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WORKING PAPER 102

August 2020

Land Deals and Social Fabrics: The Impact of Large-Scale Land Acquisitions on Social Trust in sub-Saharan Africa

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Abstract
The livelihoods of rural populations in sub-Saharan Africa are closely tied to small-scale farming and other types of land use. In recent years, private investors as well as governments have shown a growing interest in large-scale acquisition of arable land across the continent. While authors have started to analyze the local economic impacts of such investments, their socio-political as well as psychological consequences remain poorly understood. This paper investigates how changes in land ownership patterns caused by large-scale land acquisitions affect the level of trust among rural communities. We maintain that the transition from community and individual-smallholder land ownership into large-scale investor property has a negative impact on this particular dimension of social capital. To test our hypotheses, we rely on georeferenced information on land deals, tenure systems as well as survey data from Afrobarometer at the individual level of analysis. Employing a quasi-experimental design based on different matching techniques and difference-in-means estimations, our models show that the global land rush indeed disrupts local social fabrics and social cohesion by reducing interpersonal as well as institutional trust. Moreover, our findings indicate that the negative effect of agrarian transformations on local trust levels is particularly strong among women.

Keywords: *Large-Scale Land Acquisitions, Social Capital, Trust, sub-Saharan Africa*

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Acknowledgements
The authors would like to thank Katharina Michaelowa and Carl Müller-Crepon for their excellent comments on our manuscript.

Introduction

Social capital is a major asset in rural Africa. Livelihoods and the well-being of farmers are closely tied to the prevalence of social networks and interpersonal trust. Among smallholders and family farmers, social capital is a key determinant of economic wealth, access to education and health, collaborative land managements, knowledge flow and innovation, resilience of rural co-operatives as well as climate change adaptation. Rural sub-Saharan Africa – traditionally characterized by small and family-operated plots (c.f. Lowder et al. 2016) – has been considered a "storehouse of rich social capital" (Kansanga et al. 2019a, p. 1).

In the last two decades, the continent's agrarian landscape has increasingly undergone a far-reaching structural transformation. The increasing penetration of small-scale agriculture by domestic and foreign capital through large-scale land acquisitions (LSLA) is promoting mechanization, the adoption of market-oriented crops, land concentration and a shift from subsistence and family farming to agricultural wage employment. While several quantitative and qualitative case-studies have gathered empirical evidence on the potential economic impacts of large-scale land investments, the effects on local social fabrics are still poorly understood.

Given the importance of cooperation-enhancing social structures for ensuring sustainable rural livelihoods, this paper addresses the extent to which the ongoing transformation of agricultural systems is affecting local social capital in sub-Saharan Africa. In particular, it investigates the impact of LSLA on interpersonal and institutional trust. Theoretically, we claim that land deals erode social trust by transforming social reciprocity relations within families and villages through three main channels: the enforcement of structural shifts in rural labor regimes, the redefinition of land use rights (in particular, by transforming common property systems that have traditionally encouraged mutual cooperation into private property) and the promotion of intra-familial and interregional conflict. In addition, we argue that large-scale land acquisitions depress institutional trust by furthering local elite capture (particularly when traditional leaders and local governments make use of discretionary power to seal land deals.

To test our claims, we use georeferenced information on land deals from the Land Matrix project (Land Matrix Global Observatory 2016) as well as survey data from Afrobarometer for all available sub-Saharan African countries. Relying on a combination of different matching techniques and difference-in-means estimations, our results largely confirm our hypotheses:

respondents affected by land deals report lower levels of generalized and personalized trust compared to a control group with no large-scale land investments in their neighborhood. In addition, our treatment group shows less trust in local political institutions and traditional leaders. As expected, we find that the negative effect of land deals on various forms of trust is particularly strong among women.

The paper is structured in the following way: the next section reviews the empirical evidence on the socio-economic effects of LSLAs and underlines the importance of investigating how the present transformation of agrarian systems impacts on local social capital in sub-Saharan Africa. We then proceed by defining key concepts and presenting our theoretical arguments and hypotheses. Section 4 outlines the research design and the employed data. Our analysis and discussion of results are presented in the subsequent section. The final section concludes.

The Socio-Economic Effects of Large-Scale Land Acquisitions on Rural Households

The emerging phenomenon of large-scale acquisitions of arable land in foreign countries (also referred to as land grabbing) has gained global momentum since the financial and food crises of 2008/09 and has generated considerable public debate and media attention. While estimates on the scope of land deals diverge considerably (c.f. Schoneveld 2014, p. 34), there's consistent empirical evidence that – particularly between 2005 and 2012 – land investments have accelerated and reached a new level of internationalism.[1] In fact, recent data on the patterns of large-scale land deals reveal that land deals "seem fully integrated as investment strategies across industries" (Mechiche-Alami et al. 2019, p. 1).

The implications of large-scale land investments[2] on local living working conditions are the subject of a disputed scholarly debate. Proponents of a more optimistic view claim that – particularly under good land governance institutions and strong regulatory capacity – local rural populations could profit from land investments through different channels. Through contract farming schemes, local farmers could have improved access to several inputs and training. Moreover, the supply of much needed capital and technology could foster rural

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[1] For a recent contextualization of the evolution and patterns of LSLAs, see Mechiche-Alami et al. (2019).

[2] Throughout the paper, we will use the terms large-scale land acquisitions, land grabbing, land rush, land deals and land investments interchangeably. Thereby, we rely on the definition from the Land Matrix' (LM) Global Observatory according to which LSLAs imply the (potential) conversion of land from smallholder production, local community use or important ecosystem service provision into commercial use. Only land leased or sold to governments or companies covering an area of 200 hectares or more are considered.

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development and encourage linkage to other economic sectors, thereby increasing job creation capacity and promoting (non-farming) income. LSLA may also ameliorate rural producers' access to world markets and local populations could benefit from community development funds. More critical voices maintain that the poor institutional and regulatory setting that characterizes most of the countries commonly targeted by land investments, render many of these potentially beneficial effects unsustainable and unlikely (c.f. Byerlee and Deininger 2013; D'Orico et al. 2017; Hall et al. 2017; Palliere and Cochet 2018).

A series of quantitative case studies have advanced our understanding of land deal's impact on job creation, household income, food security, environmental outcomes and local inequalities in selected African and Asian states. Most studies analyzing the labor market impacts of large-scale land investments find that job creation expectations - commonly attributed to these agricultural projects – are rarely fulfilled. Several authors demonstrate that the net job creation effect of LSLA is negative: the destruction of jobs in family farming and smallholder agriculture seems higher compared to the creation of new jobs in industrial farming (Ali et al. 2019; Nolte and Ostermeier 2017; Palliere and Cochet 2018). In addition, the analyzed cases reveal that land deals are often tied to a transformation of rural labor markets: from subsistence, family and small-scale farmers to wage laborers and contract farmers.

Empirical evidence on the income effect of large-scale land investments is rather nonconclusive. Jiao et al. (2015), for example, find that economic land concessions have a negative impact on household total income as well as environmental income in Cambodia. Similar results are reported by Shete and Rutten (2015) for a large agricultural investment in Ethiopia. Relying on district-level evidence for Tanzania, Osabuohien et al. (2019) show that female-headed households living in areas hosting large-scale agricultural investments earned lower agricultural wages compared to those not working for land investments projects. Bottazzi et al. (2018), in contrast, find that villages in northern Sierra Leone impacted by large-scale biofuel investment exhibit increased total monetary income food consumption expenditure. The authors note that the agriculture investment transformed "livelihood structures toward a more wage-dependent system" (Ibid: 128).

In addition to land deals' effects on employment and income, some authors have analyzed the extent to which LSLA impact on local food security. The regional quantitative evidence is also mixed: while some studies find that the transformation of smallholder agriculture into large-scale farming has reduced local communities' food security status (Shete and Rutten 2015) or did not reduce the lack of food during lean seasons (Bosch and Zeller 2019), others report that villages affected by large-scale agricultural investments show improvements in food and water security (Bottazzi et al. 2018). Regarding the environmental consequences of land investments, a literature review by Dell'Angelo et al. (2017a) reports several negative environmental consequences of LSLA including water shortage, agrochemical contamination of water and land resources, accelerated deforestation or loss of biodiversity. Finally, several authors caution against increasing social and gender inequalities as a result of large-scale agricultural projects (Bottazzi et al. 2018; Osabuohien et al. 2019).

In light of these contradictory findings, future studies should better distinguish between different project types and contract schemes. For the socio-economic effects reported above, the investment purpose (e.g. land speculation, biofuel project or food production) is likely to matter. In addition, the kind of contract may be crucial: large-scale land investments that promote more inclusive commercial models such as outgrower schemes, for example, are believed to have higher potential to support local rural development (Büntrup et al. 2018; Glover and Jones 2019).

While the reported (mostly quantitative) studies have advanced our understanding of the socio-economic consequences of LSLA in a substantial way, they all provide empirical evidence for specific regions within particular countries. Thus, the external validity of the findings is rather limited. Furthermore, authors have largely failed to address the effect of land deals on one major asset for rural livelihoods: social capital. An increasing body of literature points to the key role of social capital in agricultural settings (Hunecke et al. 2017; Rivera et al. 2019). Particularly by facilitating trust, reciprocity and cooperation, social capital has been shown to promote information exchange and the adoption of new farming technologies (Hunecke et al. 2017; Kansanga 2017; Saint Ville et al. 2016), to enhance collaborative natural resource management (Musavengane and Simatele 2017;), to reduce rural household poverty (Baiyegunhi 2014), to strengthen rural cooperatives' resilience (Beltran Tapia 2012; Borda-Rodriguez et al. 2015), to foster positive food security outcomes (Sseguya et al. 2018) and to improve adaptation strategies and self-insurance against climate risks of smallholders (Groenewald and Bulte 2013; Ng'ang'a et al. 2016).

