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FACTOR MARKET ACTIVITY AND THE INVERSE FARM SIZE-PRODUCTIVITY RELATIONSHIP IN TANZANIA

By

Ayala Wineman and Thomas S. Jayne

Food Security Policy *Research Papers*

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ABSTRACT

Although the inverse farm size-productivity relationship (IR) is sometimes used to motivate arguments in favor of smallholder-led agricultural development, it remains unclear what drives this relationship. It may be attributed to market imperfections that compel small farms to use land more intensively than large farms. Using a three-wave longitudinal household survey from Tanzania, we examine whether the intensity of the IR is related to local factor market activity for land, labor, credit, and animal and machine traction. The IR is evident in Tanzania, although it disappears when family labor is valued at the prevailing local agricultural wage rate. This suggests that labor market imperfections (possibly linked to other market failures) drive the IR. Furthermore, the IR is significantly weakened in the presence of relatively active markets for most factors of production. This suggests that the IR is at least partly driven by imperfections in rural factor markets, underscoring the importance of strategies to improve the functioning of these markets.

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ACRONYMS

GPS	Global Positioning Systems
ha	hectare
IHST	Inverse hyperbolic sine transformation
IR	Inverse farm size-productivity relationship
kg	kilogram
LSMS	Living Standards Measurement Study
TSh	Tanzanian shillings
NBS	National Bureau of Statistics
UNFPA	United Nations Population Fund (formerly United Nations Fund for Population Activities)
USAID	United States Agency for International Development

1. INTRODUCTION

It is by now a stylized fact that land productivity tends to be inversely correlated with farm size, a phenomenon known as the inverse farm size-productivity relationship (IR) (Eastwood, Lipton, and Newell 2010). First noted in Russia (Chayanov 1926), this pattern has since been documented across a wide range of settings, including Sub-Saharan Africa (Barrett, Bellemare, and Hou 2010; Carletto, Savastano, and Zezza 2013; Carletto, Gourlay, and Winters 2015; Larson et al. 2014). However, the reasons for the IR have long puzzled economists, with explanations ranging from systematic variation in land quality across farm sizes (Barrett, Bellemare, and Hou 2010; Benjamin 1995), to measurement error in land area (Carletto et al. 2013), to market imperfections (Feder 1985; Sen 1966), to an edge effect (Bevis and Barrett 2017). Consensus on the causes of the IR riddle remains elusive. Still, the IR continues to feed into debates on the design of agricultural policies in developing countries (Hazell et al. 2010; Larson et al. 2014; Larson, Muraoka, and Otsuka 2016; Lipton 2009). In this paper, we consider whether the IR can be explained by imperfections in rural factor markets. Specifically, we examine the relationship between the intensity of the IR in Tanzania and the local rate of market participation for various factors of agricultural production.

Analysts endeavor to disentangle the causes of the IR for several reasons. If land productivity inherently varies with farm size, it indicates that land redistribution can, at least in principle, bring about greater aggregate productivity. Particularly in Sub-Saharan Africa, the need to raise average agricultural productivity is widely acknowledged (Larson et al. 2014), and if smaller farms are more productive, it follows that policies should aim to facilitate the transfer of land from larger to smaller holdings. In fact, the IR has served as justification for land reforms in developing countries (Lipton 2009), and further serves to motivate a strategic focus on smallholders within agricultural development policy (Larson et al. 2014). Alternatively, if the IR is merely an artifact of mismeasurement, no policy prescription is necessary. And if the IR is understood to reflect factor market failures, this would shift the policy focus toward improving the functioning of those markets (Assunção and Braido 2007; Heltberg 1998).

When small farms are unable to optimally adjust their on-farm factor ratios, this may prompt them to allocate inputs intensively (especially labor), resulting in higher per-hectare crop yields (Feder 1985; Sen 1966). If that is the case, we would expect the IR in Sub-Saharan Africa to weaken as factor markets emerge or grow increasingly active. In this paper, we consider the case of Tanzania and exploit variation in factor market activity over time and space to explore whether the level of local market activity conditions the relationship between farm size and productivity. We hypothesize that the negative relationship between farm size and crop revenue per hectare will be diminished in the presence of more active factor markets for land rental, agricultural labor, agricultural credit, and oxen and tractor rental. To our knowledge, no other study tests this relationship directly within a single equation to discern whether market imperfections (with attention to multiple factor markets) seem to drive the IR.

Our main finding is that, consistent with the observations of others (Carter 1984; Ali and Deininger 2015; Lamb 2003), farm-households apply labor more intensively on smaller farms. However, this is less true for households that face relatively high levels of local market activity for land and labor. Econometric results confirm that, with regard to most markets considered (with the exception of tractor rental), the IR is diminished in its intensity in the presence of greater market activity. However, the vast majority of cropping households in Tanzania face levels of market activity that are below the point at which we estimate the IR would be completely nullified. These findings are relevant for the design of strategies to promote agricultural productivity and efficient forms of land distribution.

The rest of the paper is organized as follows. Section 2 reviews the literature on the IR, with particular attention given to the potential role of market imperfections. A conceptual framework of the relationship between factor markets and the farm size-productivity relationship is offered in section 3. A description of the data and variables used is given in section 4, and section 5 follows with an introduction to our empirical approach. Descriptive and econometric results are found in section 6, and section 7 concludes with a summary and discussion of possible policy implications.

2. BACKGROUND

As noted, researchers aim to identify the cause(s) of the negative farm size-productivity relationship because different causes lead to very different policy prescriptions. A number of explanations have been proposed, including, *inter alia*, omitted variable bias (especially from land quality), systematic measurement error, and market failures. To start with, regions with favorable land quality may see more dense settlement and, accordingly, greater land fragmentation and smaller average farm size (Sen 1966; Benjamin 1995; Larson et al. 2014). In fact, it is not uncommon to observe a negative association between land quality and farm or plot size (e.g., Ali and Deininger 2015), and if this factor is not properly accounted for in analysis, a detected inverse relationship between farm size and productivity may be specious. To address this concern, Barrett, Bellemare, and Hou (2010) examine the IR in Madagascar and also control for measured soil characteristics, including acidity, carbon content, and sand and clay content. However, their inclusion does not weaken the IR, prompting the authors to rule out this source of omitted variable bias as an explanation.

A second suggested explanation for the IR relates to measurement error, particularly with respect to land size. If farmers systematically under-estimate the size of small farms or over-estimate the size of large farms while accurately reporting the crop harvest, we would wrongly conclude that higher yields per hectare are found on relatively small farms (Lamb 2003). In other words, the IR may be merely a statistical artifact. Recently, authors examining plots measured with Global Positioning Systems (GPS) have found evidence that undercuts this argument. Farmers in Uganda tend to systematically over-estimate the size of small plots, often rounding up to a larger whole number, while the area of larger farms is typically under-estimated (Carletto, Savastano, and Zezza 2013). As a result, using accurately measured plot areas strengthens the estimated intensity of the IR.[1,2]

Other explanations for the IR have also been proposed. Henderson (2015) examines the IR in Nicaragua and finds that controlling for technical or allocative efficiency does not make the IR disappear. Thus, this factor does not, on its own, solve the IR puzzle. Barrett (1996) argues that the absence of an insurance market drives small farmers who are net food buyers to apply family labor intensively in order to avoid being later exposed to price volatility. And Bevis and Barrett (2017) argue that crops near a plot's edge receive more sunlight and attention from the farmer. Therefore, small plots may exhibit higher yields because a greater proportion of their crops are positioned close to an edge.

A final explanation for the IR, and the focus of this paper, is that factor market failures drive small farms to allocate inputs (especially labor) with greater intensity, resulting in higher crop yields. With perfectly functioning markets, one would expect the returns to land to be equal across farms of different sizes. However, the prevalence of market failures in developing countries has long been recognized (De Janvry, Fafchamps, and Sadoulet 1991; Dillon and Barrett 2017). As demonstrated by Feder (1985) and Sen (1966), the failure of at least two markets for factors of agricultural production will result in shadow prices that vary across households, which leads to heterogeneous input application rates. If these shadow prices are correlated with farm size, land productivity would

[1] This pattern is also seen in Tanzania, although it is found to vary across different African countries. Nevertheless, across all countries considered, the IR is evident when GPS measurements are used (Carletto, Gourlay, and Winters 2015).

