.064	0.040**	0.109*	-0.078***	-0.031	-0.031	22.140**	-0.012
	(3.231)	(0.020)	(0.057)	(0.024)	(0.062)	(0.047)	(11.248)	(0.031)
Extension (dummy)	0.934	0.012	-0.012	-0.004	-0.005	0.075***	12.718**	0.023*
	(1.442)	(0.009)	(0.025)	(0.011)	(0.028)	(0.021)	(5.018)	(0.014)
Gender - male (dummy)	-0.371	-0.022**	-0.060**	0.034***	-0.019	0.074***	-11.670**	0.020
	(1.452)	(0.009)	(0.026)	(0.011)	(0.028)	(0.021)	(5.057)	(0.014)
Age (years)	0.049	0.001***	-0.000	0.001***	0.001	0.001	0.583***	-0.001*
	(0.056)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.196)	(0.001)
Number of household members (count)	-0.063	-0.003	0.000	0.009***	-0.004	0.002	-0.893	-0.016***
	(0.388)	(0.002)	(0.007)	(0.003)	(0.007)	(0.006)	(1.351)	(0.004)
Motorized transportation (dummy)	3.007	0.016	0.017	0.022	0.121***	0.052*	4.212	0.037*
	(2.015)	(0.013)	(0.035)	(0.015)	(0.039)	(0.029)	(7.018)	(0.020)
Covid-19 (dummy)	2.817*	-0.010	0.048	0.016	0.075**	-0.033	-4.024	0.008
	(1.662)	(0.010)	(0.029)	(0.012)	(0.032)	(0.024)	(5.786)	(0.016)
Most important income - off-farm (dummy)	-1.168	-0.023**	-0.006	-0.005	-0.018	-0.040	-5.870	-0.020
	(1.727)	(0.011)	(0.030)	(0.013)	(0.033)	(0.025)	(6.014)	(0.017)
Non-agricultural income (dummy)	4.375***	0.022**	0.024	0.017	0.095***	0.052**	8.004	0.011
	(1.465)	(0.009)	(0.026)	(0.011)	(0.028)	(0.021)	(5.094)	(0.014)
Remittances (dummy)	-4.233	0.002	-0.054	0.006	-0.067	0.002	-8.417	-0.048*
	(2.581)	(0.016)	(0.045)	(0.019)	(0.050)	(0.037)	(8.988)	(0.025)
Full set of controls[a]	Yes							
Splines: Travel time	Yes							
Interaction	Yes							
RE	Yes							
Observations	2,292							
AIC	24255.88							
Deviance explained	0.411							

Note: *p<0.1; **p<0.05; ***p<0.01

Standard errors in parentheses, [a] see Table 9 and 10 for a full list of all control variables and reference groups for categorical variables.