Considering the pivotal role of social capital for rural societies, it is rather surprising that – to the best of our knowledge – there is no systematic study on the extent to which LSLAs affect local social capital. Historical case studies suggest that agrarian transformations encouraging larger-scale commercial farming at the expenses of collective farming traditions and smallholder agriculture may have long-lasting consequences for social capital. Relying on a comparative-historical method in order to explain changes of social capital across rice farmers in Vietnam's Mekong Delta, Tuan et al. (2014:69), for example, conclude that increasing land concentration and the privatization of rice production after the Land Law of 1993 was accompanied by a decrease in reciprocity, cooperation, mobilization capacity for collective action and social capital among farmers. Studying land enclosures in Spain in the 19th and early 20th century, Beltrán-Tapia (2016) shows that the privatization of common land led to a deterioration of the stock of social capital. In addition to these historical accounts, econometric studies suggest that land inequality – a common co-product of large-scale land investments – has a negative impact on the stock of social capital and cooperation (Fernández 2014; Krishna 2007; Zak and Knack 2001).

This paper seeks to address two major shortcomings of the reviewed literature. By focusing on the impact of large-scale land deals on interpersonal and institutional trust – two major components of social capital – it addresses a question of utmost relevance for rural development that has been largely neglected by previous studies. Furthermore, when analyzing land deals' consequences for local social fabrics, we rely on a comparative quasi-experimental design that allows for a better causal identification of effects and increases the generalizability of our findings.

Understandings of what social capital means differ considerably (c.f. Kansanga et. al. 2019a, pp. 710-714; Rivera et al. 2018, pp. 68-70) and the concept has been criticized for being vague and ambiguous (Ostrom & Ahn 2009, p. 18). One major dimension of social capital is trust. Conceptually, we follow a widely-used definition according to which social (or interpersonal) trust is the horizontally stratified "belief that others will not deliberately or knowingly do us harm, if they can avoid it, and will look after our interests, if this is possible" (Newton 2007, p. 343). It entails an expectation that individuals can rely on each other on the basis of "shared norms, mutual reciprocity and cooperative behavior (Moreno 2011, p. 2672). The literature commonly classifies social trust in generalized trust (the ability to trust people outside one's own family or kinship circle) and particularized trust (capacity to trust one's immediate family, neighbors, or identity group). Institutional trust, in contrast, can be viewed as "a vertical sense of confidence in the formal, legal organizations of government and state, as distinct from the current incumbents nested within those organizations" (Mattes and Moreno 2018, p. 357).

In this paper, we concentrate on social and institutional trust for three main reasons. Added as a new component of social capital by Putnam et al. (1994), trust is viewed as the best or single indicator of social capital by various authors (c.f. Delhey and Newton 2003, p. 94). Furthermore, trust is considered a core condition for facilitating collective action and enabling cooperation (Ostrom & Ahn 2009, p.22; Putnam et al. 1994, p. 167). Sufficiently high levels of trust may allow groups and individuals to self-insure against various types of risks by encouraging joint action. Given its capacity of helping to solve collective action problems, promoting cooperation and strengthening property and contractual rights, trust is of utmost importance for the livelihood of rural livelihoods. It is viewed as a key component of agricultural commons and cooperatives (Durante 2009; Fernández 2014). Finally, our employed survey data (Afrobarometer) contains well-established indicators of both interpersonal as well as institutional trust (whereas other dimensions of social capital such as social networks are barely covered).

Agrarian Transformation and Social Trust: The Arguments

As noted by several authors, agrarian structures in sub-Saharan Africa are undergoing considerable structural transformations. Changes in land tenure systems, rural labor relations, land distribution, the degree of mechanization and reliance of new seeds and farm inputs are observable throughout the continent (c.f. Brooks 2014; Dawson et al. 2016; Dell'Angelo et al. 2017b). We maintain that large-scale land acquisitions – a major source of agrarian transformation in Africa – affect local trust by promoting the privatization of common land, the transition of smallholder (family and subsistence) agriculture into wage-labor and contract farming, intrafamily and intergroup disputes as well as regional elite capture.

Common Grabbing and Shifts in Rural Labor Relations

While common property systems remain a dominant form of landholding in Africa, studies suggest that common land is particularly targeted by land investments (Wily 2011). Conducting a systematic literature review and qualitative comparative analysis, Dell'Angelo et al. (2017) find that 44 out of their 56 identified cases of land grabbing exhibit the characteristics of grabbed commons. In a similar vein, D'Odorico et al. (2017) present some evidence that land, held in common property, is preferentially targeted by land investors, most likely because of the communities' inability to defend their land rights due to lacking formal land titling.

Thus, as a consequence of LSLAs, land is often no longer held as common-pool resource (CPR) with access granted to local individual farmers, families and other community members, but is transferred to private land in the hands of the investors (Adams et al., 2019). Long-term leases and concessions given to investors are tantamount to a redefinition of use rights to land and therefore a shift in agrarian property relationships between customary small-scale farmers and incoming investors (Cotula et al., 2009; D'Odorico et al., 2017; Adams et al., 2018). Moreover, LSLAs do not merely induce a reorganization of production processes from individual smallholder, community and subsistence farming into large-scale commercial surplus production, but is often tantamount to far-reaching changes in land property relations, labor regimes and local livelihoods (Borras and Franco 2012; Bottazzi et al. 2016).

As noted by several authors, commonly managed land may be a reservoir of social trust. Traditionally, common land "played a crucial role in the organization of production in organic economies, source of pasture, fuel and wood" (Beltrán Tapia 2012, p. 514). Common property systems can be seen as the breeding ground that fostered the establishment of networks, values and norms that promote predictable behavior, mutual obligation, diffusion of information as well as the creation of mutual knowledge and trust among individuals and communities (Beltrán Tapia 2016, p. 120; Ostrom and Ahn 2009). While trust can be considered an important precondition for communal land management, common-property regimes strengthen social ties and trust by formal or informal arrangements such as rotation schemes for water allocation or risk sharing institutions that prescribe reciprocal obligations in times of abundance or shortage, (c.f. Cole and Ostrom 2012).

Under customary tenure and commonly managed ownership, livelihoods are secured mostly by subsistence production and economic exchange relations are based on reciprocity. Informal mutual support practices, for example, are one key characteristic of the complex social system of smallholder networks and common property management. In order to cope with seasonal labor shortage or to mobilize labor particularly during weeding or harvest periods, peasant societies across the developing world often rely on cooperative labor (c.f. Abizaid et al. 2015; Grimm and Lesorogol 2012). Also known as reciprocal labor, farmers receiving help on their fields are expected to reciprocate by working on others' field. These forms of traditional labor sharing arrangements are an important source of group identity and solidarity.

Another important informal mutual-aid practice based on reciprocity is the traditional seed exchange, according to which farmers swap seed for other seed or goods such as vegetables. It is an important assurance mechanism against harvest failure and enhances "social cohesion through strengthening community and familial ties" in sub-Saharan Africa (van Niekerk and Wynberg 2017, p. 1099). In a similar vein, smallholders' major source of information and knowledge is often based on interpersonal communication with friends, neighbors and relatives. Issues related to crop production, acquisition of agricultural inputs or marketing of farm products are discussed on a daily basis. Farmers' ability to make decisions may be closely connected with "the networks they maintain for daily information updates with friends, residential neighbors and relatives" (Tuan et al. 2014, p. 85). This interpersonal exchange is likely to foster social cohesion and trust.

The shift to private property, as induced by land deals, undermines the possibility of resorting to such cooperation mechanisms (c.f. Beltrán Tapia 2012). As the reviewed studies show, land investments often enclose common land, replace the complexity of reciprocity networks with a single source of cash income and reduced rural employment opportunities. In fact, ethnographic observations, statistical analyses and experimental economics games show that the privatization of commonly managed land has led to a decline of cooperative practices such as cooperative farm labor in Kenya (Grimm and Lesorogol 2012; Lesorogol 2005, 2008). A qualitative analysis of collective rice farming practices in Vietnam by Tuan et al. (2014) reveals that mutual aid groups (e.g. neighbors helping each other to repair or build houses), collective action and social trust declined after the 1993 Land Law that increased land concentration, wage labor and the share of absentee ownership. According to the study, the new land law also negatively affected daily communication among neighbors and hampered local collaboration for the maintenance of commonly-used irrigation systems.

The studies above provide evidence for the assumption that when (non-cash) reciprocal solidarity expenses are replaced by merely monetary relations, divisions occur and trust may be destroyed among members of the broader family and the village (c.f. Adams et al., 2018). Consequently, monetization of reciprocal social networks is likely to cannibalize the solidarity needed for collective action and trust, therefore harshly inferring with the social fabrics of the affected communities.

We maintain that – by transforming rural neighborhoods, enclosing common land and shifting family and subsistence labor force towards wage labor – LSLAs weaken formerly established social ties, reduce the potential for mutual support activities and thereby negatively affect social trust.