[2] Recently, potential measurement error in terms of crop harvest has received attention (Gourlay, Kilic, and D. Lobell 2017; Desiere and Jolliffe 2017). Given that many analyses of agricultural outcomes in developing countries (e.g., the returns to intensification) rely on estimated yields and often produce logical results, it is not clear that systematically misreported yields are pervasive. We consider this an open-ended question.

also vary systematically by farm size. Thus, when peasant farmers are unable to adjust their farm size and also face labor market imperfections that distort their shadow wage, they apply excess family labor to their own small farms at levels unmatched by larger farms (Lamb 2003). Along these lines, the more intensive use of land on small farms has been widely observed (Carter 1984; Deininger, Zegarra, and Lavadenz 2003; Ali and Deininger 2015; Lamb 2003).

The mechanisms through which imperfections in various factor markets can lead to the IR vary, depending on the factor in question. For example, while small farms tend to rely on family labor, large farms are more likely to draw in hired labor. Frictions in the labor market, such as search or contracting costs, would lend a disadvantage to larger farms (Eswaran and Kotwal 1986). (The tendency for hired labor to shirk and the consequent need for supervision has also been highlighted as a potential disadvantage for large farms (Feder 1985; Eswaran and Kotwal 1986; Deininger et al. 2016).) Consequently, in a given setting, small farms have an advantage. Relatively large farms are also more likely to use machinery because lumpy inputs produce economies of scale (Eastwood, Lipton, and Newell 2010). Again, transaction costs for machinery rental would differentially affect small and large farms. Land market imperfections can be found with restrictions on land transactions, ambiguous property rights, or if land prices absorb the value of non-productive uses (Heltberg 1998; Deininger, Hilhorst, and Songwe 2014; Wineman and Jayne 2017). If land markets are missing or thin, it may be impossible for small farms to expand their farm size to effectively use their labor endowment.

The available evidence is often consistent with the notion that factor market performance plays a role in the IR. In Rwanda, where farm sizes tend to be small, Ali and Deininger (2015) find that the IR holds when net profits are calculated with family labor valued at shadow wages, but disappears when family labor is valued at the local prevailing wage rates. This is consistent with labor market imperfections being a key driver of the IR. In rural China in the 1930s, Benjamin and Brandt (1997) find that excess returns to land were highest where factor markets were less developed or less active. In India, Deininger et al. (2016) find that the IR has attenuated and maybe even disappeared between 1982 and 2007, and the authors attribute this to an increasingly complete labor market in which the household labor endowment is no longer a strong determinant of on-farm labor demand. A similar pattern of IR attenuation or reversal over time is evident in Vietnam (Liu, Violette, and Barrett 2016) and Indonesia (Yamauchi 2016), although this is somewhat differently attributed to rising agricultural wages (a proxy for heightened factor market activity) and/or the introduction of labor-saving technology, which is favorable to larger farms.

It should be noted that a number of analysts have conducted tests for the IR at plot-level with the inclusion of household fixed effects and concluded that the IR is not attributed (or only limitedly attributed) to market failures (Assunção and Braido 2007; Carletto, Savastano, and Zezza 2013; Carletto, Gourlay, and Winters 2015). This is because the market conditions faced by a single household (in a single year) would be controlled for in this model specification, and yet, the inverse relationship between plot area and crop production persists. However, Barrett, Bellemare, and Hou (2010) do note that controlling for household fixed effects reduces the magnitude of the size-yield relationship by about one-third, and it therefore seems likely that multiple factors (including market conditions) drive the IR.

A brief overview of the Tanzania setting will provide context for our analysis. Approximately three-quarters of Tanzania's population of over 50 million reside in rural areas, and 80% of the working population is engaged in agriculture. What's more, roughly one third of the rural population lives in poverty (USAID 2011). Thus, the health of the agricultural sector affects a wide swath of the population and is highly relevant to poverty alleviation efforts. In addition, Tanzania's population is growing quickly at a rate of 2.9% per year, with almost three-quarters below the age of 30 (UNFPA 2009). Particularly in rural areas, this may present a labor surplus if young people cannot find adequate employment. Recently, concerns have been raised regarding land distribution in Tanzania, where 91% of farms are considered to be small-scale (up to 5 ha), though medium-scale farms account for 44% of all operated farmland (among farms up to 100 ha) (Jayne et al. 2016). The latter group is both a source of commercial dynamism and a potential threat to land access for small-scale farmers. This is among the reasons for policy makers to consider whether agricultural policies favor –or should be designed to favor– relatively small or large farms.

3. CONCEPTUAL FRAMEWORK

As noted, there are reasons to expect that better functioning factor markets would diminish the intensity of the IR. Generally, whenever a factor of production is more suitable for large farms, an improvement in market activity for that item can be expected to benefit large farms (i.e., to decrease their relative *dis*advantage) and weaken the IR. And when a factor market imperfection inhibits small farms from adjusting their land or labor endowments, an increasingly well-functioning market could likewise weaken the IR by alleviating the conditions that drive smaller farms to allocate family labor so intensively. Below, a more detailed explanation is offered for each factor of production considered in this paper.

- *Land:* As farmland can be transacted more fluidly and with fewer transaction costs, both large and small farms would be better able to optimally match their farm size to their labor endowment (Deininger, Zegarra, and Lavadenz 2003; Lamb 2003; Bliss and Stern 1982). Thus, small farms with excess family labor might expand their farm size (if they can afford to do so). Larger farms with insufficient labor might rent out land, resulting in less severe productivity differences across relatively small and large farms.
- *Labor:* Larger farms are more likely to rely on hired labor, as the family labor endowment tends to be insufficient as farm size increases. When the agricultural labor market becomes more fluid and spatially integrated, the search costs associated with finding and selecting laborers will fall, and larger farms particularly stand to benefit (Lamb 2003). Note that improved communications, such as the widespread use of mobile phones, may ease the process of securing laborers. Better functioning labor markets may present a different benefit to small farmers, who intensively allocate labor to the family farm (Benjamin 1992). With more fluid agricultural (and other off-farm) labor markets, these farm-households may be able to sell their excess labor in their rural communities and would therefore divert it from their own farms, resulting in moderated crop yields (see Deininger et al. 2016).
- *Credit:* If larger farms are better able to offer suitable collateral (see Kevane 1996), the greater availability of credit might, in the short term, particularly benefit larger farms. Alternatively, if small farms can more easily access credit at the start of the growing season, it might be used for something like land rental to optimally adjust the farm's land-to-labor ratio (Benjamin and Brandt 1997; Heltberg 1998; Feder 1985; Eswaran and Kotwal 1986).
- *Traction:* As with hired labor, it is larger farms that are more likely to already rely on non-manual traction (oxen or tractors) for land preparation. Thus, as search and contracting costs fall with more fluid markets, so would the relative *dis*advantage of larger farms. Furthermore, scale economies are likely to be found in the use of non-manual traction, such that larger farms will more readily adopt non-manual traction as it becomes easier to access (Yamauchi 2016). Note that labor and traction are often regarded as substitutes, particularly at the time of land preparation (Liu, Violette, and Barrett 2016). However, these may be complementary if the same farm uses traction (and is therefore able to expand in size) and hires in labor at different times during the growing season.

This discussion points to the following hypothesis: Across the various factors of production considered, the inverse relationship between farm size and productivity should be attenuated in the presence of greater factor market activity (a proxy for better functioning markets).

4. DATA AND VARIABLES

This study draws from three waves of the Living Standards Measurement Study (LSMS) for Tanzania, a nationally representative longitudinal data set collected in 2008/09, 2010/11, and 2012/2013 (hereafter referred to as survey years 2009, 2011, and 2013). The LSMS is implemented by the Tanzania National Bureau of Statistics and is a research initiative of the World Bank. The data set captures detailed information on landholdings and agricultural production over the previous year, as well as household demographics. 2,250 cropping households were interviewed in 2009, and because the survey followed households that split apart, 2,581 were interviewed in 2011, and 3,219 were interviewed in 2013. Our household fixed effects regression analysis is limited to those who were present in the 2009 survey wave, and among these, 2,048 were re-interviewed in all three survey waves, bringing the rate of attrition to 7.3%.[3] Regression-based tests for attrition bias (Wooldridge 2002: 581) indicate that our analysis is not generally influenced by systematic attrition with respect to our main dependent variable (see Table A1 in the appendix). Four observations of farms larger than 100 hectares in size are dropped from analysis in order to avoid the undue influence of these outliers. We also make use of additional variables appended to the LSMS data set, including local population density estimates, distance to agricultural markets, and annual weather outcomes (NBS 2014). Population weights are included in all analyses, and monetary values are adjusted for inflation using the consumer price index and are reported in 2013 Tanzanian shillings (TSh).

