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Somewhere in between towns, markets, and jobs – Opportunity costs of agricultural intensification in the rural-urban interface

Linda Steinhübel*
Department of Agricultural Economics and Rural Development, Georg-August-University Göttingen, Platz der Göttinger Sieben 5, 37073 Göttingen, E-mail: lsteinh2@gwdg.de

Stephan von Cramon-Taubadel
Department of Agricultural Economics and Rural Development, Georg-August-University Göttingen, Platz der Göttinger Sieben 5, 37073 Göttingen, E-mail: scramon@gwdg.de

*Corresponding / Presenting author

Abstract
We propose a flexible conceptual and methodological framework to model the dynamics of agricultural intensification in the complex rural-urban interfaces of large cities. In doing so, we focus particularly on effects of polycentric urbanization patterns and tradeoffs between agricultural intensification and off-farm employment. In our conceptual framework—modeling household decision-making based on utility maximization—we show that agricultural intensification in the rural-urban interface is likely to exhibit non-linear and complex spatial patterns due to relative changes in location-dependent effective output prices and wage rates. This is confirmed by our empirical analysis based on a primary data set of 638 smallholder farms in the rural-urban interface of Bangalore. Applying Structured Additive Regression (STAR) techniques, we model two-dimensional urbanization effects using household and village coordinates. Results imply that proximity to secondary towns and road infrastructure are the primary channel of urbanization effects on the uptake of modern agricultural inputs. Furthermore, proximity to the large urban center of Bangalore seems to be connected to increasing opportunity costs of agricultural intensification due to better access to off-farm labor opportunities. Finally, we show that agricultural intensification around urban centers does not necessarily occur in concentric and uniform patterns.

Keywords: Agricultural intensification, household model, India, Structured Additive Regression, urbanization

1. Introduction

Today more than half of the world population lives in cities and this share is expected to increase to two-thirds by 2050 (United Nations Population Division 2015). Cities in Asia and Africa are growing especially rapidly, and the implications of urbanization are attracting increasing attention in the fields of development and agricultural economics. Heinrich von Thünen's (1826) pioneering model of agricultural activity surrounding a city predicts the formation of concentric rings of land use as a function of yields, prices, production costs, and transport costs to the city for different agricultural products. While the model's assumption of an isolated city located on a uniform plain is unrealistic, von Thünen's approach to analyze the effects of proximity to urban centers on land use remains relevant today. Many recent studies include proxies for urbanization to analyze the effects of cities on the livelihoods or productivity of smallholders (Asfaw et al. 2016, Vandercasteelen et al. 2017, Vandercasteelen et al. 2018). Proximity to an urban center is expected to improve access to markets, information, and technology, and thus increase the likelihood that smallholders modernize their production systems and improve their standards of living (Chamberlin & Jayne 2013). Common urbanization proxies used in empirical analyses include distance to the next city center or market, transportation costs, or travel times (Damania et al. 2017, Ebata et al. 2017, Minten et al. 2013). The list is long and often variables are chosen based on the characteristics of a region such as topography or traffic conditions, or simply availability (Chamberlin & Jayne 2013). Regardless of which proxies are used, most studies show that proximity to urban centers and market access can significantly improve smallholders' productivity, as farmers who are closer to urban centers tend to receive higher output prices and are more likely to adopt modern inputs (Vandercasteelen et al. 2017) .

While these insights are important, to date the literature on the effects of proximity to urban centers on smallholders has not considered two important characteristics of urban expansion into surrounding agricultural areas. The first of these is the complex, polycentric nature of most urban expansion. Cities do not expand into the empty, uniform rural plains posited in von Thünen's seminal work. Indeed, in von Thünen's model the city does not expand at all, it is simply there. In reality cities emerge from networks of settlements in heterogeneous space. Which settlements eventually come to dominate and grow most rapidly in a region is determined by a complex, path-dependent interaction of geography, chance, and agglomeration effects (Fujita & Thisse 2014, Krugman 1996). As it expands, a city will encounter and affect the growth of the other, surrounding settlements. The resulting expansion and coalescence processes generate polycentric urban hierarchies (Schneider & Woodcock 2008). Smallholders in the rural-urban interface therefore often find themselves in between an expanding urban center and surrounding secondary towns, and subject to a web of interacting economic forces that pull in different directions. Hence, their production systems, choices, and welfare are influenced not only by yields, prices and proximity to a single urban center. In a polycentric rural-urban interface, for example, a smallholder might face a choice between delivering to the urban center or delivering to a closer, perhaps specialized alternative market that is located farther away from the center. In such settings it is unrealistic to assume linear or monotonic gradients of agricultural intensification and productivity radiating out from the urban center, and standard urbanization proxies based on proximity to the center will not perform well.

The other salient characteristic of urban expansion is that it provides alternative employment opportunities to the members of smallholder households in the rural-urban interface. Economists have generated a rich literature on the push and pull factors that drive rural-urban migration and urban population growth (Harris & Todaro 1970, Jedwab et al. 2017). However, smallholder households in the rural-urban interface do not necessarily have to migrate to switch from rural to urban. Indeed, such households will often be rural-urban composites, with some members engaged in farm and others in off-farm pursuits and this mixture shifting over time as household demographics evolve and urbanization draws closer. Especially where urbanization is driven by strong economic growth that generates pull forces, as is the case in the setting that we explore below, households in the rural-urban interface will face a choice between allocating labor to increasingly human capital-intensive modern agricultural production, or allocating it to off-farm employment opportunities. These effects might also lead to complex, non-linear patterns of agricultural intensification surrounding large, growing cities. While recent studies (e.g. Christiaensen et al. 2013, Vandercasteelen et al. 2018) do account for the varying effects of city size on surrounding smallholders, they maintain the assumption that farmers are production maximizers only affected by access to input (including on-farm labor) and output markets. In addition, they generally assign one town of reference to each farm household to measure its urban proximity. Thus, these studies do not account for complex, polycentric patterns of urbanization, and for the potential role of off-farm earning opportunities in the rural-urban interface.

This is the point of departure for our study. We derive theoretical and empirical models that are sufficiently flexible to capture the effects of polycentric urbanization on the agricultural management decisions made by smallholder households. We develop a household model following Barnum & Squire (1979) in which both output prices and off-farm wage rates vary in space. The result is an economic model that can explain and predict non-linear pattern of agricultural intensification that are driven by antagonistic dynamics in access to output and off-farm labor markets.