Conflicts and Local Elite Capture

In addition to potentially hampering the kind of cooperation-enhancing activities that characterize smallholder and common land farming systems, LSLAs may erode trust by promoting interfamilial and neighborhood conflict or fostering elite capture and the discretionary power of traditional local leaders. Recent transformations in land tenure systems from commonly-owned agricultural land that is managed collectively under extended family systems into private property may generate considerable local power imbalances, prompting exclusion of certain community members and fostering inequalities and social differentiation (Adams et al., 2019; Samberg et al., 2016). These changes in agrarian structures may foster intrafamilial as well as interregional disputes.

Land investors often consider customary management rights of chiefs, elders and other authorities as ownership rights (c.f. Ahmed et al. 2018). This misperception can lead to alienation processes of those branches of family or kin who enjoy use and access rights but are excluded from management choices. Consequently, inter-lineage or intra-family conflicts can occur. According to Kansanga et al. (2018: 216), smallholder farmers in Ghana facing increasing agricultural modernization are "re-inventing custom to secure access to shared agricultural land at the family level, and thereby dispossessing weaker individuals of their land – either partially or fully." In a similar vein, Adams et al. (2019: 1435) note that the implementation of contract farming schemes at the expenses of common land has transformed "local family institutions by carefully selecting a few household members with influence into the scheme and selectively dispossessing the poor community members." Large-scale land transactions may also prompt regional conflict. In cases in which land deals target areas where boundaries and jurisdictions are not clearly defined (flexible and permeable borders are a common feature of customary land use in Africa) or are disputed, demarcation activities inherent to land investment stiffen the borders and aggravate division among villages (Bottazzi et al., 2016). A recent study by Kansanga et al. (2019c) indicates that increasing pressure on customary lands by LSLAs shape customary land boundary disputes. According to the authors, land investment has prompted intercommunity boundary contestations particularly by increasing the value of land and generating incentives for land leasing in Ghana.

Both intrafamilial as well as intercommunity tensions due to increased monetization of land is likely to threaten the maintenance of a village's sociopolitical structure and depress local levels of social trust. In addition, LSLA may affect institutional trust by encouraging elite capture. Traditional authorities such as chiefs, religious leaders and councils of elders are often considered the owners of common land and investors directly negotiate with them. Local residents and land users often lack knowledge on who is in fact responsible for processes of land acquisitions and lease transfers within communities. Given the poor and largely discretionary land administration systems as well as overlapping use rights inherent to most sub-Saharan states, traditional authorities may take advantage of their roles as land custodians.

Studying large-scale land acquisitions in Sierra Leone, Yengoh et al. (2016: 333) for example note that “many of the arrangements regarding land leases were made by local chiefs and other power brokers, while land owners and users were alienated.” This finding is supported by two studies on the role of chiefs in processes of LSLAs in Ghana by Ahmed et al. 2018 and Lanz et al. 2018. The authors show that local chiefs often act as brokers of land investments and misuse their position by breaking customary as well as statutory land laws. Thereby, traditional authorities would often be “motivated by expected economic gains for themselves at the expense of the communal interests” (Ahmed et al. 2018, p. 570). Community members that maintain close connections to traditional leaders also benefit from large-scale land transactions.

As shown above, privatization of land in the form of LSLA may provide opportunities for rentierism to local elites that may profit from illicit practices or may directly appropriate land and its resources. We argue that – apart from eroding social trust – this also leads to a deterioration of the credibility of local traditional authorities. Based on the channels outlined in our theoretical section - land deals promoting common land enclosure, shifts in rural labor relations as well as elite capture and land claim tensions – we hypothesize that:

H1: *LSLAs reduce local levels of particularized and interpersonal trust.*

H2: *LSLAs reduce local levels of institutional trust.*

Furthermore, we expect these effects to be particularly strong among women and when common land is targeted by land investments. As shown in this section, common agricultural land encourages social reciprocity relations, mutual support activities, cooperation and trust. Thus, we expect the impact of LSLAs on trust to be particularly strong when common land is transformed into private use. In addition, we expect that livelihoods of women are more affected by land deals compared to that of men. The traditional role of women in rural societies is often closely tied to the cultivation of subsistence crops and they constitute the majority of the rural labor force in developing countries (SOFA Team & Doss, 2011), being largely responsible for household food production and agricultural activities. Agricultural transformation promoted by LSLAs should therefore affect women’s occupation and social interactions more than that of men.

In addition, women often belong to the more vulnerable and marginalized groups in rural societies, lacking access to land titles and being more affected by low incomes and poverty compared to men (c.f. Meinzen-Dick et al. 2019). Women in rural African communities are often politically underrepresented as they are rarely entitled to serve as traditional authorities. In light of increasing rentierism and elite capture provoked by large-scale land investments, women are less likely to prevail in land claim or expropriation disputes. For these reasons, we expect that women's social and institutional trust to be disproportionally affected by LSLAs.

H3*: LSLAs reduce local levels of social and institutional trust particularly when common land is targeted.*

H4: *The negative effect of LSLAs on social and institutional trust is stronger among women than among men.*

Research Design

In order to tests our formulated hypotheses, we utilize a quasi-experimental design based on different matching techniques and georeferenced information on land deals as well as survey data from Afrobarometer. In doing so, our design connects answers of circa 130,000 Afrobarometer respondents to spatial data on 232 large-scale land acquisition deals across Africa.

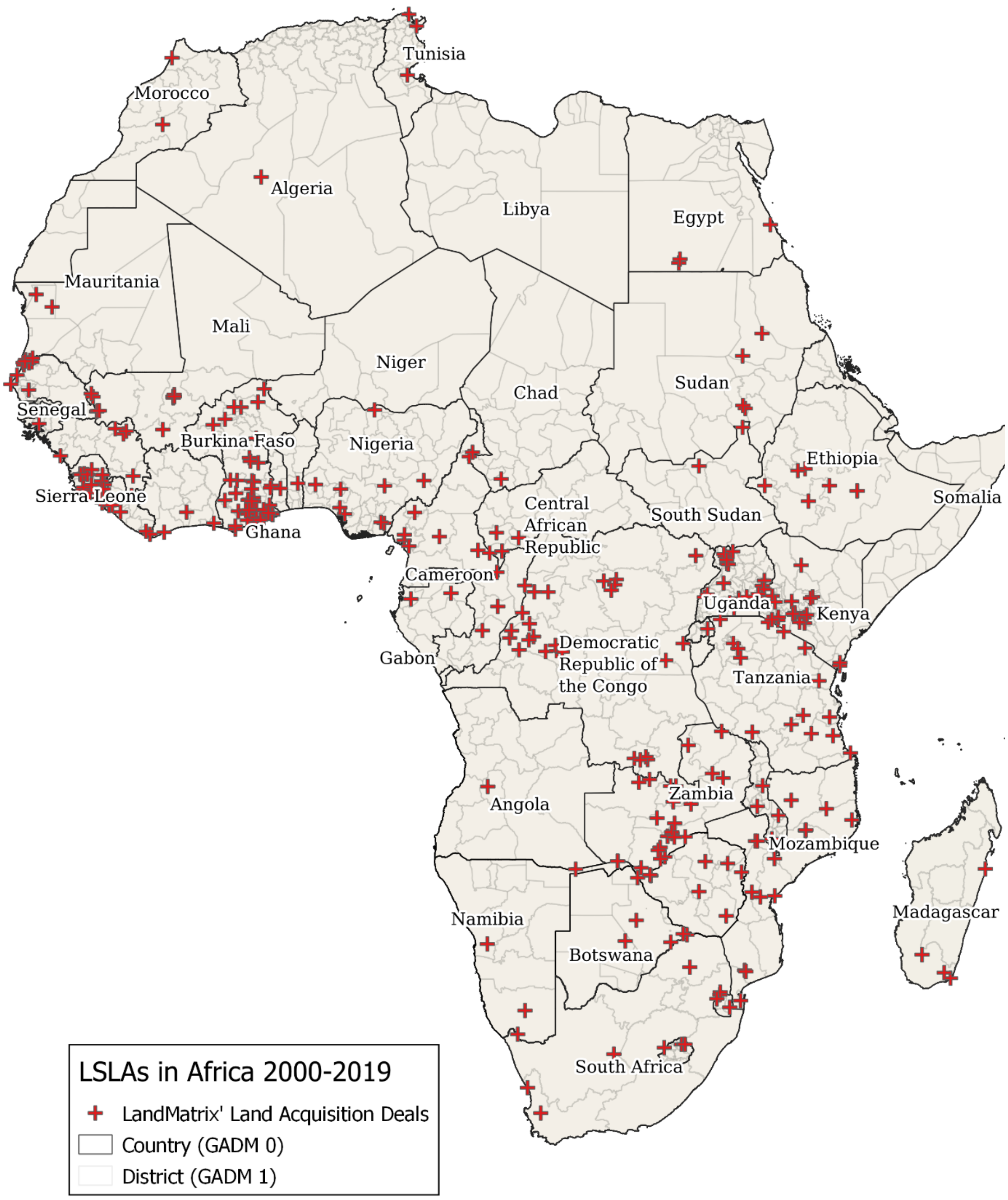
Data and Variables

Information on land acquisition deals in Africa are drawn from the Land Matrix initiative (LMI). The Land Matrix' Global Observatory collects data on "intended, concluded and failed attempts to acquire land through purchase, lease or concession for agricultural production, timber extraction, carbon trading, industry, renewable energy production, conservation and tourism in low- and middle-income countries" (Nolte et al. 2016). For our sample, we only considered concluded deals with signed contracts and a sufficient level of spatial accuracy. Besides, our sample is restricted to deals occurring before 2014 as this year marks the beginning of the latest Afrobarometer round. The remaining observations were split into three sub-samples of land deals covering different timespans matched to Afrobarometer survey schedules.[3] Map 1 provides an overview of all land deals in Africa for which geo-referenced information is available.