The definitions of key variables used in analysis are provided in Table 1. Because the proper measure of productivity is not obvious, this analysis is repeated with a set of dependent variables, including the *gross* value of crop production per hectare planted in the main season, as well as the *net* value of crop production per hectare planted in the main season. In the latter case, the netted-out costs of production include expenditures on land rental, seed and chemical inputs, and hired labor. We focus on the main season both because the area cultivated can be directly estimated and to ensure that all observations in a given survey year are in reference to the same season. However, 29.1% of cropping households plant some seasonal crops outside of the main season, often because they reside in areas with a bimodal rainfall distribution. In a robustness check, we will repeat the analysis at the year-level (aggregating all variables over the previous year).

The level of market activity among various factors of agricultural production is captured as the proportion of cropping households in a region that participate in the market (as renters or customers).[4] While this is not a direct measure of the extent to which a market is characterized by transaction costs or other imperfections, it is used here as a proxy for the level of market fluidity. Although both rental and sales markets for land and traction would be of interest in a study of market imperfections, data availability limits our focus to rental markets. This is because the data set does not capture acquisitions through the sales market, making it impossible to estimate the time-variant level of sales activity.

[3] It is possible for households to shift in and out of cropping, so the exact rate of attrition for the subset of cropping households in our analysis is not precisely calculated.

[4] The LSMS data set is not precisely representative at region level (NBS 2014). However, these variables serve as a rough estimate of the level of local factor market activity.

Table 1. Definitions of Key Variables

Variable	Construction
Area planted (ha)	Estimated area under crops, based on estimated plot areas and the proportion cropped. For tree or permanent crops, per-plant (or per-tree) area estimates are used (source: NBS (2011)). Where this method produced areas under cultivation that together exceed the plot area, all area estimates for that plot are scaled proportionally to sum to the plot size.
Gross value crop production per ha (100,000s TSh)	The value of all crop production on the farm, divided by area. Values are estimated by respondents (for seasonal crops) or derived from sales reports. For households that did not sell a given crop, prices are imputed using the median sales value observed that year. (Note: The main season crop production includes all permanent and tree crop production for the farm.)
Net value crop production per ha (100,000s TSh)	Gross value of crop production minus the costs of inputs for land rental, seed and chemical inputs, and hired labor, divided by area. In some model specifications, the value of family labor is also netted out of the numerator, with labor valued at either the household-specific shadow wage or the market wage.
Shadow wage of family agricultural labor	A household's shadow wage is estimated with a simple production function and is calculated as $\hat{\beta}(\frac{\hat{Y}}{L})$, where $\hat{\beta}$ is the estimated coefficient on logged family labor, $\hat{Y}$ is the predicted value of output, and L is the number of family labor days (Jacoby 1993).
Market wage for agricultural labor	For households that hired in labor, this is the average per-day wage observed (total expenditure on wages/total person-days of hired-in labor). For households that did not hire in labor, this is the median value observed at the smallest local geographic area for which at least 10 observations are found in the same rural/urban category. Geographic areas considered include district, region, and agro-ecological zone.
Factor market activity level	The proportion of cropping households in the region that rent in or hire in a given item (or access credit). For all items except credit, this involves an expenditure and excludes borrowing arrangements or use of an owned item.

Source: Authors.

5. EMPIRICAL APPROACH

We first confirm that the IR is evident across farms in Tanzania using the following general equation:

$$Y_{it} = \alpha + \beta[Area_{it}] + \boldsymbol{X}'_{it}\boldsymbol{\theta} + \varphi_t + \delta_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is gross or net value of crop production per hectare cultivated for household i at time t; $Area_{it}$ is hectares cultivated; $\boldsymbol{X}_{it}$ is a vector of variables that may include characteristics of the household (composition and wealth) and farm (distance from the nearest agricultural market, seasonal weather outcomes), crop composition (proportion of area devoted to various crop categories), and inputs (irrigation, manure, fertilizer, and labor); φ_t is a year fixed effect, δ_i is a household fixed effect, and ε_{it} is a stochastic error term.[5] Our focus is on β, and because the dependent variable is divided by area, a negative and statistically significant value of β indicates that the IR is evident in Tanzania. In other words, a marginal increase in area cultivated is associated with lower land productivity.

Household fixed effects, δ_i, are thought to control for unobservable factors relevant to agricultural production and farm size, such as a farmer's skill or ability. Though farm size changes over time, the household fixed effect also controls for some time-invariant aspects of local land quality. Following the approach of Ali and Deininger (2015), we alternately value family labor in three ways, assigning it a value of zero and valuing it at the household-specific shadow wage or the market wage rate. Because this empirical strategy does not account for all possible sources of endogeneity, including the area cultivated in a given year, our results should be regarded as descriptive. Heteroskedasticity robust standard errors are used in all regression analyses.

To test our main hypothesis that the inverse farm size-productivity relationship is weaker in the presence of better functioning factor markets, we apply the following general equation:

$$\begin{aligned} Y_{it} &= \\ &\alpha + \beta[Area_{it}] + \lambda\left[Area_{it} \times Activity\_level^{k}_{it}\right] + \rho\left[Activity\_level^{k}_{it}\right] + \\ &\boldsymbol{X}'_{it}\boldsymbol{\theta} + \varphi_t + \delta_i + \varepsilon_{it} \end{aligned} \tag{2}$$

where $Activity\_level_{it}$ is the level of local factor market activity for household i at time t for a given factor of agricultural production (indexed with k), and all other variables are as in equation (1). Our focus is on λ, and we would expect this to be positive if greater levels of factor market activity are associated with a weakened IR. Note that the key independent variable (the level of factor market activity) is exogenous to the household.[6]

[5] Many studies of the IR use a log-log model, but we prefer to use level terms because the interpretation of results, including a key interaction term in equation (2), is more straightforward.

[6] An alternative model specification was considered involving the individual farms' factor market participation. However, this was deemed unsuitable in light of the data limitations. As noted in section 3, for both labor and land markets, the mechanism through which the IR would be attenuated may relate to small farms renting out/hiring out their endowments. Unfortunately, this side of the market is crudely captured in the data set, with only a binary indicator for agricultural wage work (and only if this was the main employer for a household member) and evident under-reporting of rented out land (as noted by Deininger, Savastano, and Xia (2017)).

6. RESULTS

6.1. Descriptive Results

To understand the relationship between area and land productivity, farms in the pooled sample are divided into three terciles of farm size. (Farm size refers to the total land area held by each household.) Summary statistics of key variables to be used in analysis are given in Table 2, where the last column presents a test for the difference in mean values between the smallest and largest terciles. Because our analysis is focused mostly on crop production during the main growing season, these statistics refer strictly to the main growing season. It is evident that small farms see a higher gross value of crop production per ha cultivated, as compared with large farms (P=0.000). Thus, within the farm sizes captured in this data set, the IR is present in Tanzania. On average, small farms apply manure more intensively than large farms (P=0.056), though the difference in the inorganic fertilizer application rate is not statistically significant. Consistent with patterns observed elsewhere (Carter 1984; Ali and Deininger 2015), small farms apply labor more intensively than large farms (224 labor days per ha cultivated, as compared with 124 labor days for large farms; P=0.000). Most of this is sourced from the family labor endowment.

In terms of participation in factor markets, large farms exhibit higher rates of participation (on the demand side) in markets for agricultural labor, credit, and oxen. Specifically, 52% of large farms hire in labor, as compared with 30% of small farms (P=0.000); 4% of large farms access agricultural inputs using credit, while almost no small farms do so; and 13% of large farms rent in oxen, as compared with just 6% of small farms (P=0.000). Interestingly, tractor rental does not vary by farm size category (P=0.991), although the rate is rather low (4%) across all categories. Small farms are more likely to rent in land (12%, as compared with 8% of large farms, P=0.000), which is consistent with the notion that small farms rent in land to compensate for their limited initial owned endowment (Bliss and Stern 1982). As crop composition may vary systematically across farm sizes (Carter and Wiebe 1990; Bharadwaj 1974; Barrett 1996), we also account for crop choices on the farm. Large farms allocate, on average, a greater proportion of area to legumes, cash crops, and a residual category for sugar cane, spices, and timber, while small farms place a greater emphasis on fruits and vegetables (P=0.000 in all cases). In some model specifications in section 6.2, crop composition will be included among the controls.