We illustrate the application of this model by analyzing the adoption of modern agricultural inputs in the rural-urban interface of Bangalore, a rapidly growing megacity of roughly 12 million inhabitants

(as of 2018) in southern India. As India's "Silicon Valley", Bangalore exerts not only a strong demand for food and other agricultural products on the surrounding rural areas; it also provides households in these areas with a variety of off-farm employment opportunities. Furthermore, its rural-urban interface includes multiple secondary towns of different sizes that provide smallholders with opportunities for marketing agricultural produce and for non-farm employment as well. Thus, it exhibits the polycentric characteristics that we aim to study. Our analysis is based on primary data collected in a survey of 638 farm household covering the production year of 2016.
Empirically, we test the implications of our theoretical model by estimating the effect of a household's location on its adoption of modern agricultural inputs. Standard models predict that the use of such inputs will increase monotonically with increasing proximity to the urban center. The model that we propose considers the effects of location in two-dimensional space rather than proximity to a unique urban center. The result is a framework that builds on but is more flexible than and subsumes previous models such as that of Vandercasteelen et al.(2018). To operationalize the model we employ Structured Additive Regression (STAR) techniques that allow us to directly model two-dimensional location effects based on household and village coordinates. We compare the results of this model with results generated using standard one-dimensional urbanization proxies based on distance to Bangalore city center. Thus, we determine whether and under which circumstances a model that explicitly considers two-dimensional effects will generate richer insights into the effects of urbanization on smallholder decision-making in the rural-urban interface.
The remainder of this paper is structured as follows. In chapter 2 we introduce our conceptual framework and in chapter 3 we present our study design and data set. Afterwards we describe our empirical strategy in chapter 4 and discuss the results in chapter 5. Chapter 6 summarizes our findings.

2. Conceptual framework

Access to input and output markets, represented by transportation costs, is the most frequent identified mechanism of urbanization effects on agricultural management. Damania et al. (2017) and Vandercasteelen et al. (2017, 2018) develop economic models that predict a monotonic relationship between decreasing transportation costs and agricultural intensification—measured by the uptake of new and modern agricultural technologies—with increasing proximity to a city. However, a number of empirical studies on labor allocation demonstrate that smallholder households are likely to diversify their income if off-farm employment is available (Deichmann et al. 2009, Fafchamps & Shilpi 2003, Imai et al. 2015). Just as access to input and output markets varies in space, so do off-farm employment opportunities and effective wage rates. There is theoretical (Krugman 1991) as well as empirical (Fafchamps & Shilpi 2003) evidence that wage rates and off-farm employment increase with proximity to cities. Thus, in this study we focus on the antagonistic effects between improved access to agricultural markets and off-farm employment opportunities on household agricultural production decisions. We build on the conceptual frameworks introduced by Vandercasteelen et al. (2017, 2018) and Damania et al. (2017), which assume that household decision making is based primarily on farm profit maximization, and extend these to comprehensive household utility maximization considering opportunity costs of agricultural intensification in terms of off-farm income. The general setup of the framework is based on the Barnum-Squire "Model of an Agricultural Household" (Barnum & Squire 1979). Following this model and the notation proposed by Ellis (1994), we assume that a farm household maximizes its utility given in equation (1).

(1) $U = f(C, M, T_Z)$

C is the amount of the total farm output Q consumed by the household, and M are purchased goods for consumption. In addition to C and M the household also consumes goods Z.These are goods that do not have market value but are produced and consumed by the household (e.g. tailoring, cleaning). Therefore, the utility of a household also depends on the time available for the production of Z denoted by T_Z.

This utility function (1) is maximized subject to a production function (equation 2), a time constraint (equation 3), and an income constraint (equation 4).

(2) $Y = f(A, L, V)$

(3) $T = T_Z + T_F + T_W$

(4) $p(Q - C) + wT_W - vV = mM$

The farm output (equation 2) depends on land (A), labor (L), and other inputs (V). The total time available to the household, T, is split among time to produce goods Z, (T_Z), time to produce Q (T_F), and wage labor (T_W) (equation 3). A negative sign for wage labor ($T_W < 0$) means that labor is hired in for farm production; a positive sign ($T_W > 0$) implies off-farm employment. The income constraint (equation 4) states that all household expenditures have to equal the net household earnings, where p is the market price for the farm output Q, w is the wage, v is the price of the inputs V, and m is the price of the purchased goods M.
To solve the maximization problem, two equilibrium conditions have to be met: a production equilibrium and a consumption equilibrium. The production equilibrium is established when the marginal products of labor and inputs (MPP_L, MPP_V) equal the ratio of the wage to the output price (w/p) and the ratio of the input to the output-prices (v/p), respectively ($MPP_L = w/p$ and $MPP_V = v/p$). The consumption equilibrium is met when the marginal rates of substitution (MRS) of all possible pairs of arguments in U equal the price ratios between the respective pairs. A partial graphical depiction of these equilibrium conditions is given in figures 1 and 2 ($MPP_L = w/p, MRS_{C,T_Z} = w/p$).
To model the effects of location on agricultural intensification, we propose two extensions of the Barnum-Squire Model. First, in equations (5) and (6) we assume that there are two different production systems that reflect different stages of agricultural intensification, each represented by a distinct production function:

(5) $Y_M = f(\bar{A}, L, \overline{V_M})$

(6) $Y_T = f(\bar{A}, L, \overline{V_T})$

For simplicity we limit the number of production systems to two: Y_M representing a modern production system, and Y_T a traditional one. The household maximizes its utility subject to either of the two production systems (equations (5) and (6)), and chooses the system, that yields the highest utility in equilibrium. Household land use is assumed to be constant ($\overline{A}$) and therefore neglected in the following. The package of inputs used ($\overline{V_M}$ or $\overline{V_T}$) is assumed to be fixed given the choice of a specific production system (modern or traditional, respectively). The interesting factor is labor (L). Labor productivity in a modern production system can be assumed to be substantially higher than in a traditional one (Haggblade et al. 2010). Hence, all other things equal, the shape of the total physical product (TTP) of labor and consequently the location of the production equilibrium differs between the two systems. Contrasting Figures 1 and 2, we see that in the modern production system more labor (own and hired-in) is allocated to farm production, while in the traditional system, due to its lower marginal farm labor productivity, more labor is allocated to the off-farm employment and producing Z.
In the second extension we define the effective prices and wage to be functions of household location (equation (7) and (8)).

(7) $p(l) = p^{city} - g(l)\ with\ g(l) > 0$

(8) $w(l) = w^{city} - h(l)\ with\ h(l) > 0$

Where p^{city} and w^{city} are the price of agricultural outputs and the wage rate at the urban center; the per unit transport or access cost to the city are denoted by $g(l)$ and and $h(l)$ with $\frac{\partial g(l)}{\partial l} > 0$ and $\frac{\partial h(l)}{\partial l} > 0$ respectively. More generally, the prices of purchased goods and inputs, m and v, could also be considered location-dependent. However, allowing only p and w to vary with location is sufficient to produce complex non-linear spatial patterns of agricultural intensification, and further generalization would increase the complexity of the model without generating fundamental additional effects.
Based on these extensions, we turn to Figures 1 and 2 to analyze the effect of location on a households' choice between the traditional and modern production. In both figures we assume that at an initial location l^* the indifference curves (I) and the slopes of the price ratio $w(l)/p(l)$ are identical. Hence, at location l^* traditional and modern production lead to the same utility and the household will be indifferent to which production system it chooses.