In order to assess local perceptions of trust, survey data provided by Afrobarometer – one of the most comprehensive data sources on socioeconomic development and attitudes of citizens in more than African 35 countries – is utilized.

[3] Only considering concluded land deals reduced our sample from over 1,600 cases to roughly 1,300; excluding all deals without precise geo-referenced information further reduced our sample to 324 deals; limiting the time period provided the final samples: 103 deals before 2008; 202 deals before 2012; 232 deals before 2014.

Map 1: Land Deals with Georeferenced Information (Land Matrix Global Observatory)



Afrobarometer conducts cross-national comparative population sample surveys. National samples comprise 1200 or 2400 vis-a-vis interviews with randomly selected adult respondents (18 years or older). Surveys rely on a clustered, stratified, multi-stage area probability sampling design to ensure representativeness. Within a primary sample unit

(PSU) sampling starting points are randomly selected. Interviewers then randomly select households. Within each household one individual respondent is randomly selected. Due to Afrobarometer's data policy as well as representativeness concerns regarding the earlier rounds, we only consider the three most recent rounds, i.e. the 4th, 5th and 6th round.[4]

We focus on survey items related to interpersonal and institutional trust. Institutional trust is assessed by trust levels expressed towards formal institutions at the local (and regional) level, i.e. local councils, traditional leaders and courts. Respondents are asked *"How much do you trust each of them?"* – with answer options on a 4-point Likert scale ranging from "not at all" to "a lot". In a similar fashion, personalized trust is gauged via survey items on *"trust in people you know"* (rounds 4 and 5); *"trust in relatives"* (rounds 4 and 5); *"trust in others"* (round 4 only) as well as *"trust in neighbors"* (round 5 only). Again, all possible answers are given on a 4-point Likert scale ranging from "not at all" to "a lot". Generalized trust is measured by a standard question *"Generally speaking, would you say that most people can be trusted or that you must be very careful in dealing with people?"* which is mimicked from other surveys such as the World Values Survey (WVS). Unfortunately, this dimension of social trust is only evaluated in Round 5 of the Afrobarometer surveys.

As it can be seen, some outcomes of interest can only be operationalized imperfectly and measured unregularly. Additionally, the usual caveats surrounding survey inquiries including social desirability bias, pre-survey selection bias and uncertainty about how different respondents interpret given answer options, are worth remembering. Hence, examining the impact of certain factors of interest on perceptions is methodologically challenging because it is difficult to isolate effects (Hvidman and Andersen 2016). Nevertheless, given the large samples of Afrobarometer surveys, it can be assumed that key impact patterns on local perceptions can reliably be identified. Since survey-based measures often tend to be correlated with behavioral indicators of trust (Glaeser et al. 2000) and different dimensions of social capital and trust are not distinctly separable, we argue that the above-mentioned operationalizations provide a solid ground for further examination.

[4] Round 4 covers 26,866 (mappable) respondents from 20 countries, with surveys conducted in 2008; Round 5 covers 47,007 (mappable) respondents from 34 countries surveyed between late 2011 and 2013; Round 6 covers 53,935 respondents from 36 countries, with surveys conducted during the years 2014-2015.

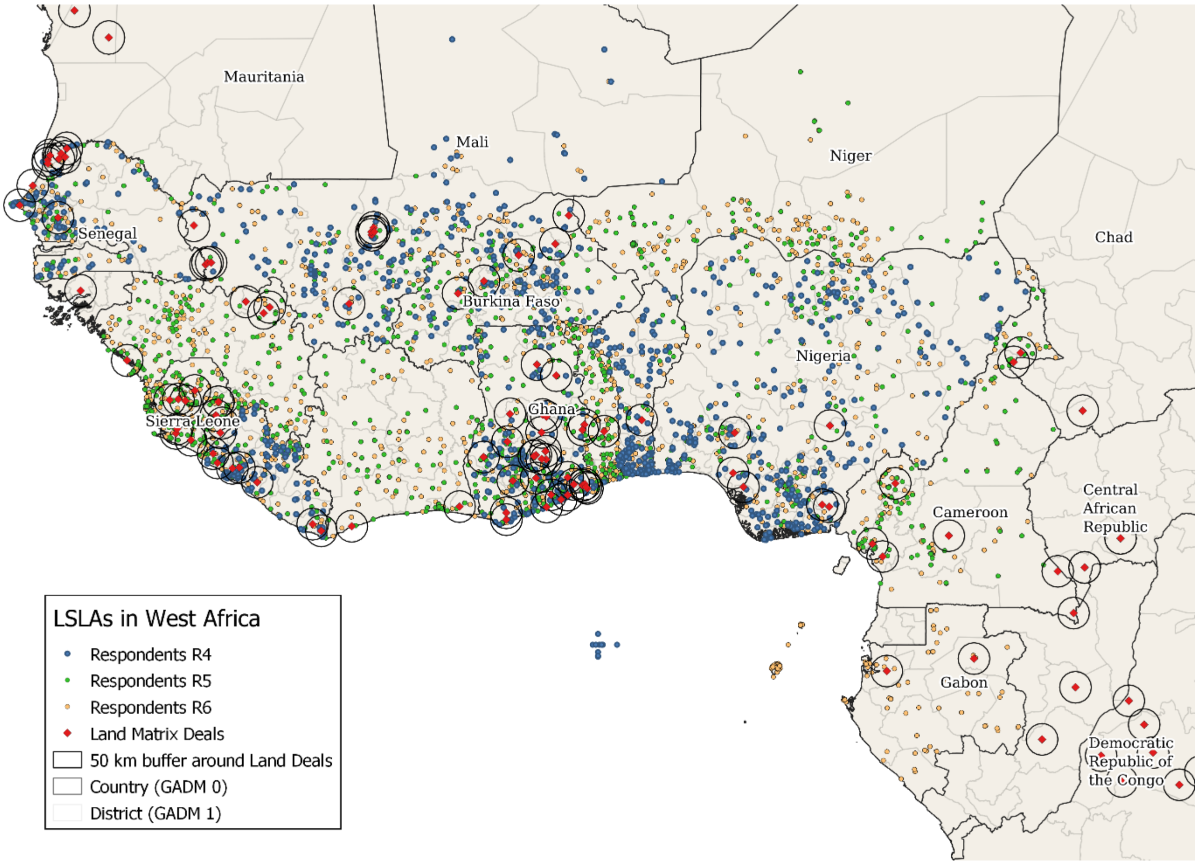
Empirical Strategy: A Quasi-Experimental Design

One of our paper's main contribution is the adoption of a quasi-experimental design to study the effects of LSLAs on the social fabric of rural communities. Our methodological approach resembles a quasi-experimental setting by linking land investments to Afrobarometer survey data based on spatial proximity. Thereby, we match the point coordinates from Land Matrix deal locations with those of Afrobarometer respondents in order to identify individuals that are affected by land grabbing and compare them to those who are not affected.

Assuming that land grabbing will not only cause direct impacts on rural people in the immediate vicinity, but that awareness of its existence will sooner or later sprawl into the surrounding areas, a circular 50km radius buffer zone is calculated around each deal's location. Afrobarometer respondents living within these 50km buffer zones are identified as being "affected" by land grabbing, i.e. they constitute the experiment's *treatment group*. All individuals outside these areas are considered "unaffected" by land deals, i.e. they represent the comparison or *control group*. After executing this process, the treatment group consists of 27.318 individuals, the comparison group of 100.489 respondents. Individuals are accordingly coded as *receiving the treatment* with a binary indicator taking value of D=1 if someone lives within a land deal's buffer zone. Respondents without any overlap are coded as *not receiving the treatment* – taking the value of D=0. 50-kilometer have proven to be solid and justifiable standard size. Research on commuting distances suggests that 50km constitute a practical commutable distance in Africa (Chen et al. 2017). Smaller cutoff zones tend to quickly limit the sample of affected individuals which makes it hard to identify any effects. Furthermore, smaller buffer zones may reinforce possible errors related to imprecisely referenced spatial data – which could cause nontreated individuals to be defined as treated, and vice versa.

Map 2 exemplifies how the paper's quasi-experimental setting looks like for states in Western Africa. By mapping geo-referenced land acquisitions and Afrobarometer respondents, a "treated" group of respondents, being affected by land deals, and a "control" group of non-affected persons are identified.

Map 2: Afrobarometer Respondents and Land Deals in Western Africa



In an ideal experiment, individuals are randomly assigned to treatment and control status. This requires that all subjects have the same ex ante chance of receiving the treatment. In this case, characteristics of participants and non-participants are independent of whether a person actually receives the treatment. Applying these premises to the context of this paper, a large-scale land acquisition constitutes an exogenous intervention, that assigns citizens in the targeted countries to either of two groups: those being affected (treatment) and those who are not affected (comparison) by land grabbing.