A key variable in equation (2) is the regional rate of factor market participation among cropping households. Figure 1 illustrates these activity levels across regions and over the three survey waves for each market considered. Among all cropping households, 9.9% rent in land. However, Figure 1 reveals that land rental participation rates are far from uniform. Furthermore, some regions see an increase in participation rates over time, while others see rates that fluctuate. With regard to hiring in agricultural labor, 40.2% of households turn to the market to supplement their own labor endowment. Again, these rates have a geographic pattern, with some regions growing noticeably darker (i.e., seeing higher rates) over time. Similar patterns are also found for the oxen and tractor rental markets, with active oxen rental markets toward the west and active tractor rental markets concentrated in the east. Just 1.8% of cropping households access some agricultural inputs with the use of credit, and this low participation rate is evident in the maps of Figure 1. However, where this market can be found, it appears to be growing.

Table 2. Summary Statistics of Key Variables, by Farm Size Tercile

	(1) Tercile 1		(2) Tercile 2		(3) Tercile 3		Test: (1) = (3)
	Mean	SD	Mean	SD	Mean	SD	P-value [a]
Gross value crop production per ha cultivated in main season (100,000s TSh)	6.39	(8.24)	5.25	(6.73)	4.32	(5.67)	0.000
Area cultivated in main season (ha)	0.43	(0.23)	1.06	(0.44)	3.04	(4.43)	0.000
Landholdings (ha)	0.51	(0.23)	1.34	(0.27)	4.55	(6.47)	N/A
Inputs (main season)							
1= Irrigated	0.04	(0.20)	0.04	(0.18)	0.04	(0.20)	0.684
Kgs manure per ha cultivated	69.56	(206.01)	77.69	(205.60)	58.58	(175.10)	0.056
Kgs fertilizer per ha cultivated	11.67	(34.36)	11.09	(30.61)	10.71	(30.43)	0.295
Family labor days per ha cultivated	209.23	(191.44)	168.17	(179.98)	113.16	(131.37)	0.000
Total labor days per ha cultivated	224.41	(196.99)	180.08	(186.37)	124.05	(137.08)	0.000
Factor market participation (year)[b]							
1= Rent in land	0.12	(0.33)	0.10	(0.30)	0.08	(0.27)	0.000
1= Hire in agricultural labor	0.30	(0.46)	0.39	(0.49)	0.52	(0.50)	0.000
1= Access agricultural credit	0.00	(0.06)	0.01	(0.12)	0.04	(0.19)	0.000
1= Rent oxen	0.06	(0.25)	0.11	(0.32)	0.13	(0.33)	0.000
1= Rent tractor	0.04	(0.20)	0.04	(0.21)	0.04	(0.20)	0.991
Proportion of cultivated area in main season under:							
Maize	0.41	(0.35)	0.41	(0.32)	0.39	(0.29)	0.204
Rice	0.11	(0.27)	0.09	(0.22)	0.09	(0.20)	0.009
Other cereals	0.06	(0.19)	0.08	(0.19)	0.07	(0.18)	0.023
Tubers	0.12	(0.24)	0.11	(0.22)	0.09	(0.19)	0.000
Legumes	0.20	(0.25)	0.21	(0.24)	0.24	(0.25)	0.000
Cash crops	0.02	(0.10)	0.04	(0.13)	0.06	(0.15)	0.000
Fruits and vegetables	0.07	(0.16)	0.05	(0.12)	0.03	(0.10)	0.000
Sugar cane, spices, timber	0.01	(0.05)	0.01	(0.07)	0.01	(0.07)	0.009
Observations	2,490		1,966		2,350		

[a] P-values of a t-test for a significant difference in means between farm size terciles 1 and 3.

[b] Values for the main season are very similar.

Figure 1. Factor Market Activity across Tanzania (2009, 2011, 2013)

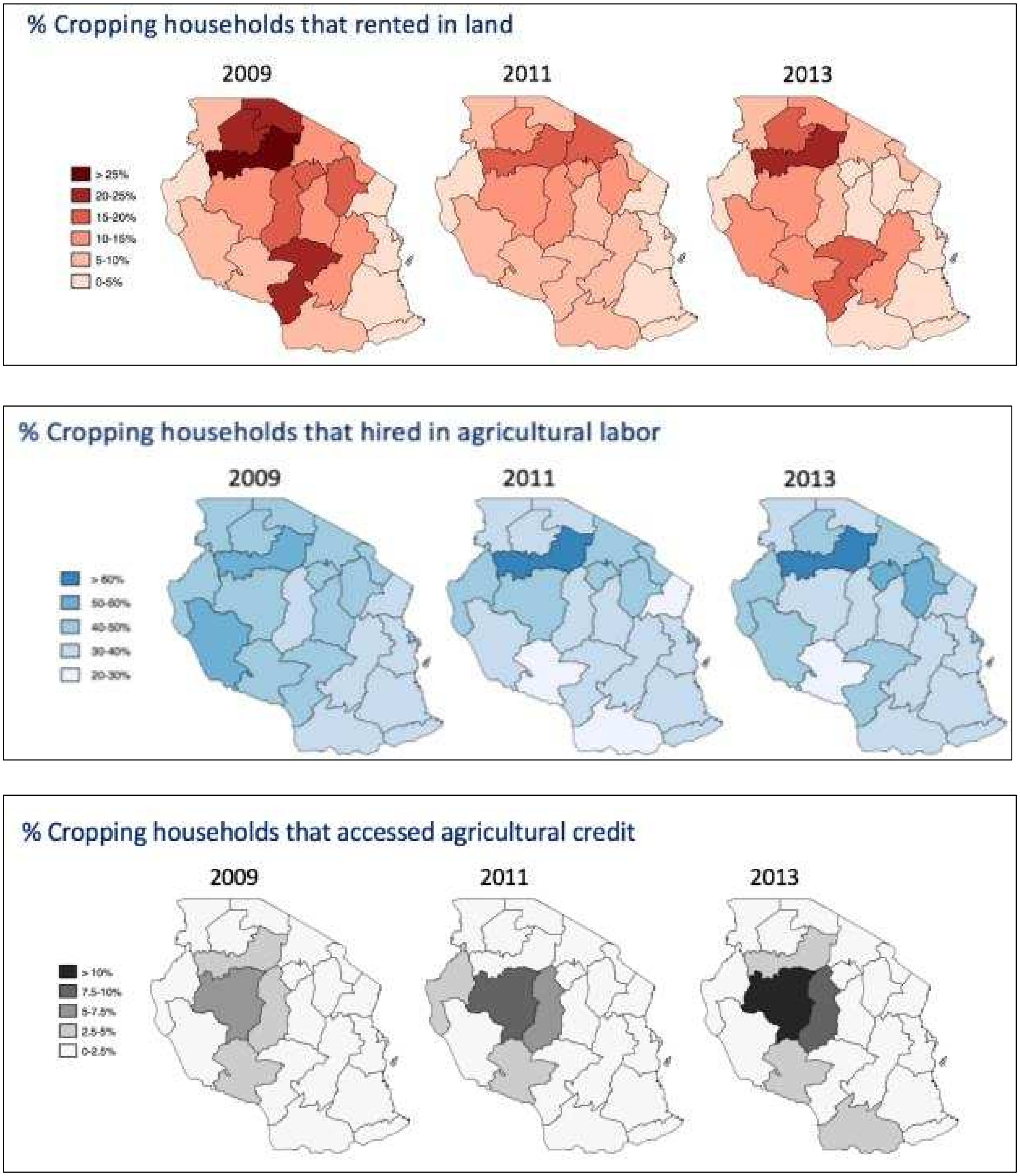
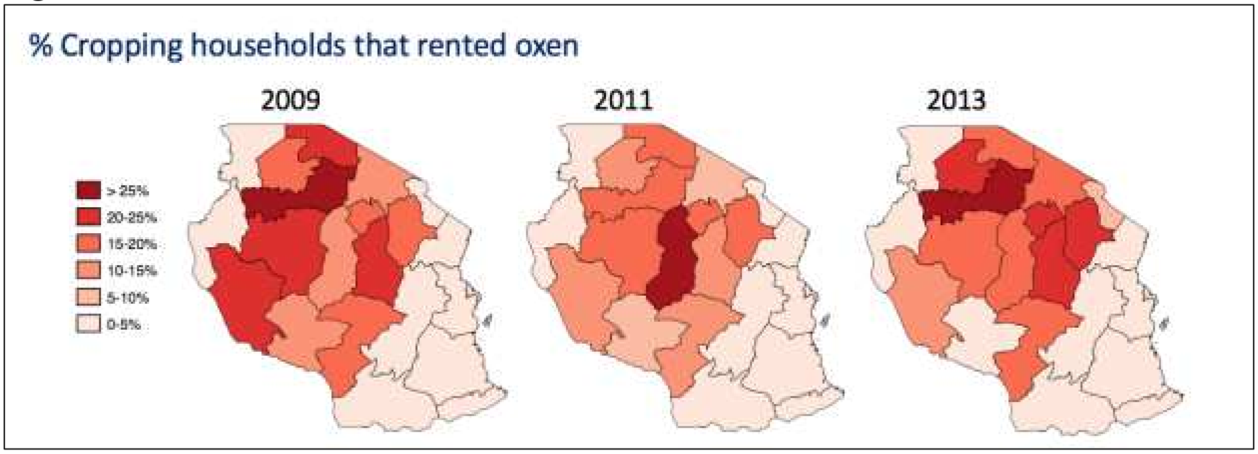
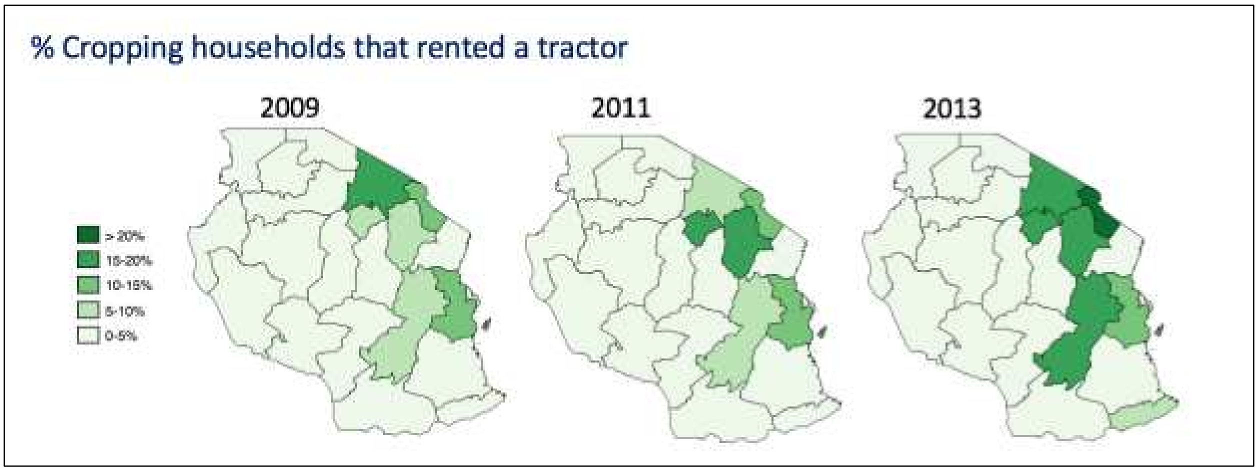