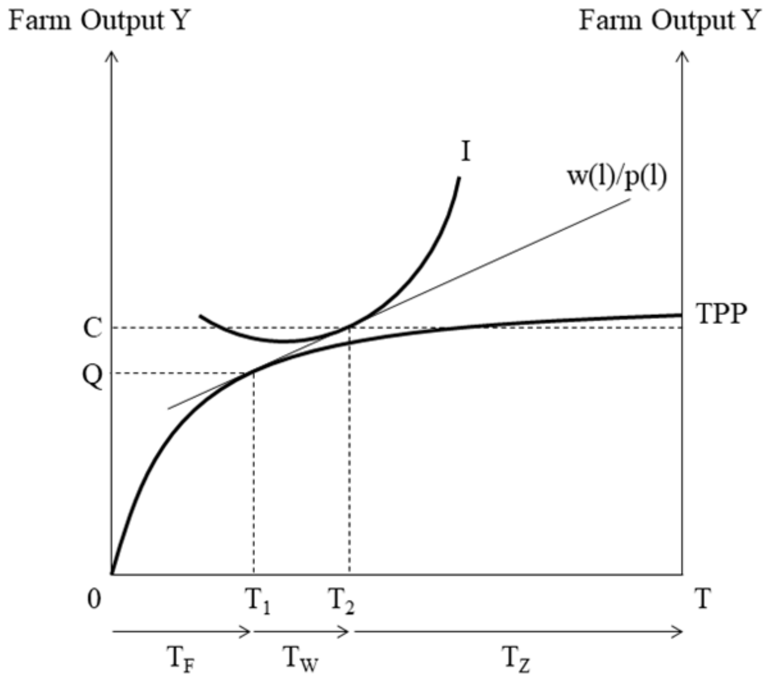

Figure 1: Equilibrium in a traditional management system at location l^*

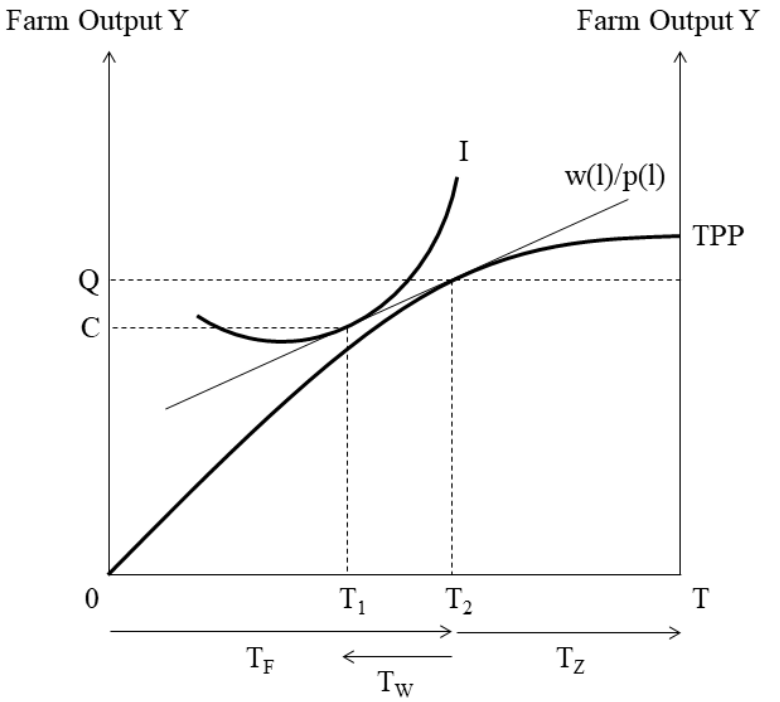

Figure 2: Equilibrium in a modern management system at location l^*

However, when we consider an otherwise identical household at another location l^{**} the price ratio $w(l)/p(l)$ will change depending on the relative slopes of $g(l)$ and $h(l)$. Hence, new equilibrium solutions will be obtained for the traditional and modern production systems, and the household will choose the production system that generates the highest utility. For example, if the wage rate increases more than the farm output price with increasing proximity to the urban center, then the ratio $w(l)/p(l)$ will become steeper in both figures, increasing the utility level that is attained in the traditional management system (by reducing agricultural production and allocating more labor to off-farm employment), but reducing the utility that is attained in the modern management system (as hired-in labor becomes more expensive). Hence, moving towards the urban center from location l^* we would expect to see more traditional and less modern agricultural production, which is the opposite of the outcome that is generally predicted in the literature. Several authors mention that the size of a city, i.e. the magnitude of demand by its population, determines the degree of agricultural intensification in its hinterlands (Vandercasteleen et al. 2017, 2018, Fafchamps and Shilpi 2003). This is true to the extent that increasing city size will affect the spatial pattern of output prices. Yet, the introduction of space-dependent wages implies that not only the size of a city but its structure will determine the spatial pattern of agricultural intensification in its surroundings. A city with a large industrial sector with a high demand for unskilled labor will have a different effect on farm households' management decisions than a city with a large service sector that demands more skilled labor. In addition, not every household is defined by the specific indifference curves and production functions presented in Figure 1 and 2. With different preferences and different endowments (labor skills, land, availability of irrigation, etc.), different initial equilibria will obtained for different households, and the ratio $w(l)/p(l)$ will vary differently over space. As a result, agricultural intensification might increase or decrease moving inwards towards the urban center depending on the distribution of household types in space. This is especially the case if we extend the model to distinguish between labor with higher and lower levels of human capital and different degrees of complementarity between human capital and other inputs in modern compared with traditional production systems. For example, the ratio $w(l)/p(l)$ might increase with proximity to the urban center for labor with high levels of human capital, but increase at a lower rate or even decrease for other labor. This will have implications for spatial patterns of agricultural intensification if the

successful implementation of modern production systems requires higher levels of human capital. The spatial pattern of agricultural intensification will be further complicated by polycentric urbanization that can lead to non-linear variations in the ratio $w(l)/p(l)$ over space depending on the location of satellite towns or the quality of transportation infrastructure.
It follows that the assumption of a monotonic relationship between the distance to a city or comparable household location proxies and agricultural intensification can be problematic. It is, thus, necessary to find alternative strategies and proxies to capture urbanization effects on agricultural intensification in the empirical analysis.

3. The study area, survey design and dataset

Bangalore, one of the largest and fastest growing cities in India, is located in the South Indian state of Karnataka. The last official census published in 2011 counted 9.6 million people living in the *Bengaluru urban district* (Directorate of Census Operations Karnataka 2011), an increase of more than 30 percent compared with the previous census in 2001. Estimates of the population in 2018 range around 12 million (Sharma 2018). Bangalore thus represents the type of mega-city urbanization that is predicted for many cities in developing countries in future decades (United Nations Population Division 2015), especially in Asia.
There are several secondary towns within a 70 kilometer radius around Bangalore that have also experienced substantial growth during the last decades, developing their own industries, services, and market infrastructure in the process (Figure 3). In addition, the infrastructure linking these smaller towns to Bangalore has be continuously upgraded, although congestion and daily traffic jams have, if anything, become more severe. Hence, our study area is best characterized as a polycentric urban hierarchy with Bangalore in the center.