If a quasi-random assignment procedure of respondents to either of the two groups is warranted, then there will be no relationship between a respondent's assignment and possible covariates. Made statistically, this would guarantee that ex post differences (after the treatment, D=1) in mean outcomes between treatment (affected) and comparison (non-affected) groups are attributable to the treatment intervention, in this case: land grabbing. This requires that averages of possible covariates have to be balanced across treatment and comparison group.

Covariates

Social Capital and trust levels of individuals may be affected by a range of household- and person specific characteristics. Table 1 and 2 show summary statistics of a respondent's age, gender, level of education, living conditions and employment status as well as certain regional characteristics, i.e. information on whether a respondent lives in an urban or rural area; what sort of infrastructure is available in the area (schools), and which livelihood risks are reported (gone out of food or cash income) for controlled and treated respondents respectively. Looking at the sample means it becomes clear that there exists a relationship between most of the covariates and treatment assignment, i.e. being affected by large-scale land acquisitions is not independent from the above-mentioned covariates.

Table 1: Summary Statistics Covariates for Control Group

Statistic	N	Mean	Std. Dev.	Min	Max	Treatment
urbrur	100,417	1.6076	0.4883	1.00	2.00	0
hh_size	100,303	3.4172	2.4657	0	59.00	0
gender	100,411	1.5017	0.5000	1.00	2.00	0
age	99,682	37.2495	14.6015	18.00	110.00	0
educ	100,154	3.2963	2.1524	0	9.00	0
job	100,124	1.1999	1.1704	0	3.00	0
livcond	99,943	2.7106	1.1680	1.00	5.00	0
inc_risk	100,016	1.9599	1.4224	0	4.00	0
food_risk	100,294	1.0127	1.2082	0	4.00	0
school	100,227	0.8835	0.3209	0	1.00	0

Table 2: Summary Statistics Covariates for Treatment Group

Statistic	N	Mean	Std. Dev.	Min	Max	Treatment
urbrur	27,302	1.5516	0.4973	1.00	2.00	1
hh_size	27,273	3.7844	2.8078	1.00	54.00	1
gender	27,318	1.5027	0.5000	1.00	2.00	1
age	27,105	36.3955	14.3508	18.00	105.00	1
educ	27,238	3.4463	2.1040	0	9.00	1
job	27,197	1.3339	1.1686	0	3.00	1
livcond	27,135	2.5780	1.2408	1.00	5.00	1

inc_risk	27,216	1.9818	1.3610	0	4.00	1
food_risk	27,270	0.9937	1.1721	0	4.00	1
school	27,206	0.8789	0.3262	0	1.00	1

Made statistically, using a multinomial logit to predict treatment assignment as a function of all 10 covariates confirms that they are not independent of each other. An according likelihood ratio test with 10 degrees of freedom is strongly significant (LR = 1409.4, p = 2.2e-16). This indicates that the two groups are unbalanced in terms of the observed covariates. Certain household, area and individual characteristics significantly influence a respondent's likelihood of being assigned to treatment status. Since balance across treatment and control groups is not warranted, a differences-in-means comparison for the outcome variables would yield biased estimates of the treatment effect. In order to deal with this issue and ensure that the distributions of the covariates are the same for treated and untreated respondents, we employ matching procedures based on Propensity Scores (PS) and Coarsened Exact Matching (CEM). For all provided statistics, the free R software for statistical computing is used (R Core Team 2013).

Analysis

Propensity Score Matching

Propensity Score Matching (PSM) is a semi-parametric statistical technique that matches a treatment observation with one or more comparison observations based on an observation's propensity score (Iacus et al. 2012). The key intention of any matching technique is to prune observations from the available data so that the remaining sample has a better balance between the treated and control groups. In PSM the Propensity Score represents a unit’s predicted probability of being treated given a set of covariates. In this case, the propensity score of an Afrobarometer respondent indicates how likely it is that this respondent will be affected by a large-scale land acquisition based on individual, household and regional characteristics. The PS is calculated with a Logit model:

$$PS = Prob\ (D = 1|X) = Prob(\beta_0 + \beta_1 X_1 + \ \beta_2 X_2 + \ldots + \beta_n X_n + \ \varepsilon > 0),$$

where the PS is the probability of being treated (D = 1) dependent on a multidimensional vector
of pretreatment covariates X.

Figure 1: Distribution of Propensity Scores Among Treatment and Control (PSM)

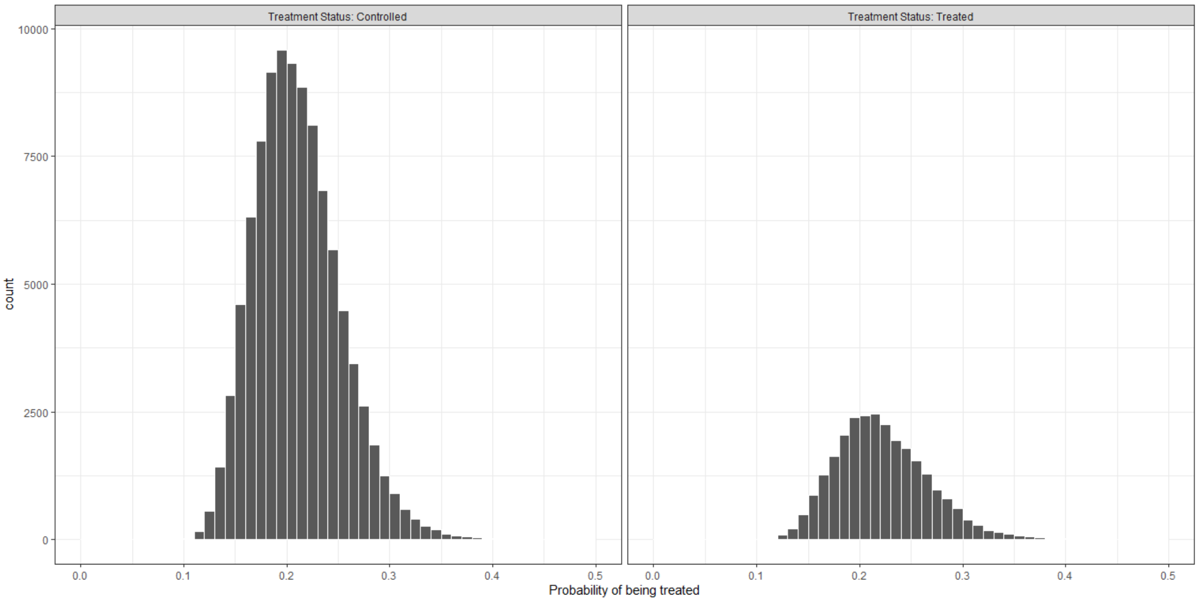


Figure 1 shows the distributions of the calculated propensity scores for the two groups. What can be seen is that the distributions cover the same range of probability (PS) values. That indicates that it should be possible to find suitable pairs of treatment and control units in the matching process. Furthermore, the small Propensity scores mirror the fact that the likelihood of being affected by a LSLA is rather small. Given the large number of control units as compared to size of the treatment group, this does not come as a surprise.

Based on the calculated propensity scores it is possible to match treated to non-treated respondents.[5] Rosenbaum and Rubin (1983) have shown that matching on the propensity score
is equivalent to matching on covariates. Matching is performed with a nearest neighbor technique and one-to-one ratio, i.e. each treated unit is matched to the one control unit which is closest in terms of a distance measure – here the distance measure is the propensity score. Table 3 presents the summary statistics for our covariates after one-to-one ratio PS-Matching. The post-matching distribution of mean values of the covariates indicates that the matching algorithm was performed successfully. The covariate means of the two groups are now better balanced.