Figure 1 cont.



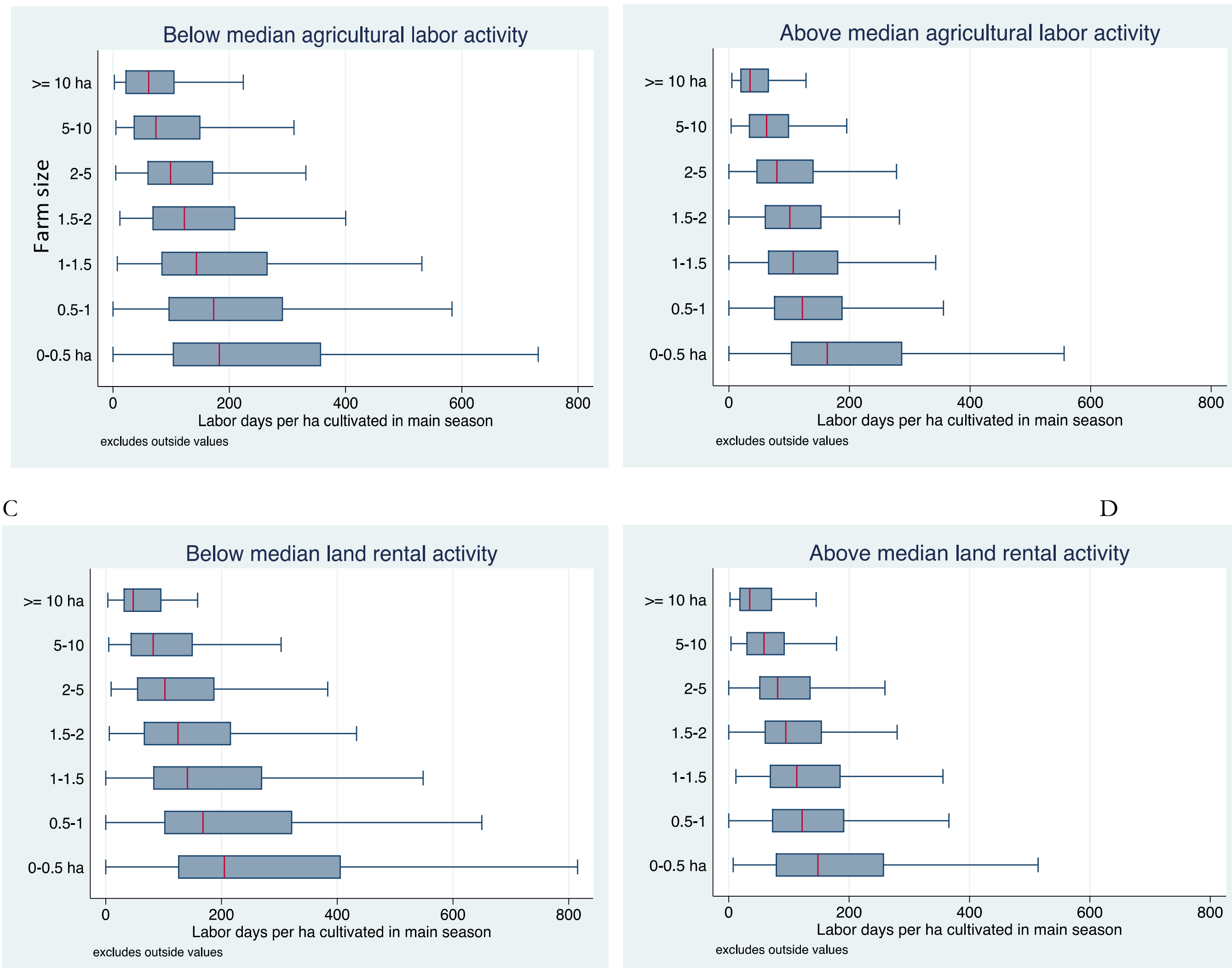


Source: Authors' calculations.

Recall that relatively small farms tend to apply labor with greater intensity than larger farms (Table 2). We now ask, does this relationship vary depending on whether households face a more robust market for either labor or land? In Figure 2, households are divided by whether they face a below- or above-median local level of market activity, and the distribution of labor intensity across farm sizes is presented in a series of box plots. For agricultural labor (panels A and B), it is again clear that smaller farms allocate incrementally more labor per ha. However, this relationship is somewhat muted in settings with more active labor markets (panel B). Small farms, in particular, appear to apply less labor to the family farm. This is consistent with the notion that smallholders facing a more active agricultural labor market are able to sell their excess labor within their rural communities, rather than apply the entirety of their labor endowment to their own farms. A similar visual pattern is seen in locations of low versus high land rental activity (panels C and D), where relatively small farms seem to exhibit lower labor-to-land ratios when faced with a more active land rental market.