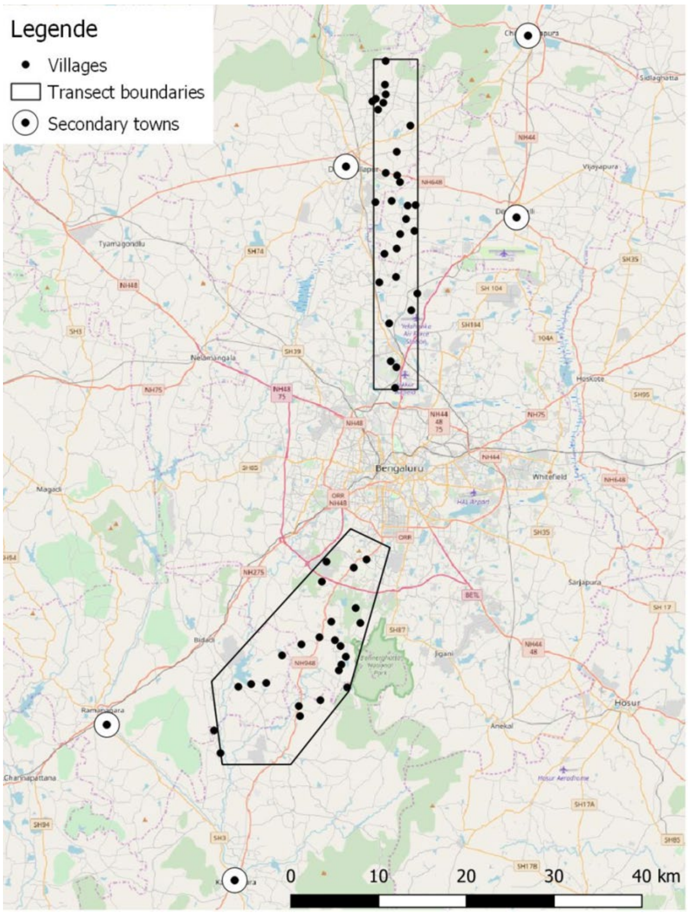

Figure 3: Rural-urban interface of Bangalore, research transects, village location, and secondary towns

Rapid urbanization notwithstanding, agricultural production still dominates the rural-urban interface surrounding Bangalore and the secondary towns (Directorate of Census Operations Karnataka 2011). Individual household land holdings are small—about two acres—but the variety of crops produced is large and ranges from traditional staples to fruits and vegetables, tree crops, mulberry for silk production and even turf production for urban lawns. In addition, dairy cattle and other livestock are common. State regulated wholesale markets (referred to as APMC) and other retail formats (e.g. contracts, supermarkets, cooperatives, farmers' markets) in Bangalore and the secondary towns offer farmers a variety of marketing channels for their produce driven by increasing demand for agricultural products caused by economic and population growth in Bangalore, and by national and international trade.

Our empirical analysis is based on socioeconomic survey data that was collected from 1,275 households between December 2016 and May 2017. All households were selected in two pre-defined research transects that cut across the rural-urban interface of Bangalore (see Figure 3). One transect is located to the north of Bangalore (hereafter referred to as the northern transect) and the other transect to the southwest (the southern transect). To ensure an even distribution of households in the transects and, thus, a valid representation of the spatial heterogeneity in the rural-urban interface, household selection followed a two-step sampling procedure based on the *Survey Stratification Index* (SSI) introduced by Hoffmann et al. (2017). Accordingly, each transect was separated into three strata, namely urban, peri-urban, and rural. In each of the resulting six strata (three per transect) 10 villages were randomly selected. The 60 villages thus selected cover about 30 percent of the total number of villages in the transects. In a second step, an average of just over 21 households per village was randomly drawn from household lists provided by the preschool teachers in each village. The exact number of household selected per village was proportional to total village population.

The survey was designed to produce a representative sample of households in the rural-urban interface, both agricultural and non-agricultural. As we are interested in agricultural intensification in the following, we only consider households that managed at least one agricultural plot in 2016. Therefore, our final sample contains 638 farm households; 354 households in the northern and 284 households in the southern transect. Figure 3 shows the villages in which these agricultural households are located. All data are geo-referenced as we collected village and household coordinates. This allows us to calculate the distance to the Bangalore city center for every household, but also to model location effects using the exact coordinates of each village and household in two-dimensions.

Each household was asked to provide detailed information on its socio-economic characteristics and the agricultural management and marketing practices that it applied in 2016. The result is a complex data set with information on different scales. The smallest scale of observation is the crop level with 1,926 crop observations. At this scale, 72 different crop and 90 different inputs were recorded. Additional scales of observation are the plot, household, village and transect level. At the crop level, for example, we recorded information on the growing season, the use of inputs including irrigation, yields and the use (own consumption, marketing) of the output. At the plot level we recorded information on which crop was produced in which growing season, soil quality and slope. Household level information includes information on the number of plots cultivated, as well as socio-economic characteristics such as caste, education, income, wealth indicators such as durable assets, and off-farm employment. An overview of the collected data is provided in Table 1. In the next section we describe how we handle potential problems resulting from the scaling of the data set.

Table 1: Descriptive statistics of all control variables

Variable	N	All	Northern transect	Southern transect
Modern inputs (count)	1926	1.7747 (1.3592)	1.8808 (1.5565)	1.6837 (1.1568)
Crop scale				
Irrigation (dummy)	1926	0.4766	0.3476	0.5873
Purpose production	1926			
0: none of the others		0.3624	0.4151	0.3173
1: Marketing		0.3240	0.2857	0.3568
2: exclusively fodder		0.1267	0.1159	0.1360
3: fodder and home consumption		0.1869	0.1834	0.1900
Sowing season	1926			
0: continously		0.2347	0.2385	0.2314
1: Kharif 2015		0.0223	0.0112	0.0318
2: Rabi 2015		0.1054	0.0765	0.1302
3: Summer 2016		0.0737	0.0720	0.0752
4: Kharif 2016		0.4927	0.5422	0.4503
5: Rabi 2016		0.0711	0.0596	0.0810
Plot scale				
Plot property	1108			
1:Owned		0.9179	0.9425	0.8839
2:Rented		0.0659	0.042	0.0989
3:Common area		0.0009	0.0016	0
4:Government (permission)		0.0072	0.0062	0.0086
5:Government (no permission)		0.0081	0.00778	0.0086
Size (acres)	1105	1.8229 (3.9854)	1.6991 (3.6441)	1.9926 (4.4092)
Slope	1104			
1:None		0.4092	0.4593	0.3412
2:Moderate		0.4420	0.4158	0.4378
3:Steep		0.1486	0.0956	0.221
Soil quality	1104			
1:Poor		0.0362	0.0392	0.0322
2:Middle		0.471	0.4765	0.4635
3:Very good		0.4928	0.4843	0.5043
Time to plot (minutes)	972	14.1472 (13.4997)	13.7256 (12.459)	14.7789 (14.9188)
Household scale				
Age household head (years)	629	45.0254 (13.5583)	44.8357 (13.6167)	45.2589 (13.5066)
Car (dummy)	638	0.0345	0.0452	0.0211
Dairy (dummy)	638	0.7743	0.7684	0.7817
Durable assets (count)	638	2.8151 (1.2779)	2.8107 (1.2778)	2.8204 (1.2802)
Education household head (years)	600	6.275 (5.1595)	6.7868 (5.2273)	5.6367 (5.0104)
Experience household head (years)	632	28.5997 (14.299)	28.1543 (14.0771)	29.1525 (14.5759)
Extension (dummy)	619	0.0969	0.0977	0.0959
Gender household head (dummy)	629	0.1653	0.1672	0.1631
Household size (count)	629	4.6391 (2.0785)	4.732 (2.1745)	4.5248 (1.9517)
Caste				
1:General		0.5192		0.4646
2:SC		0.1314		0.1159
3:ST		0.0483		0.0697
4:OBC		0.2648		0.3116
5:Other		0.0363		0.0382
Off-farm employment (dummy)		0.6191	0.6271	0.6092
Off-farm employments (count)		1.0204 (1.0443)	1.0312 (1.0302)	1.007 (1.0633)

Note: Std. Deviation in brackets. For dummy and factor variables percentages are given. The number of observations N depends on the scale the variable was collected on.