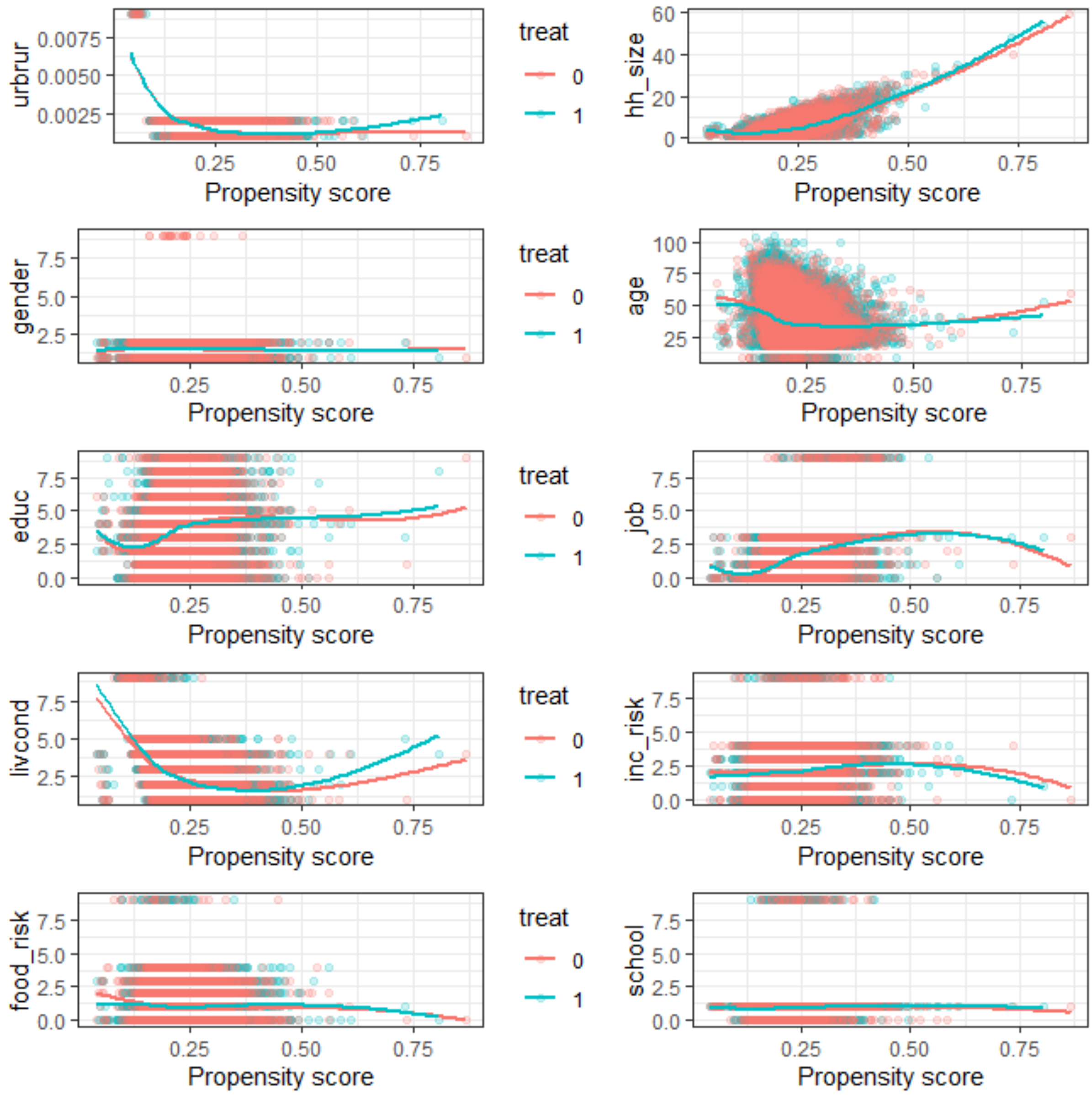
[5] Matching is performed with R package “MatchIt” (Ho et al. 2011)

Table 3: Summary Statistics Covariates After PS-Matching

Statistic	Mean (D=0)	Mean (D=1)	Unmatched Mean Diff.	Matched Mean Diff.	Improvement
urbrur	1.5564	1.5560	-0.0570	-0.0005	99.1647
hh_size	3.7834	3.7930	0.3654	0.0095	97.3955
gender	1.5047	1.5027	-0.0048	-0.0019	59.2656
age	35.9895	36.1819	-0.8408	0.1924	77.1163
educ	3.4657	3.4626	0.1473	-0.0031	97.9121
job	1.3729	1.3679	0.1397	-0.0050	96.4091
livcond	2.6293	2.6211	-0.1237	-0.0082	93.3714
inc_risk	2.0137	2.0080	0.0150	-0.0056	62.4492
food_risk	1.0001	1.0077	-0.0204	0.0076	62.9076
school	0.9098	0.9122	0.0076	0.0024	68.7031
N	27,318	27,318	127,807	54,636	

Figure 2 plots the mean of each covariate against the estimated propensity score, separately by treatment status (blue and red lines indicate the the area of common support). It shows that the treatment and control groups have almost identical means in all ten covariates at each value of the propensity score. A Likelihood Ratio test (LR=4.9206, p=0.8964) and according T-tests (all p-values between p=0.11 and p=0.91) confirm the null hypothesis of no mean differences in the covariates.

Figure 2: Covariates' Means and Estimated Propensity Score



The described procedure shows that finding a matching solution able to improve balance between controlled and treated units seems accomplishable for the covariates. What remains unaddressed by matching techniques such as PSM is the fact that balancing covariates often worsens the balance for other variables of the utilized observational data. So called "equal percent bias reducing" (EPBR) matching methods like PSM do not per se "guarantee any level of imbalance reduction in any given data set, its properties only hold on average across samples" (Iacus et al. 2012, p. 2).

Coarsened Exact Matching

Corasened Exact Matching (CEM) is a member of the class of matching methods called "Monotonic Imbalance Bounding" (MIB). In contrast to EPBR matching techniques, MIB allows that the maximum imbalance between groups is chosen by the user ex ante (instead of being calculated by a process of ex post checking and repeated re-estimations). Adjusting imbalances for single variables then comes with no effect on imbalances of any other variable (Iacus et al. 2011). The main idea of CEM is to (temporarily) coarsen each variable in *X* for the purpose of matching. Variable values are grouped and sorted into strata based on the same values of the coarsened *X*. With an "exact matching" algorithm, units in strata that contain at least one treated and one control unit are retained, all other units in any stratum are pruned from the data set (Iacus et al. 2011, 2012).

To assess the level of balance, we compare a multivariate imbalance measure for the Propensity Score Matching and the Coarsened Exact Matching. This measure is based on a $\mathcal{L}_1$ difference between the multidimensional histogram of all covariates in both treated and control group.[6] Table 4 shows summary statistics for various imbalance measures after the PS matching process. Table 5 does the same for the CEM algorithm. The second column of either of the two tables reports the differences in means. The third, L1, reports the imbalance measure for the *j*-th variable. The remaining columns show the difference in the empirical quantile of the distributions for the treatment and control group. Beyond that, a multivariate imbalance measure ($\mathcal{L}_1$) and the percentage of local common support (LCS) are computed. Comparing PSM and CEM, the CEM algorithm does a slightly better job in reducing imbalances in the data. Not only are the mean differences balanced – which is also the case after PS matching – but also the quantiles of the distributions are rendered more similar. In our case, CEM reduces the multivariate imbalance measure from L1=0.907 for propensity score matching to L1=0.886. The percentage of local common support increases from 4.8% to 7.6%. Whereas PSM makes use of all 27.318 treated observations matching them to 27.318 control units, CEM matches 12.955 treatment units to 26.274 control respondents and thereby creates more similar pairs of matched treatment and control units.

[6] All CEM computation is performed with R package "cem" developed and provided by Iacus et al. (2018).

Table 4: Imbalance Measures for Propensity Score Matching

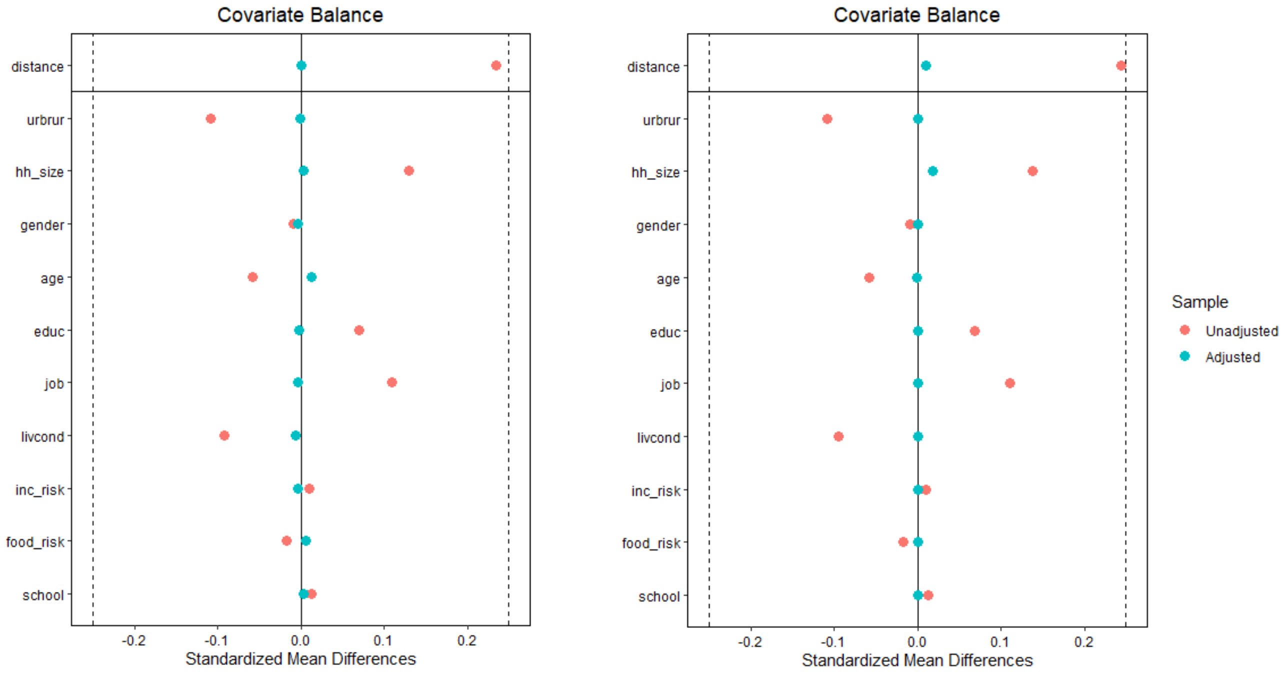
Variable	Statistic	type	L 1	Min	25%	50%	75%	Max
urbrur	-0.0004758767	(diff)	0.000732118	0	0	0	0	0
hh_size	0.0095175342	(diff)	0.022768870	0	0	0	0	-5
gender	-0.0019401127	(diff)	0.004209679	0	0	1	0	-7
age	0.1924006150	(diff)	0.030163262	0	0	0	0	5
educ	-0.0030748957	(diff)	0.015813749	0	0	0	0	0
job	-0.0050150084	(diff)	0.016509261	0	0	0	0	0
livcond	-0.0081997218	(diff)	0.042682480	0	0	0	0	0
inc_risk	-0.0056373087	(diff)	0.025294678	0	0	0	0	0
food_risk	0.0075774215	(diff)	0.016838714	0	0	0	0	0
school	0.0023793836	(diff)	0.009920199	0	0	0	0	0