Figure 2. Family Labor Allocation across Farm Sizes, Disaggregated by Levels of Agricultural Labor Activity and Land Market Activity

A B



Note: The boxes show the 25th quartile, the median value (in red), and the 75th quartile in each category of farm size. Farm size includes all land held by the household (not necessarily what was cropped in the main season). This refers to the pooled sample, and the number of observations ranges from 157 in the largest category to 1,783 in the 2-5 ha category. Median values: Agricultural labor (33.4%); Land rental (8.9%).

6.2. Econometric Results

In this section, we confirm that the IR is evident in Tanzania using regression analysis. We then estimate the household-specific shadow wage and consider whether the area-productivity relationship varies, depending on how family labor is valued when calculating the net value of crop production. Finally, we turn to equation (2) to explore whether the intensity of the IR varies along with the level of activity for various factor markets. From this point forward, all analyses are restricted to households that were present in the 2009 survey wave, though the number of observations in each model can vary, depending on whether we limit our attention to the main growing season or the entire agricultural year.

Using equation (1), we first consider the correlates of the gross value of crop production per hectare cultivated in the main growing season with a linear regression (Table 3). All variables are therefore in reference to the main season. We begin with a parsimonious model (column 1), incrementally adding controls across the columns to account for household and farm characteristics (including weather), crops produced, and inputs applied. Table 3 displays the key coefficient on area cultivated in each model specification, and the negative and statistically significant values signify that the IR is, indeed, present in Tanzania. The magnitude of this coefficient does shrink when we account for crops on the farm (column 3) and falls by about half (from 0.66 to 0.30) when we account for the intensity of inputs applied (column 4). This suggests that the greater intensity of labor allocation observed on small farms is at least partly responsible for the IR. The full results from column 4 are also provided in the appendix (Table A2). Not surprisingly, variables that represent crop composition are often significant correlates of the value of production, and as expected, the intensity of some inputs (notably fertilizer and labor) are positive and statistically significant determinants of land productivity. Specifically, an additional kg of fertilizer per ha (or an additional workday per ha) is associated with an additional 3,182 (1,334) TSh in the value of crop production per ha.[7]

Table 3. The Area-Productivity Relationship with Gross Value of Crop Production

	(1)	(2)	(3)	(4)
	Dependent variable: Gross value crop production per ha (area under crop in main season) (100,000s TSh)			
Area (ha)	-0.72***	-0.76***	-0.66***	-0.30***
	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y
Household/Farm characteristics		Y	Y	Y
Crop composition			Y	Y
Inputs applied				Y
Observations[a]	5,135	5,135	5,135	5,135
Households	2,002	2,002	2,002	2,002

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1

a Regression analyses use an unbalanced panel as it is possible for households to move in and out of crop production (or main season production) over the survey years.

[7] Because the focus of our paper is on the subsequent tables, several additional robustness checks of Table 3 are not reported here. These results are quite robust when the smallest 2% of farms are removed from analysis, when household fixed effects are removed, and when a quadratic term for area is included (with results revealing a convex area-productivity relationship).

Recalling that some households produce seasonal crops in the short season, we confirm that the focus on the main season does not influence our results. In Table A3, the same exercise is repeated using the gross value of crop production over the previous year, divided by the area of land held by the household. (Because plots can be planted twice in a year, it is not possible to precisely estimate the area cultivated.) All explanatory variables are now in reference to the year's production, and crop composition is captured through the proportion of the total value of crop production that is sourced from various crop categories. These results confirm that the IR is also evident at this level of analysis, although now, when inputs are included as controls in the final column, our key coefficient on area is no longer statistically significant (column 4). At least with regard to yearly production, it seems that the greater application rates of certain inputs, such as labor, can entirely explain the IR. It is still unclear, however, what drives these differential application rates across farm sizes.

We next estimate the household-specific shadow wages for family labor using a simple production function in which the gross value of crop production is regressed on area cultivated, the monetary value of inputs (including hired labor), and total family labor applied to the farm in the main season. All continuous variables are transformed using the inverse hyperbolic sine transformation (IHST) to account for values of zero, with coefficients that can be interpreted similar to those of a log-log model (Burbidge, Magee, and Robb 1988). This loosely follows the approach of Jacoby (1993), and results are presented in Table 4. The formula used to derive the shadow wage from these regression results is given in Table 1. Note that the shadow wage should equal the market wage where markets are complete. We now calculate the ratio of the shadow wage to the prevailing local market wage for agricultural labor. Across different farm size categories, Figure 3 displays the distribution of this ratio. Up until the largest category (at least 10 ha), the median value for this ratio is below one, which is consistent with there being imperfections in the agricultural labor market. As farm size increases, it is more likely that a household's estimated shadow wage will meet or exceed the market wage.

Following the approach of Ali and Deininger (2015), we now run a series of linear regressions using the net value of crop production per ha as the dependent variable, netting out expenditures on land rental, purchased seed, fertilizer, chemical inputs, and labor.[8] While hired labor is always valued at the observed wage, family labor is alternately valued at zero, at the household-specific shadow wage estimated from Table 4 (and illustrated in Figure 3), and using the local market wage rate. The key coefficients from this exercise are given in Table 5. Panel A, with family labor assigned no value, shows that the IR can also be found with respect to net profits. Panel B confirms that this relationship remains strong when the value of family labor is deducted from the dependent variable. In fact, because the shadow wage of family labor on larger farms is greater than smaller farms, and these large farms do apply considerable family labor (see Table 2), the IR seems to be even stronger with this specification. In Panel C, when family labor is valued at the market wage rate –which exceeds the shadow wage for 63.8% of households– the IR disappears entirely. This points to market imperfections as a key driver of the IR in Tanzania. Note that such imperfections are not necessarily limited to the labor market, as market failures can spill over from other markets to affect labor allocation decisions (Hazell et al. 2010).

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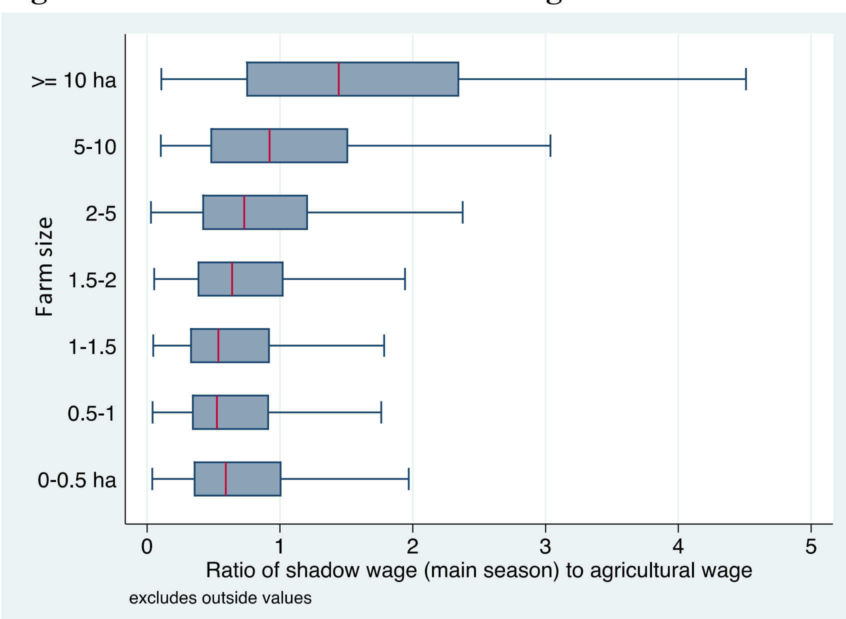
[8] As noted by Muyanga and Jayne (2016), these net values of production should ideally account for the fixed costs of production, including the purchase of oxen, machinery, and land. In most cases, we lack the necessary information to impute seasonal or annual values, and estimating the opportunity cost of land in the Tanzanian context (where land is often but not always transferable through the market) is particularly daunting.

Table 4. Production Function Used to Estimate Household-Specific Shadow Wages

	Gross value of crop production in main season (100,000s TSh, IHST)
Area cultivated (ha, IHST)	0.66***
	(0.000)
Value of inputs (TSh, IHST)	0.05***
	(0.000)
Family labor (days, IHST)	0.42***
	(0.000)
1= Year 2011	0.15***
	(0.003)
1= Year 2013	0.34***
	(0.000)
Constant	9.62***
	(0.000)
Observations	6,806[a]
R-squared	0.212

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1
Note: Value of crop production, area, value of inputs applied (including expenditures on hired labor), and family labor are transformed using the inverse hyperbolic sine transformation (IHST) to account for values of zero.
[a] This is a pooled sample.