Following Sharma et al. (2011), Lohr & Park (2002), Wollni et al. (2010), and Teklewold et al. (2013), we use a count of modern inputs applied per crop as a measure of agricultural intensification. We classified all inputs observed in our data set into six categories: (a) organic fertilizer, (b) traditional seed varieties, (c) new seed varieties, (d) pesticides, (e) inorganic fertilizer, and (f) hormones. We use a count of all inputs in categories (c) to (f) per crop observation—hereafter referred to as *modern* inputs—to locate each household on a scale from traditional to modern production. In the conceptual framework presented in section 2 we assumed a strict dichotomy between traditional and modern production, but the rural-urban interface is characterized by transition between systems. Any attempt to classify each household into one of two categories would be arbitrary and would not take advantage of the richness of our survey data.

4. Methods

For our empirical analysis, we chose a Structured Additive Regression (STAR) framework. STAR models allow for different types of covariates in addition to classical linear effects (Fahrmeir et al. 2013). This flexibility allows us to account the multiple scales of our data and to incorporate non-linear one- and two-dimensional spatial effects. Following Sharma et al. (2011), we assume that the dependent variable (number of adopted modern inputs) is Poisson distributed. We log-transform the rate $\boldsymbol{\lambda}$ of the Poisson distribution to ease interpretation and defined the additive and semiparametric predictor $\boldsymbol{\eta}^{struc}$ as follows:

(9) $\boldsymbol{y} \sim Po(\boldsymbol{\lambda}),\ \ with\ \log(\boldsymbol{\lambda}) = \boldsymbol{\eta}^{struc} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \ \boldsymbol{f_{Dist}} + \boldsymbol{f_l}$

The predictor consists of four elements, namely linear effects of standard control variables $\boldsymbol{X\beta}$, random intercepts for the different scales of the data set $\boldsymbol{Z\gamma}$, where $\boldsymbol{Z}$ is an $n \times n$ identity matrix, a non-linear effect (one-dimensional spline) distance to the Bangalore city center $\boldsymbol{f_{Dist}}$, and a vector of two-dimensional splines $\boldsymbol{f_l}$ to capture the effects of explicit household location.
A list and descriptive statistics of all variables in $\boldsymbol{X}$ can be found in Table 1. As control variables we include information on crop, plot, and household characteristics.
The main purpose of the random intercepts was to handle effects at different scales. Because the northern and the southern transects differ considerably in agricultural and economic structure, we estimate separate models for each transect and do not include random effects at the transect level. However, we do include random effects at the crop, plot, household, and village levels: $\boldsymbol{\gamma} = (\gamma_{crop}, \gamma_{plot}, \gamma_{household}, \gamma_{village})'$. The crop level is especially important due to the high crop diversity observed in our sample. By introducing random effects for different crops, we allowed each crop to have an individual random intercept that captures its individual input requirements as difference to the overall sample intercept. The interpretation for the other random effects is equivalent.
Many models in the literature include distance to the next city or market as a standard linear effect. Our conceptual framework shows that urbanization effects can be non-linear. We therefore estimate the effect of distance to Bangalore city center as a one-dimensional P-spline with a second order random walk penalty and 20 knots, $\boldsymbol{f_{Dist}}$. The explicit spatial effects $\boldsymbol{f_l}$ are estimated as a two-dimensional P-spline surface smoother. This smoother estimates the direct effect of household or village coordinates (bivariate variable), $\boldsymbol{f_l} = (\boldsymbol{f}(\boldsymbol{s_{household}}), \boldsymbol{f}(\boldsymbol{s_{village}}))'$, on the number of adopted modern inputs. It can be interpreted as a bivariate non-linear effect that results purely from a position in the plane and thus captures complex location effects in a polycentric setting.
Inference of model (9) is based on a mixed model representation and estimation follows an empirical Bayesian approach; from a frequentist perspective this is comparable to penalized likelihood estimation. The main difference between the Bayesian and frequentist perspectives is the definition

of the penalty in the non-linear smoothers of $\boldsymbol{f_{Dist}}$ and $\boldsymbol{f_l}$, either as a smoothing parameter or as a variance component, respectively (Kneib & Fahrmeir 2006).[1]

4.1 Model specifications

We start our estimations with a first or 'base model' specification that does not include any urbanization proxies and the predictor is therefore:

(10) $\log(\boldsymbol{\lambda}) = \boldsymbol{\eta}^{struc} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma}$

With 20 control variables and four sets of random effects this model is already quite large and possibly subject to convergence and computational challenges, especially when we attempt to include the two-dimensional splines, $\boldsymbol{f_l}$, in subsequent models specifications. To avoid these problems and over-parameterization, we apply an adaptive algorithm based on the improved Akaike information criterion (iAIC) to eliminate covariates in $\boldsymbol{X}$ and random effects $\boldsymbol{\gamma}$ that do not contribute to the fit of the base model (for details see Belitz et al. 2012, Brezger & Lang 2006).

Afterwards we extend the base model by adding two-dimensional location effects $\boldsymbol{f_l}$. We compared estimates of $\boldsymbol{f_l}$ based on household and village coordinates and find that two-dimensional splines based on village coordinates yield a lower AIC. Therefore, we only considered village coordinates, $\boldsymbol{f}(\boldsymbol{s_{village}})$, for the rest of the analysis:

(11) $\log(\boldsymbol{\lambda}) = \boldsymbol{\eta}^{struc} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \boldsymbol{f}(\boldsymbol{s_{village}})$

The third model extends the base model by adding the one-dimensional urbanization proxy distance to the Bangalore city center, $\boldsymbol{f_{Dist}}$:

(12) $\log(\boldsymbol{\lambda}) = \boldsymbol{\eta}^{struc} = \boldsymbol{X\beta} + \boldsymbol{Z\gamma} + \boldsymbol{f_{Dist}}$

Estimating models (11) and (12) allows us to determine how well the one-dimensional and two-dimensional non-linear effects capture spatial heterogeneity, and whether there are substantial differences between the two effects.