Table 5: Imbalance Measures for Coarsened Exact Matching

Variable	Statistic	type	L 1	Min	25%	50%	75%	Max
urbrur	-0.003303426	(diff)	0.003577335	0	0	0	0	0
hh_size	0.222590474	(diff)	0.045043172	0	0	0	1	0
gender	-0.012019416	(diff)	0.012019416	0	0	0	0	0
age	0.680571619	(diff)	0.037154566	0	0	0	1	1
educ	-0.070456338	(diff)	0.004084463	0	0	0	0	0
job	0.021955700	(diff)	0.025025654	0	0	0	0	0
livcond	-0.151875968	(diff)	0.056701424	0	0	-1	0	0
inc_risk	0.178258411	(diff)	0.076028351	0	0	0	0	0
food_risk	0.071890707	(diff)	0.048006989	0	0	0	0	0
school	-0.017426290	(diff)	0.017426290	0	0	0	0	0

In other words, both Propensity Score as well as Coarsened Exact Matching techniques are capable to successfully remove imbalances in the data as it is shown in Figure 3 plotting the standardized mean differences in the covariate balances for the samples before and after matching is performed, with CEM (right panel) performing slightly better than PSM (left panel).[7]

Figure 3: Standardized Men Differences in Covariate Balances with PSM (left) and CEM (right)



Estimation techniques

As soon as there are no systematic differences left in the covariate distributions, it is possible to estimate the average treatment effect on the treated units:

$$ATT = E\ [Y(1) - Y(0)|D = 1] = E\ [Y(1)|D = 1] - E\ [Y(0)|D = 1],$$

where E (Y1 | D = 1) = E (Y1) denotes the average potential outcome under treatment in the treatment group. Under the premise of (un-)conditional randomization, a simple differences-in-means comparison of the outcome variables of interest serves as an unbiased estimator of the average treatment effect: $ATE = E[Y(1) - Y(0)] = E[Y(1)] - E[Y(0)]$.

[7] We also performed two additional matching algorithm, namely nearest neighbor Propensity Score matching with a 1:2 ratio – matching each treat unit to the two control units with the smallest distance in the PS. Results do not significantly differ from 1:1 ratio PSM. Furthermore, an algorithm based on Exact Matching saw the sample reduced to 3180 control units and 2640 units resembling pairs with exactly the same values in *X*. Since the results do not change much, we only report estimates for 1:1 ratio PSM and CEM.

Findings

Each of the following tables report summary statistics for all outcome variables by treatment status to enable an easy difference-in-means comparison. The results are presented in sections referring to the different outcomes of interest. This allows to differentiate between directions and magnitudes of effects across various forms of trust.

Institutional Trust

Table 6a: Institutional Trust - Differences-in-Means (PS)

Statistic	Trust in Local Councils	Trust in Courts	Trust in Traditional Leaders
Mean (D=0)	1.4883	1.7059	1.8813
Mean (D=1)	1.4185	1.6896	1.8630
Mean Diff.	- 0.0698***	- 0.0163*	- 0.0183
Observations	50,461	52,197	29,627

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

Table 6b: Institutional Trust - Differences-in-Means (CEM)

Statistic	Trust in Local Councils	Trust in Courts	Trust in Traditional Leaders
Mean (D=0)	1.5277	1.7625	1.8802
Mean (D=1)	1.4375	1.7190	1.8702
Mean Diff.	- 0.0902***	- 0.0435***	- 0.0100
Observations	36,191	37,516	20,892

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

Tables 6a and 6b show the results for the three institutional trust measures. As can be observed, treatment group respondents (D=1) display lower levels of trust than their control group counterparts (D=0) across all three institutions. However, only the differences for "Trust in Local Councils" and "Trust in Courts" are statistically significant. It is also worth noting that the estimates' magnitudes tend to be larger in the sample matched with Coarsened Exact Matching as compared to Propensity Score Matching. The direction of the effects however is negative across both samples and all outcomes of interest. Since our outcome data is coded in Likert scales, these shifts in mean differences are somewhat difficult to interpret. Odds ratios calculated from Ordinal Logistic Regression (OLR) models that regress the outcomes of interest on the treatment status can provide some helpful insight in this regard.

The odds ratio of a binary treatment indicator for "Trust in Local Council" is 0.857 which means that respondent who are affected by land grabbing are 14.3% ((1-0. 857) * 100) less likely to trust their local administrators. Likewise, the decrease in the odds ratio for trust toward courts amounts to 5.3% (OR: 0.9747). These results support the expectations from our hypothesis H2.

Generalized Trust

Table 7 presents the mean differences for the "Generalized Trust" item asking respondents if they think that most people can be trusted (coded 1), or one must be careful when dealing with people (coded 0).

Table 7: Generalized Trust - Difference-in-Means (PS and CEM)

Statistic	Generalized Trust (PSM sample)	Generalized Trust (CEM sample)
Mean (D=0)	0.1959	0.1921
Mean (D=1)	0.1489	0.1442
Mean Diff.	- 0.0470***	- 0.0479***
Observations	20,796	14,282

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

These results indicate that “Generalized Trust” is lower among individuals of the treatment group. The mean differences are statistically significant at the 1-percent-level. Since “Generalized Trust” is assessed via a binary indicator, a Logistic Regression can provide additional insight into the effects LSLAs have on displayed trust levels.

Table 8: Output of Binary Logistic Regression for Generalized Trust

	Dependent variable:			
	Generalized Trust			
	PSM sample	CEM sample	PSM sample and covariates	CEM sample and covariates
Treatment	-0.3311***	-0.3450***	-0.3267***	-0.3484***
	(0.0370)	(0.0473)	(0.0380)	(0.0483)
Urban vs. Rural			0.1650***	0.0957*
			(0.0411)	(0.0531)
Household size			0.0122*	0.0131
			(0.0068)	(0.0135)
Gender			-0.1012***	-0.0822*
			(0.0391)	(0.0477)
Age			0.0029**	0.0045**
			(0.0014)	(0.0019)
Education			-0.1144***	-0.1305***
			(0.0108)	(0.0154)
Job			-0.0983***	-0.0592***
			(0.0177)	(0.0223)
Living Conditions			0.0900***	0.1559***
			(0.0165)	(0.0222)
Facing food risk			-0.0061	0.0548**
			(0.0180)	(0.0250)
Facing income risks			0.0524***	0.0603***
			(0.0160)	(0.0213)
School			0.0382	-0.0857
			(0.0599)	(0.1160)
Constant	-1.4123***	-1.4361***	-1.5713***	-1.6618***
	(0.0256)	(0.0268)	(0.1561)	(0.2289)
Observations	20,796	14,282	20,145	14,189
Log Likelihood	-9,466.7500	-6,577.9770	-8,980.2490	-6,384.0810
Akaike Inf. Crit.	18,937.5000	13,159.9500	17,984.5000	12,792.1600
Note:	*p<0.1; **p<0.05; ***p<0.01			

Results from Table 8 confirm that respondents who are affected by land investments in their vicinity are less trusting towards strangers. The treatment coefficients are statistically significant at the 1-percent-level across all model specifications. Also note that the effect sizes are very similar with minor changes in the second decimal only. This reassures us that the covariates are independent from treatment assignment and that our matching procedures made the findings robust to different model specifications. The odds ratio for the binary treatment indicator is 0.7057 (CEM with covariates). Accordingly, treatment group respondents are about 29.5% less likely to report that they feel that most people can be trusted.

Personalized Trust

A similar picture can be reported regarding “Personalized Trust”. As Table 9a and 9b display, treatment group respondents show significantly lower levels of trust towards their relatives, people they know as well as their neighbors across both samples. Only the coefficient on “Trust in others from your country” fails to reach statistical significance – however, showing a negative sign, too. The decrease is sharpest for “Relatives”. An odds ratio of 0.786 indicates a 21.4% drop in the odds of treatment group respondents trusting their relatives. Similarly, the odds for neighbors decrease by 15.7% (OR: 0.843) and by 9.5% (OR: 0.905) for fellow countrymen.

Table 9a: Personalized Trust - Difference-in-Means (PSM)

Statistic	Trust in Relatives	Trust in People you know	Trust in Neighbors
Mean (D=0)	2.4202	1.4615	1.7686
Mean (D=1)	2.3292	1.4095	1.7007
Mean Diff.	- 0.091***	- 0.0520***	- 0.0679***
Observations	30,525	30,411	21,080

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

Table 9b: Personalized Trust - Difference-in-Means (CEM)

Statistic	Trust in Relatives	Trust in People you know	Trust in Neighbors
Mean (D=0)	2.4330	1.4622	1.7773
Mean (D=1)	2.3296	1.4071	1.6860
Mean Diff.	- 0.1034***	- 0.0551***	- 0.0913***
Observations	23,258	23,183	14,444

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

Tying the findings for generalized as well as personalized trust together with the mean differences found in the institutional trust measures, the results suggest that large-scale land acquisitions do indeed decrease trust levels among surveyed respondents. For 6 out of 7 trust measurements, treatment group observations appear to be less trusting than non-treated units. Respondents who are affected by large-scale land acquisitions perceive their local councils and courts institutions less trustworthy and tend to view other people – including their relatives and neighbors – more sceptic than individuals from the control group. These findings suggest that our first two hypotheses can be confirmed. LSLAs reduce local levels of institutional and interpersonal trust.