Figure 3. Ratio of Shadow to Market Wages across Farm Sizes



Source: Authors.

Table 5. The Area-Productivity Relationship with Net Value of Crop Production

	(1)	(2)	(3)	(4)
	Dependent variable: Net value crop production per ha (area under crop in main season) (100,000s TSh)			
PANEL A				
Family labor assigned no value				
Area (ha)	-0.63***	-0.66***	-0.57***	-0.57***
	(0.000)	(0.000)	(0.000)	(0.000)
PANEL B				
Family labor valued at household's shadow wage & netted out of LHS variable				
Area (ha)	-0.84***	-0.91***	-0.63***	-0.63***
	(0.000)	(0.000)	(0.005)	(0.004)
PANEL C				
Family labor valued at prevailing local market wage & netted out of LHS variable				
Area (ha)	0.45	0.69	0.56	0.57
	(0.440)	(0.422)	(0.331)	(0.325)
Year fixed effects	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y
Household/Farm characteristics		Y	Y	Y
Crop composition			Y	Y
Inputs applied (irrigation and manure only)				Y
Observations	5,135	5,135	5,135	5,135
Households	2,002	2,002	2,002	2,002

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Finally, the relationship between the IR and local levels of factor market activity is explored directly, using equation (2). This directly tests the main hypothesis of this paper. In Table 6, the gross value of crop production per ha is now regressed on both area cultivated and an interaction term between area cultivated and the regional rate of participation in land rental markets (as renters), agricultural labor markets (as employers), agricultural credit markets (as borrowers), or oxen or tractor rental markets (as customers). Other controls include household and farm characteristics and household and year fixed effects. The results show that, while the coefficient on area remains negative and statistically significant, the interaction term is positive and strongly statistically significant (at the 1% level) for all markets except tractor rental. (Recall from Table 2 that, contrary to our expectations, tractor rental rates did not vary systematically with farm size tercile.) These results suggest that the IR is weaker when markets are more active.

At the bottom of Table 5, we estimate the local factor market activity level (participation rate) at which the slope of area is zero ($-\frac{\beta[Area_{it}]}{\lambda[Area_{it} \times Activity\_level_{it}]}$). These values range from 0.188 for agricultural credit to 0.742 for agricultural labor. Strikingly, almost no households in the study reside in regions with levels that meet or exceed these points. These results are robust when variables related to crop composition are included as controls (Table A4), and when the same exercise is conducted using the net value of crop production (with household labor valued at zero) (Table 7). It is also robust when we consider agricultural production over the entire year, not just the main season (Table A5).

Table 6. The Area-Productivity Relationship and Factor Market Activity Level (with Gross Value of Crop Production)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Gross value of crop production per ha cultivated in main season (100,000s TSh)				
Area planted in main season (ha)	-1.11***	-1.78***	-1.05***	-1.45***	-0.79***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Area * Land rental market activity level	3.09***				
	(0.002)				
Land rental market activity level	-0.74				
	(0.824)				
Area * Ag labor market activity level		2.40***			
		(0.001)			
Ag labor market activity level		-2.69			
		(0.276)			
Area * Ag credit market activity level			5.57***		
			(0.000)		
Ag credit market activity level			-33.57***		
			(0.000)		
Area * Oxen rental market activity level				5.09***	
				(0.000)	
Oxen rental market activity level				-13.41***	
				(0.000)	
Area * Tractor rental market activity level					0.76
					(0.711)
Tractor rental market activity level					-3.40
					(0.505)
Year fixed effects, Household fixed effects	Y	Y	Y	Y	Y
Household / Farm characteristics	Y	Y	Y	Y	Y
Activity level at which slope of area = 0	0.362	0.742	0.188	0.284	N/A
% Households beyond this point	0%	0%	0%	1.2%	
Observations	5,135	5,135	5,135	5,135	5,135
Households	2,002	2,002	2,002	2,002	2,002

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 7. The Area-Productivity Relationship and Factor Market Activity Level (with Net Value of Crop Production)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Net value of crop production per ha cultivated in main season (100,000s TSh)				
Area planted in main season (ha)	-0.98***	-1.63***	-0.93***	-1.31***	-0.70***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Area * Land rental market activity level	2.82***				
	(0.000)				
Land rental market activity level	0.88				
	(0.789)				
Area * Ag labor market activity level		2.28***			
		(0.000)			
Ag labor market activity level		-3.25			
		(0.172)			
Area * Ag credit market activity level			5.17***		
			(0.000)		
Ag credit market activity level			-33.55***		
			(0.000)		
Area * Oxen rental market activity level				4.83***	
				(0.000)	
Oxen rental market activity level				-12.01***	
				(0.000)	
Area * Tractor rental market activity level					0.94
					(0.581)
Tractor rental market activity level					-5.28
					(0.275)
Year fixed effects, Household fixed effects	Y	Y	Y	Y	Y
Household / Farm characteristics	Y	Y	Y	Y	Y
Activity level at which slope of area = 0	0.349	0.715	0.179	0.272	N/A
% Households beyond this point	0%	0%	1.6%	3.0%	
Observations	5,135	5,135	5,135	5,135	5,135
Households	2,002	2,002	2,002	2,002	2,002

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

7. DISCUSSION AND CONCLUSION

In this paper, we explore the relationship between the intensity of the inverse farm size-productivity relationship and the level of local factor market activity in Tanzania. Relatively small farms allocate significantly more labor per hectare cultivated and tend to exhibit a shadow wage of family labor that is below the prevailing local agricultural wage. Using a longitudinal household data set to control for time-invariant household fixed effects, we find that the IR is evident in Tanzania and robust across various model specifications, including those that control for crop composition. However, the intensity of the IR is weakest (i.e., the magnitude of the coefficient on area is smallest) when inputs are included as controls, reflecting the manner in which small farms apply inputs more intensively than large farms. We further find that the IR disappears entirely when family labor is valued at the market wage rate, which indicates that market imperfections (whether in the labor market or other markets that also affect factor ratios) are responsible for the IR, consistent with the findings of Ali and Deininger (2015) for Rwanda.

Accordingly, when cultivated area is interacted with the local level of factor market activity in regression analysis, we find that the IR is significantly weakened in the presence of more active markets for most items considered. This is true for land rental, agricultural labor, agricultural credit, and oxen rental. Across these items, the vast majority of households face a level of market activity that is considerably lower than the level estimated to nullify the IR. Although these results should be interpreted as correlations and not definitive causal relationships, they are consistent with the notion that the IR is at least partly driven by imperfections in factor markets. This finding is also consistent with other studies that apply different empirical approaches in other settings (Lamb 2003; Deininger et al. 2016).

If the IR is attributed to market imperfections, it follows that interventions may be warranted to address rural market failures (Heltberg 1998) rather than to promote a particular size category of farms. Examples include improved land tenure security and greater safeguarding of the rights of landlords and tenants, particularly under multiple year rental arrangements; improved access to the judicial system to efficiently resolve small claims related to contracts or property rights; or policies that encourage private firms to invest in and expand the range of services offered in rural markets. Across all markets, the improvement of transport infrastructure, communications through mobile phone service, and access to electricity would facilitate market participation.

Furthermore, these results would seem to diminish the efficiency-based argument for agricultural policies that prioritize smallholder farmers. They may also allay concerns that the rapid growth of medium-scale farms in Sub-Saharan African countries (Jayne et al. 2016) could reduce aggregate food production and exacerbate food insecurity (Liu, Violette, and Barrett 2016). This is because the lower productivity of large farms may be a reflection not of their size, but of external market imperfections. If economic growth is accompanied by increasingly well-functioning rural factor markets, we might anticipate that the relative advantage of small farms will shrink and, following the pattern observed in India and Vietnam (Deininger et al. 2016; Liu, Violette, and Barrett 2016), the IR will attenuate in Tanzania.