4.2 Linking theoretical and empirical concepts of location

Before we present results, we briefly consider the relationship between the location effects discussed in the conceptual framework above and the location effects estimated using $\boldsymbol{f_{Dist}}$ and $\boldsymbol{f}(\boldsymbol{s_{village}})$ in our empirical models. In the conceptual framework location effects are exclusively due to urbanization and the effects of proximity to urban areas on the demand for agricultural outputs and off-farm earning opportunities. The distance to the Bangalore city center represents rural-urban dynamics by definition and, thus, $\boldsymbol{f_{Dist}}$ can easily be aligned with the location effect of the conceptual framework. In contrast, $\boldsymbol{f}(\boldsymbol{s_{village}})$ is not automatically an urbanization effect. It might also represent geological or biophysical effects that the physical location of a village on agriculture.

To control for this and ensure that the location effects that we estimate using $\boldsymbol{f}(\boldsymbol{s_{village}})$ primarily capture urbanization effects we employ two strategies. First, we include plot characteristics such as soil quality and slope in $\boldsymbol{X}$, to control for small-scale biophysical factors. Second, we include village-level random intercepts to control for unobserved variation at a larger scale, for example distinct biophysical or hydrological features that affect agricultural decision making in a particular village. Examples of such features are hills, lakes, or waste water drainages, which could be used as alternative irrigation sources. We are confident that as a result of these controls the location effects

[1] The estimation of the model was conducted in R using the package "R2BayesX" (Umlauf et al. (2013), which provides an interface to the free Software "BayesX" for Bayesian inference. For more information on the estimation techniques and inference see Kneib & Fahrmeir (2006), Umlauf et al. (2015), and Fahrmeir et al. (2013).

that we estimate using $f(s_{village})$ will primarily capture the urbanization effects discussed in our conceptual framework.

5. Results and discussion

Figure 4 shows the estimates of the two-dimensional splines for the model specification (11). The splines somewhat contradict the implications and findings by Thünen (1826) and later studies (Vandercasteelen et al. 2017, Vandercasteelen et al. 2018). According to them, we should detect highest adoption rates close to Bangalore and—but not as high—close to secondary towns (see Figure 3 for the location of the secondary towns). For the northern transect we only observe an increasing adoption of modern inputs towards the northern areas, i.e. closer the secondary towns, whereas proximity to Bangalore does not exhibit an increasing effect on modern input adoption. Especially, the secondary town of Doddaballapura in the northwest of the transect appears to have an increasing effect on input adoption. In the southern transect the overall tendency of the effects goes more in the direction of what one would expect; proximity to Bangalore slightly increases modern input adoption. However, the magnitude of effects is much lower (a tenth) than in the northern transect. In addition, a closer look at the two-dimensional spline in the right panel of Figure 4 gives the impression that the orientation of the effects are less north-south (rural-urban) but east-west. If we further look at the map provided in Figure 3, we can see that the red areas in the southern transect are located around a road, which connects Bangalore to the secondary town of Kanakapura. Thus, the effect might be rather driven by proximity to infrastructure than Bangalore as such.

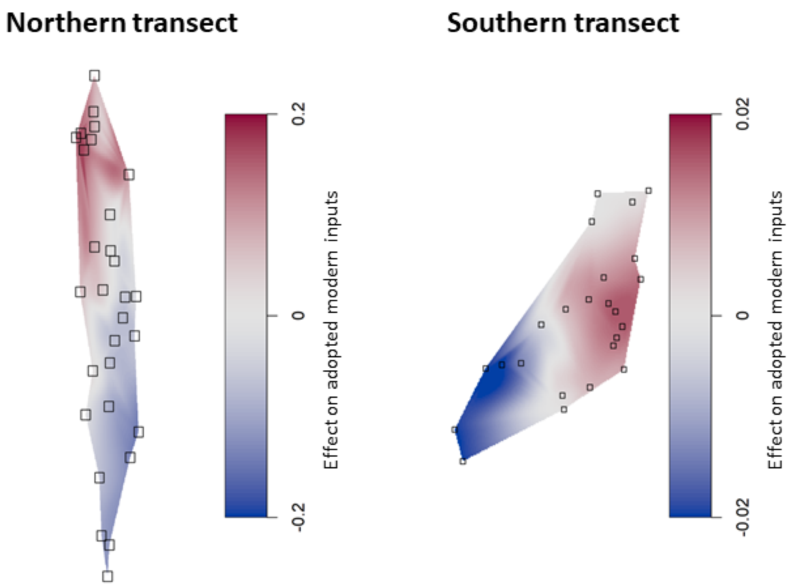

Figure 4: Estimates of two-dimensional splines, $f(s_{village})$, model specification (11) (N_{north}= 829, N_{south}= 983)

Figure 5 presents the one-dimensional effect of distance to Bangalore on the adoption of modern inputs (equation (12)). For the northern transect results imply a significant increase of modern input uptake with increasing distance to Bangalore. This coincides with the two-dimensional effect in Figure 4 but insights are less nuanced. Effects could be driven by the secondary town of Doddaballapura or overall rural-urban processes induced by Bangalore. Only the two-dimensional effect reveals the positive adoption effects around Doddaballapura (left panel Figure 4). Same holds for the southern transect. The one-dimensional effect implies a slightly positive effect of proximity to Bangalore on the agricultural intensification. However, the confidence intervals are rather wide and the effect is hardly significant. Since the two-dimensional effect shows a spatial pattern of agricultural intensification around the road in the southern transect, the simple distance to Bangalore does not capture this effect.

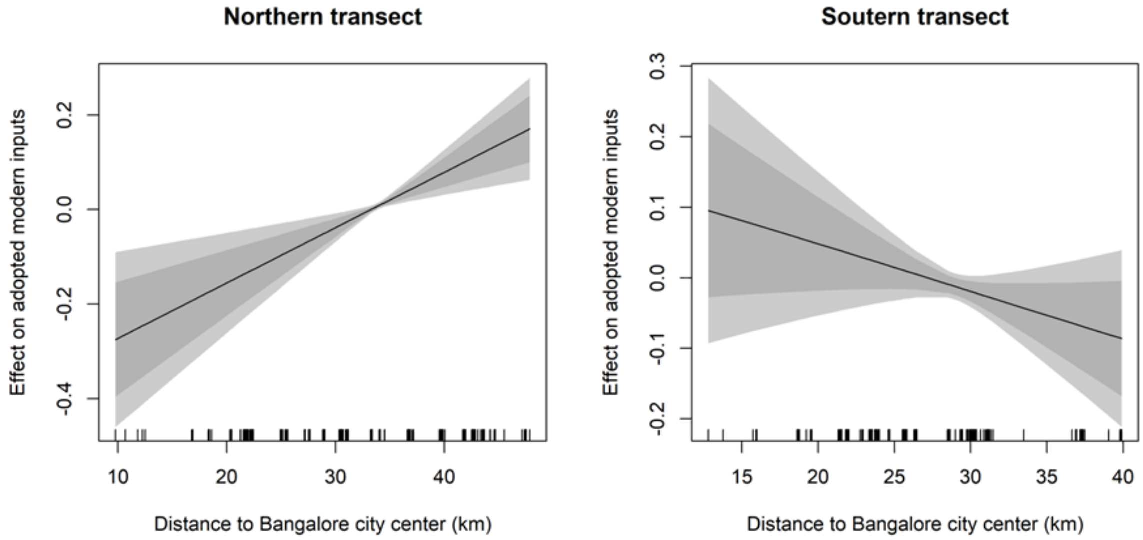

Figure 5: Estimates of one-dimensional splines, f_{Dist}, model specification (12) (N_{north}= 829, N_{south}= 983)