Subgroup Analyses: Common Land and Women

As outlined in the theoretical section, there are firm reasons to assume that the negative effects of large-scale land acquisitions on trust are particularly strong among women and when common land is targeted. However, the results in Table 10 suggest that the hypothesis regarding common land cannot be confirmed. The common land coefficient does not reach statistical significance for most of the outcomes of interest. The positive and significant coefficient for the variable “Trust in Relatives” actually contradicts our expectation.

Table 10: Comparing Regression Coefficients of all LSLAs to Common Land

	Dependent variables:							
	Trust in Local Council	Trust in Courts	Trust in Traditional Leaders	Generalized Trust	Trust in Relatives	Trust in People you know	Trust in Others from your country	Trust in Neighbors
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (all LSLAs)	-0.0777***	-0.0211*	-0.0070	-0.0511***	-0.1097***	-0.0490***	-0.0311	-0.0942***
	(0.0123)	(0.0121)	(0.0162)	(0.0068)	(0.0130)	(0.0146)	(0.0261)	(0.0176)
Common Land	0.0262	-0.0445	0.0576	0.0269*	0.0660**	0.0020	-0.1189*	0.0426
	(0.0270)	(0.0272)	(0.0351)	(0.0155)	(0.0314)	(0.0353)	(0.0709)	(0.0403)
Constant	1.0721***	1.5090***	1.4868***	0.1611***	2.3021***	1.2595***	0.8643***	1.5032***
	(0.0548)	(0.0544)	(0.0734)	(0.0320)	(0.0594)	(0.0667)	(0.1124)	(0.0824)
Observations	35,945	37,257	20,751	14,189	23,111	23,037	8,655	14,351
R^2	0.0526	0.0258	0.0725	0.0247	0.0188	0.0268	0.0272	0.0568
Adjusted R^2	0.0523	0.0255	0.0720	0.0239	0.0183	0.0263	0.0259	0.0560
Residual Std. Error	1.0262 (df = 35932)	1.0380 (df = 37244)	1.0394 (df = 20738)	0.3746 (df = 14176)	0.8753 (df = 23098)	0.9807 (df = 23024)	0.9746 (df = 8642)	0.9715 (df = 14338)
F Statistic	166.2393*** (df = 12; 35932)	82.3126*** (df = 12; 37244)	135.1488*** (df = 12; 20738)	29.9195*** (df = 12; 14176)	36.9417*** (df = 12; 23098)	52.7876*** (df = 12; 23024)	20.1399*** (df = 12; 8642)	71.9545*** (df = 12; 14338)
Note:	*p<0.1; **p<0.05; ***p<0.01							

However, it should be noted that the robustness of these estimates might be rather limited due to the fact that only 15% of the land deals in our sample contains information on the former ownership status. Accordingly, in the utilized sample there are merely 1.800 respondents affected by a land deal targeting communal land. Under these circumstances, it is hard to yield statistically robust estimates of heterogenous treatment effects. Thus, while hypothesis 3 cannot be confirmed, the reported results should be interpreted with care due to lacking information on former land tenure regimes.

A more coherent and clear-cut picture emerges when the treatment effects are compared between men and women. Tables 11a, 11b and 11c report the mean differences in trust levels for all outcome variables separated by treatment status and gender. The results indicate that women indeed appear to be more strongly affected by LSLAs compared to men. For all but one outcome measure, female respondents display a greater drop in trust levels when affected by large-scale land investments than their male counterparts. Even though men and women alike are less trusting when they are members of the treatment group, the negative effects are considerably stronger for female respondents. Accordingly, we can confirm our fourth hypothesis. Women's social and institutional trust is negatively and disproportionally affected by LSLAs.

Table 11a: Institutional Trust - Difference-in-Differences (Gender)

Statistic	Trust in Local Councils	Trust in Courts	Trust in Traditional Leaders
Mean (D=0 Women)	1.5691	1.7831	1.9105
Mean (D=1 Women)	1.4467	1.7262	1.8850
Mean Diff. (Women)	- 0.1224	- 0.0569	- 0.0255
Mean (D=0 Men)	1.4811	1.7391	1.8451
Mean (D=1 Men)	1.4277	1.7113	1.8544
Mean Diff. (Men)	- 0.0534	- 0.0278	0.0093
Diff.-in-Diff.	0.0690	0.0291	0.0348

Table 11b: Generalized Trust - Difference-in-Differences (Gender)

Statistic	Generalized Trust
Mean (D=0 Women)	0.1983
Mean (D=1 Women)	0.1460
Mean Diff. (Women)	- 0.0523
Mean (D=0 Men)	0.1849
Mean (D=1 Men)	0.1421
Mean Diff. (Men)	- 0.0428
Diff.-in-Diff.	0.0095

Table 11c: Personalized Trust - Difference-in-Differences (Gender)

Statistic	Trust in Relatives	Trust in People you know	Trust in Others from your country	Trust in Neighbors
Mean (D=0 Women)	2.4365	1.4432	1.2178	1.7820
Mean (D=1 Women)	2.3299	1.3788	1.1996	1.6637
Mean Diff. (Women)	- 0.1066	- 0.0644	- 0.0182	- 0.1183
Mean (D=0 Men)	2.4287	1.4849	1.3126	1.7719
Mean (D=1 Men)	2.3293	1.4383	1.2560	1.7107
Mean Diff. (Men)	- 0.0994	- 0.0466	- 0.0566	- 0.0612
Diff.-in-Diff.	0.0072	0.0178	- 0.0384	0.0571

Conclusion

Agrarian transformations induced by large-scale land deals may profoundly change rural livelihoods. Although there is growing evidence on the socio-economic effects of land investments, we lack proper understanding on how the transition from smallholder farming to commercial, large-scale agriculture affects social capital. Considering the utmost importance of social ties and institutional support for societal wellbeing, this paper is a first attempt to systematically test the effect of LSLAs on trust in sub-Saharan Africa.

Our findings suggest that policies aiming to transform African agriculture such as the Alliance for Green Revolution in Africa (AGRA) may disrupt local social fabrics in a considerable way.[8] Relying on a combination of matching techniques and statistical estimations, we find that individuals affected (or living close to) land investments show lower levels of trust in relatives or neighbors (particularized trust) as well in people in general (generalized trust). Furthermore, we show that trust in institutions including local councils or courts also decrease in regions hosting land deals (institutional trust). Due to the fact that our analysis was carried out based on a quasi-experimental design matching respondents on covariates, the results can be interpreted as strong and solid support for our two main hypotheses. Surprisingly, we do not find that trust in local traditional authorities changes with LSLAs. While previous research suggests that traditional leaders such as chiefs may profit from land investments at the expense of communal interests (c.f. Ahmed et al. 2018; Lanz et al. 2018; Yengoh et al. 2016), our estimations indicate that confidence in these customary authorities remains relatively unaffected.

Our hypothesis that particularly the enclosure of common land leads to reduced local trust is not supported by the analysis. This non-finding, however, may be driven by scarce information on land tenure forms in the Land Matrix Global Observatory and should be interpreted with care. In a future step, we will exploit land ownership data for specific countries to better assess whether the transformation of commonly-managed land (that encourages reciprocal behavior and cooperation) into private property is indeed linked to a particularly stark reduction in local trust.

An additional important finding of our study is that women's trust is disproportionally affected by LSLAs. As demonstrated in the theoretical section, women's traditional role in rural Africa is often tied to subsistence farming and food production. At the same time, they are clearly underrepresented in customary bodies and are particularly vulnerable to dispossession promoted by land deals. Initiatives and policies promoted by governments, multilateral institutions and private donors seeking to modernize Africa's agriculture may directly clash with several targets of United Nation's Sustainable Development Goals including equal rights

[8] The initiative focuses, among other things, on commercial crops, external inputs such as agrochemicals and synthetic fertilizers and large-scale land acquisition.

to ownership and control over land for vulnerable groups (Goal 1), access to safe, nutritious and sufficient food all year round (Goal 2) and gender equality (Goal 5).

Our findings highlight that – in addition to analyzing the impacts of land investments on economic outcomes such as local employment or income – more scholarly attention needs to be devoted towards how the global land rush may affect rural societies as a whole. The erosion of trust caused by LSLAs in rural areas may have far-reaching and irreversible consequences for social cohesion, political processes, functioning of democracies, conflict and poverty in sub-Saharan Africa.

Much room remains for future research. While we have for example highlighted several mechanisms through which LSLAs may affect trust (enclosure of common land, transformation of rural labor relations, promotion of intrafamilial as well as regional conflict as well as elite capture), qualitative research is needed to assess to plausibility of these channels. In a next step, we aim to improve the quality of our research design by using information on the size of land investments in order to respectively adjust the radius of our buffer zones. Thereby, we can better differentiate between individuals directly affected by LSLAs and those living close to LSLAs areas. Through this strategy, we would avoid the admittedly rather arbitrary choice of our buffer zone sizes.

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