At the same time, it should be noted that the rationale for prioritizing smallholder farmers does not rest simply on arguments of superior land productivity. Smallholder farms currently predominate the agricultural landscape in Sub-Saharan Africa in number, if not in land area (Jayne et al. 2016), and any effort to address poverty needs to meet poor people where they are currently found, which is often on small farms (Hazell et al. 2010; Larson, Muraoka, and Otsuka 2016). Ligon and Sadoulet (2008) find a high poverty elasticity of agriculture, and the extent to which agricultural growth will be poverty-reducing depends on the pattern of land distribution (Hazell et al. 2010). Despite prevailing market imperfections, it is evident that small farms do provide some level of gainful self-employment (Ali and Deininger 2015), and recent demographic trends in Tanzania (UNFPA 2009) present a need for employment opportunities to absorb surplus labor. Cognizant of multiplier effects, Mellor (2014) advocates for the prioritization of small commercial farmers characterized by a commercial orientation and strong linkages in the local (rural) economy. Thus, evidence that the IR is driven by potentially remediable factor market imperfections does not, in itself, undermine arguments for smallholder-led development.

Future research on the topic of the IR and factor markets may consider exogenous variation in factor market activity, such as interventions aimed at improving the fluidity of, or increasing participation in, a specific market in a specific geographic area. If this is found to weaken the IR, it would substantiate the patterns highlighted in this paper. Our results also underscore the relevance of the activation and growth of rural factor markets in analyses of agricultural development. Future research may revisit whether farm-household non-separability holds across regions and over time in Tanzania (see Sadoulet, de Janvry, and Benjamin 1998). Particularly because factor markets are likely to evolve in Africa, the IR should be monitored to confirm whether it persists or weakens in the years to come.

APPENDIX

Table A1. Tests for Attrition Bias

	(1)	(2)	(3)	(4)
	Dependent variable: Gross value crop production per ha cultivated in main season (100,000s TSh)			
1= Re-interviewed next wave	1.29	1.28	1.47	1.16
	(0.207)	(0.225)	(0.146)	(0.236)
Year fixed effects, Household fixed effects	Y	Y	Y	Y
Area	Y	Y	Y	Y
Household / Farm characteristics		Y	Y	Y
Crop composition (proportion of area)			Y	Y
Inputs applied (including labor intensity)				Y
Observations	3,444	3,444	3,444	3,444
Households	1,942	1,942	1,942	1,942

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Note: We test for attrition bias using a dummy variable method (Wooldridge 2002: 577) with the following OLS regression:

$$Y_{it} = \alpha + \tau R_{i,t+1} + \beta[Area_{it}] + \boldsymbol{X}'_{it}\boldsymbol{\theta} + \varphi_t + \delta_i + \varepsilon_{it} \quad \text{(A.1)}$$

This is based on equation (1), as introduced in section 5. Y_{it} is the gross value of crop production per ha cultivated in the main season. Added to equation (1) is $R_{i,t+1}$, a binary indicator for whether household i remains in the panel at time $t + 1$. Therefore, only years 2009 and 2011 are included in these regressions, and attrition bias is evident if the key coefficient (τ, shown above) is significant.

Table A2. The Area-productivity Relationship (Select Full Results)

Dependent variable: Gross value crop production per ha cultivated in main season (100,000s TSh)			
Area cultivated in main season (ha)	-0.30***	*Proportion of cropped area devoted to:*[a]	
	(0.000)	Rice	2.25**
Household size	-0.09		(0.025)
	(0.272)	Other cereals	-0.18
Proportion household members not of working age	-1.26		(0.754)
	(0.119)	Tubers	2.53***
Head's age	-0.08**		(0.002)
	(0.028)	Legumes	1.75***
1= Female-headed household	0.17		(0.001)
	(0.828)	Cash crops	8.40***
1= Someone in household completed primary school	-0.57		(0.000)
	(0.207)	Fruits and vegetables	9.36***
Asset index	0.34***		(0.000)
	(0.001)	Sugar cane, spices, timber	9.06***
Distance to agricultural market (km)	-0.003		(0.000)
	(0.807)	*Inputs:*	
Population density (persons/ km^2)	0.0001	1= Irrigated	1.64**
	(0.456)		(0.037)
Mean temperature over agricultural year (10s °C)	0.04	Manure (kgs/ha cultivated)	-0.0003
	(0.325)		(0.672)
Total rainfall over agricultural year (mm)	0.0001	Fertilizer (kgs/ha cultivated)	0.03***
	(0.909)		(0.000)
Year 2011	0.91***	Labor (workdays/ha cultivated)	0.01***
	(0.000)		(0.000)
Year 2013	2.59***	Constant	-2.46
	(0.000)		(0.766)
		Household fixed effects	Y
		Observations	5,135
		Households	2,002
		Within R-squared	0.279

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

[a] Proportion of area devoted to maize is omitted.

Table A3. The Area-Productivity Relationship (with Gross Value of Crop Production over the Previous Year)

	(1)	(2)	(3)	(4)
	Dependent variable: Gross value crop production over previous year per ha land held (100,000s TSh)			
Area (ha)	-0.26***	-0.27***	-0.27**	-0.08
	(0.002)	(0.003)	(0.019)	(0.147)
Year fixed effects	Y	Y	Y	Y
Household fixed effects	Y	Y	Y	Y
Household / Farm characteristics		Y	Y	Y
Crop composition			Y	Y
Inputs applied				Y
Observations	5,909	5,909	5,909	5,909
Households	2,093	2,093	2,093	2,093

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Note: In this model specification, area includes all land held by the household; variables of crop composition refer to the proportion of the values of crop production derived from various crop categories; and inputs include manure, fertilizer, and labor applied per ha over the entire year. Labor is inclusive of family and hired labor.

Table A4. The Area-Productivity Relationship and Factor Market Activity with Gross Value of Crop Production (Controlling for Crop Composition)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Gross value of crop production per ha cultivated in main season (100,000s TSh)				
Area planted in main season (ha)	-0.98***	-1.78***	-0.88***	-1.28***	-0.67***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Area * Land rental market activity level	2.82***				
	(0.000)				
Land rental market activity level	0.70				
	(0.827)				
Area * Ag labor market activity level		2.65***			
		(0.00)			
Ag labor market activity level		-2.69			
		(0.252)			
Area * Ag credit market activity level			4.50***		
			(0.000)		
Ag credit market activity level			-30.51***		
			(0.000)		
Area * Oxen rental market activity level				4.65***	
				(0.000)	
Oxen rental market activity level				-13.04***	
				(0.000)	
Area * Tractor rental market activity level					0.30
					(0.873)
Tractor rental market activity level					-0.69
					(0.888)
Year fixed effects, Household fixed effects	Y	Y	Y	Y	Y
Household / Farm characteristics	Y	Y	Y	Y	Y
Crop composition	Y	Y	Y	Y	Y
Activity level at which slope of area = 0	0.346	0.671	0.198	0.276	N/A
% Households beyond this point	0%	0%	0%	3.0%	
Observations	5,135	5,135	5,135	5,135	5,135
Households	2,002	2,002	2,002	2,002	2,002

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A5. The Area-Productivity Relationship and Factor Market Activity Level (with Gross Value of Crop Production over the Previous Year)

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: Gross value of crop production over the previous year per ha land held (100,000s TSh)				
Area planted in main season (ha)	-0.37***	-0.40***	-0.35***	-0.43***	-0.27***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)
Area * Land rental market activity level	0.96**				
	(0.030)				
Land rental market activity level	6.32				
	(0.202)				
Area * Ag labor market activity level		0.37**			
		(0.024)			
Ag labor market activity level		-14.64			
		(0.181)			
Area * Ag credit market activity level			2.68***		
			(0.002)		
Ag credit market activity level			-26.51***		
			(0.008)		
Area * Oxen rental market activity level				1.18***	
				(0.002)	
Oxen rental market activity level				-5.44	
				(0.491)	
Area * Tractor rental market activity level					-0.25
					(0.824)
Tractor rental market activity level					2.87
					(0.690)
Year fixed effects, Household fixed effects	Y	Y	Y	Y	Y
Household / Farm characteristics	Y	Y	Y	Y	Y
Activity level at which slope of area = 0	0.388	>1.0	0.129	0.365	N/A
% Households beyond this point	0%	0%	1.4%	0%	
Observations	5,909	5,909	5,909	5,909	5,909
Households	2,093	2,093	2,093	2,093	2,093

Robust p-values in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

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