In conclusion, the two-dimensional effects appear to be better suited to describe and understand the complex urbanization processes induced by Bangalore and secondary towns. These results also confirm conclusions derived in our conceptual framework that proximity to urban centers affects agriculture not only via its effects on output prices, but additional factors such as off-farm employment. This can lead to more complex patterns of agricultural intensification than anticipated by the literature to date (Damania et al. 2017, Vandercasteelen et al. 2017). For example, in the northern transect households located closer to the secondary town of Doddaballapura probably have rather low opportunity cost of agricultural intensification. The town with roughly 300,000 inhabitants has good agricultural marketing infrastructure including a state-regulated APMC wholesale market and many local vendors; nevertheless, the off-farm labor market is not as developed. In contrast, markets for skilled as well as unskilled off-farm labor in Bangalore thrive. Furthermore, the rapid expansion of Bangalore is likely to increase land prices. Consequently, opportunity costs of intensified agricultural production become higher with proximity to Bangalore. This would explain the negative location effect as farm households decide to assign more household labor to the off-farm sector. This is supported by results presented in in Table 2. We find that a higher number of household members in off-farm employment decrease the adoption of modern inputs. Even though the coefficients are only significant at 17 and 22 percent level respectively, it still implies a tendency that households weigh between different income opportunities.[2] Table 1 suggests that about 62 percent of all households have at least one member working in the off-farm sector. In the southern transect the above mentioned road appears to play an important role in defining urbanization effects. The road facilitates access to agricultural markets in Bangalore and Kanakapura as well as access to vibrant off-farm labor markets in Bangalore. As a consequence, the relative utility of a traditional and modern agricultural management system is close to one in large part of the southern transect and households can achieve comparable utility with either income composition. This would explain the low magnitude of coefficients in the two-dimensional spline in Figure 4 and the marginal significance in the one-dimensional spline in Figure 5.

[2] This effect actually becomes significant (p=0.01) when estimating model specification (11) based on a pooled data set (Appendix 1).

Table 2: Estimation results for model with two-dimensional splines, northern and southern transect separate

Variables	Exp(Coefficient)	
	Northern transect	**Southern transect**
Intercept	0.817 (0.259)	0.903 (0.532)
Crop characteristics		
Irrigation		
Yes	1.359*** (<0.001)	1.54*** (<0.001)
Purpose production (ref.: none)		
Exclusively fodder	0.943 (0.636)	0.782* (0.0497)
Fodder and home consumption	1.104 (0.212)	1.133 (0.128)
Marketing	1.363*** (<0.001)	1.076 (0.418)
Sowing season (ref.: continuously)		
Kharif 2015	1.426 (0.178)	1.050 (0.792)
Rabi 2015	1.406* (0.034)	1.215 (0.134)
Summer 2016	1.406* (0.039)	1.242 (0.134)
Kharif 2016	1.437* (0.015)	1.219 (0.122)
Rabi 2016	1.726** (0.002)	1.212 (0.178)
Plot characteristics		
Slope (ref.: None)		
Moderate	0.97 (0.605)	
Steep	1.123 (0.247)	
Household characteristics		
Car		
Yes	1.453*** (<0.001)	
Caste (ref.: General)		
SC		1.016 (0.856)
ST		1.357* (0.04)
OBC		1.227** (0.007)
Other		0.961 (0.82)
Experience household head (years)	0.997 (0.13)	0.998 (0.382)
Extension		
Yes		1.232* (0.018)
Household size (count)	1.03** (0.006)	
Off-farm employments (count)	0.959 (0.17)	0.966 (0.224)
Random effects		
Crop	+	+
Plot		
Household		+
Village	+	
	(N=829)	**(N=983)**

Note: Aterisks *, **, and *** denote significance levels below 5%, 1%, and 0.1% respectively. Exact p-value are given in parentheses. The original number of observations for the northern transect was 850 and 1037 for the southern. Differences result from dropped observations because of missing values. A +-sign indicates included random effects. Because the models were estimated in a log-linear form, the exponentials of coefficients are reported. Example interpretation for irrigation dummy: If a crop is irrigated the average number of adopted modern inputs for this particular crop increases c.p. by 35.9 percent.

Finally, the simple fact that we observe different urbanization effects between the two transects already calls for urbanization proxies that rely on explicit household location. One-dimensional proxies such as distance to a city center are based on the assumption that urbanization effects are concentric and uniform around the city under observation. Our results prove that this is an unreasonable assumption for rapid and polycentric urbanization patterns.[3] In particular, if data sets are not collected in defined transects, for which separate empirical analysis can be conducted, estimation results for one-dimensional proxies will not be able to capture different urbanization effects.

We close by briefly highlighting several effects of control variables on farmers' decision-making. First, irrigation has a highly significant positive effect on the number of adopted inputs in both transects. This is quite intuitive as the access to irrigation is often a prerequisite of modern and intensified agricultural systems (Elliott et al. 2014). Second, in the northern transect we observe that a household uses 36.3 percent more modern inputs on average, if the crop in question is grown exclusively for marketing rather than own consumption. In addition, seasonal crops such as corn, tomatoes, and other vegetables—independent of the season—receive between 40 and 73 percent more modern inputs than continuous crops such as eucalyptus or coconut. In the southern transect we do observe that fodder crops receive 22 percent fewer modern inputs, all other things equal. This might be mirroring the marketing effect of the northern transect. Table 1 shows that almost ten percent (28.57 percent in the northern vs. 35.68 percent in the southern transect) more crops in the southern transect are produced for marketing. When marketing is more common, the production of fodder crops is more likely to deviate from the mean rate of adopted modern inputs. Therefore, the general pattern in both transects is that marketing increases whereas the production of fodder crops decreases the adoption rate of modern inputs.

At the household level, household size has a significantly positive effect on the adoption of modern inputs in the northern transect. This may be a reflection of the higher labor requirements of modern agricultural production systems. A household with a larger number of members can assign more household labor to agricultural production. If households own a car in the northern transect[4], the mean rate of adopted modern inputs increases by more than 45 percent. This can be interpreted in two ways. A car can be a sign of comparably high wealth of the household and, thus, the farmer probably has enough capital to adopt more sophisticated modern inputs. Second, a car implies better access to input and output markets. In the southern transect, if a household received extension services, its average modern input use increases by 23.2 percent.

6. Conclusions

The rapid growth and expansion of Bangalore is a good example of future urbanization trends and, thus, it is important to pay more attention on the effect of rapid urbanization process on agricultural management systems in the hinterlands of such cities. The goal of this study is to understand the effect of urbanization process on agricultural intensification—measured by the amount of adopted modern inputs—in the rural-urban interface of Bangalore. We focus on two aspects in particular, which so far have been rather neglected in the literature, namely the effects of polycentric urbanization patterns and of potential opportunity costs of agricultural intensification due to off-farm opportunities.

In our conceptual framework we develop a household model following Barnum & Squire (1979) and model household decision-making as a utility maximization problem. Thus, households maximize both their production function (defining the degree of agricultural intensification) as well as their consumption preferences subject to location-dependent output prices and wage rates. As a consequence, we can show that spatial patterns of agricultural intensification in rural-urban interfaces are likely to be non-linear.

In our empirical analysis based on primary data of 638 farm households in the rural-interface of Bangalore, we produce evidence that urbanization effects ceteris paribus indeed show non-linear and

[3] In Appendix 2 we present the estimates of a one-dimensional spline based on the analysis of a pooled data set. Same empirical strategy was applied as for the separate estimations. It shows that the splines resembles the one of the northern transect in Figure 5 but with much wider confidence intervals. It follows that the pooling of the data set blurs due to the different and complex urbanization effects in both transects.

[4] Only car ownership prior to 2016 is considered to avoid endogeneity.

complex spatial patterns. Based on household and village coordinates, we estimate two-dimensional splines measuring urbanization effects in a STAR framework. The results show significant differences between our two research transects. In the northern transect the secondary town of Doddaballapura leads to an increased uptake of modern inputs, whereas no such effect is identified for areas closer to Bangalore. We argue that the vibrant market for skilled and unskilled labor in Bangalore and increasing land prices due to rapid urban expansion increase opportunity costs of agricultural intensification. In the southern transect the two-dimensional effects reveal the importance of road infrastructure connecting smallholders to Bangalore as well as the secondary town of Kanakapura. Furthermore, we compare the two-dimensional splines with estimates of one-dimensional splines based on the distance to the Bangalore city center. We find that the latter are less nuanced and spatial patterns induced by secondary towns or road infrastructure cannot be directly identified. Finally, the substantial differences in urbanization effects between the two transects implies that the assumption of concentric and uniform agricultural change around a city—in the sense of von Thünen (1826) and later studies—is at least debatable.

Therefore, we emphasize the need for more flexible theoretical as well as empirical models that are able to capture determinants of smallholder decision-making towards agricultural intensification beyond profit maximization of agricultural production. We believe that our conceptual framework based on utility maximization and the use of explicit location in two-dimensional space in empirical analysis is a first step in this direction.

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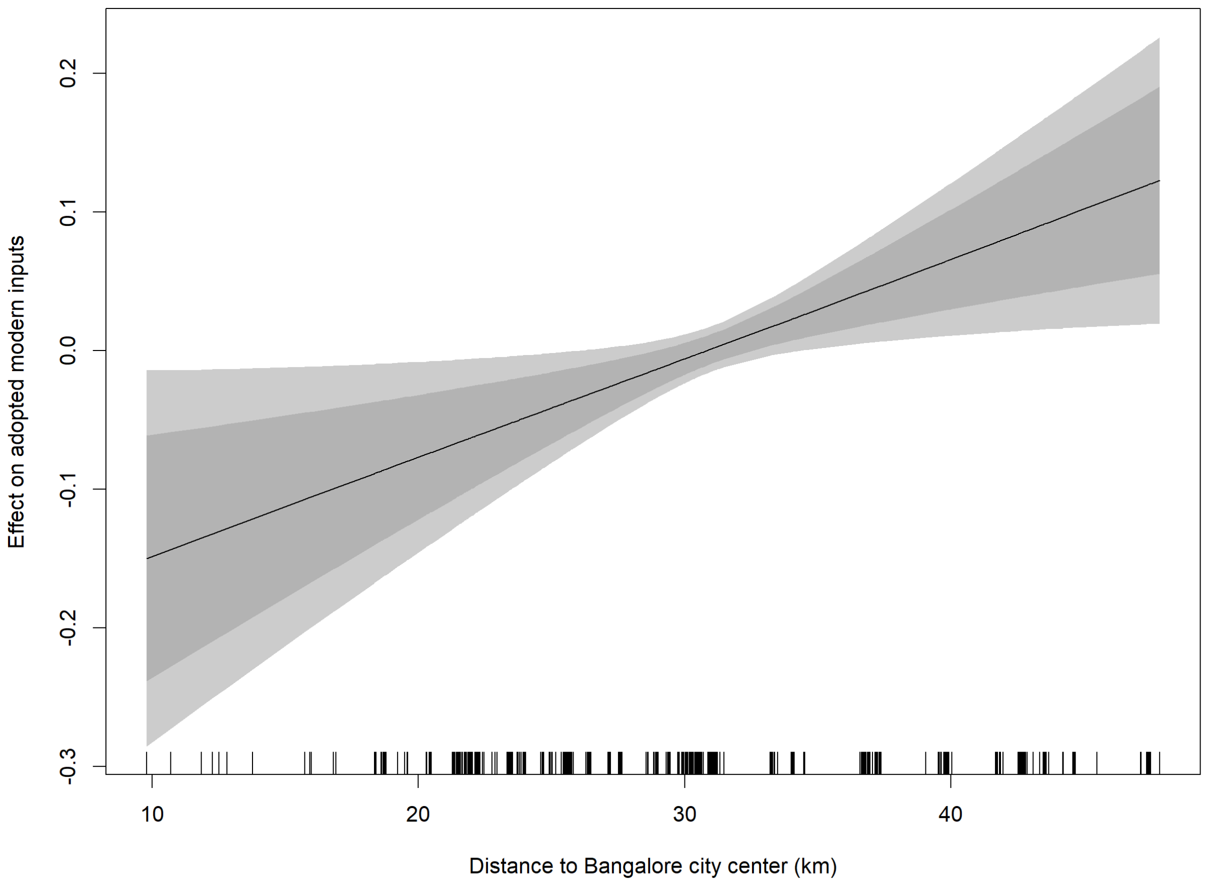
Appendix

Appendix 1: Estimation results for model with one-dimensional splines for pooled data set

Variables		**Exp(Coefficient)**
Intercept		0.931 (0.592)
Crop characteristics		
Irrigation		
Yes		1.429*** (<0.001)
Purpose production (ref.: none)		
Exclusively fodder		0.891 (0.196)
Fodder and home consumption		1.137* (0.027)
Marketing		1.255*** (<0.001)
Sowing season (ref.: continuously)		
Kharif 2015		1.147 (0.375)
Rabi 2015		1.201 (0.078)
Summer 2016		1.4239 (0.054)
Kharif 2016		1.225* (0.042)
Rabi 2016		1.299* (0.021)
Household characteristics		
Car		
Yes		1.145 (0.137)
Caste (ref.: General)		
SC		0.964 (0.588)
ST		1.107 (0.29)
OBC		1.108* (0.042)
Other		0.95 (0.657)
Experience household head (years)		0.997 (0.099)
Extension		
Yes		1.108 (0.066)
Household size (count)		1.023** (0.008)
Off-farm employments (count)		0.897* (0.01)
Random effects		
Crop		+
Plot		
Household		+
Village		+
		(N=1752)

Note: Aterisks *, **, and *** denote significance levels below 5%, 1%, and 0.1% respectively. Exact p-value are given in parentheses. A +-sign indicates included random effects. Because the models were estimated in a log-linear form, the exponentials of coefficients are reported.



Appendix 2: Estimates of one-dimensional splines, f_{Dist}, pooled data set (N_{pooled}= 1752)