# Beyond the Smoking Gun: The Role of Social Ties in Factor Allocation*

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**Abstract**

We investigate whether social structure hinders factor allocation using unusually rich data from The Gambia. We find evidence of a smoking gun: land available for cultivation is allocated unequally across households; and factor transfers are more common between neighbors, co-ethnics, and kin. Can we conclude that the former is due to the latter? To answer this question we introduce a novel methodology that approaches exhaustive data on dyadic flows from an aggregate point of view. We find that land transfers lead to a more equal distribution of land and to more comparable factor ratios across farms. But most types of equalizing transfers of land are not more likely within ethnic or kinship groups. We conclude that a smoking gun approach would have been misleading in our study, wrongly concluding that ethnic and kinship divisions hinder land and labor transfers in a way that contributes to factor inequality.

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# 1 Introduction

Economics is largely about the process by which individual resource endowments are mapped into an allocation of these resources to production and consumption units. Much of this mapping is accomplished through the market; the rest takes place either hierarchically within firms and organizations, or through gift exchange within and between households. Allocation processes are of great interest to economists because they affect both how much can be consumed in aggregate (i.e., efficiency) and how equitable the distribution of consumption is (i.e., equity). Hence much attention has been devoted to studying whether allocation processes achieve an efficient and equitable outcome and, if they do not, whether a cause for misallocation can be identified.

In this quest, economists often resort to what could be called a 'smoking gun' approach that goes as follows: (1) find evidence that a group has a lower allocation of resources relative to what would be optimal or equitable; (2) find evidence that this group is disadvantaged in accessing these resources through market or non-market exchange; and (3) conclude that the first is due to the second. Empirical investigation of these issues has followed two main tracks: testing whether goods or factors are allocated efficiently or equitably; and documenting frictions in bilateral exchange. In development economics, the former approach is examplified by Townsend's (1994) seminal contribution on risk sharing: the paper tests whether income shocks are shared efficiently among households in the same village or sub-caste, but does not document how risk sharing is achieved or what impedes it. The second approach focuses on showing that pre-existing social links shape exchange. There are numerous examples of this approach in the study of informal insurance (Fafchamps and Lund, 2003; Fafchamps and Gubert, 2007; Attanasio et al., 2012; Mazzocco and Saini, 2012) and in the selection of a trading partner – e.g., Granovetter (1995) and Topa (2001) for labor markets and Rauch (2001), Rauch and Casella (2003) and Chaney (2014) in international trade.

While there is no doubt that disadvantage in exchange *can* distort the allocation of resources, proving that it actually *does* is considerably more complicated. It is indeed possible for resources to be misallocated even though no group is disadvantaged in exchange. The reverse is also true: resources can be optimally or equitably allocated even when some exchange opportunities are severely restricted. Hence if we want to demonstrate that some economic agents have a suboptimal or inequitable resource allocation *because* they are disadvantaged in exchange, we need to move beyond the smoking gun approach: it is necessary to consider social links and aggregate allocation simultaneously. With a few exceptions ((e.g. Sadoulet et al., 1997; Holden and Ghebru, 2005; Macours et al., 2010),[1] this has seldom been done.

The purpose of this paper is twofold: to provide an approach that can identify whether

[1] Sadoulet et al. (1997) compare contracts between kin related households and non-kin related households and find that the former is more efficient. Holden and Ghebru (2005) show that tenants in communities with a larger share of contracts between kin related households face lower access constraints to the land market. More recently, Macours et al. (2010) finds that insecurity of property rights in the Dominican Republic reduces rental activity, and causes the tenancy market to match up along socio-economic lines.

resource misallocation is due to exchange restrictions between agents or groups of agents; and to illustrate its usefulness with an example that is relevant for development policy. To this effect we focus on land allocation in village economies. Land ownership is notoriously unequal in many agrarian societies. At the same time, traditional agricultural systems are often characterized by decreasing returns to scale – at least over a minimum scale of operations (see Ali and Deininger (2015) for an excellent recent review of the literature). A more efficient and equitable allocation of cultivated acreage thus requires temporary transfers of land from land-rich to land-poor farming households. It is also well known that homophyly and discrimination are common in market as well as non-market exchange: many people prefer to trade and exchange favors with people with similar characteristics. The question therefore arises of whether homophyly and discrimination contribute to the unequal allocation of cultivated acreage.

The empirical analysis takes advantage of an unusually rich dataset on land and labor transactions in the rural Gambia. The data covers all pairwise transfers of agricultural land and labor in 50 rural Gambian villages, together with detailed information on pre-existing social links between each pair of households. We focus exclusively on the factor transfers themselves, not on the form (e.g., gift, rental, sharecropping) or motivation (e.g., reciprocity, self-interest) of the transactions – these are examined in detail, for our dataset by Jaimovich (2011) and Jaimovich (2015). Indeed, the main results of the paper do not depend on the underlying mechanism behind the transfers.

Factor markets in developing countries are known to be plagued by incomplete information and unclear property rights that lead to high transaction costs and are thought to hinder the allocation of productive factors (de Janvry et al., 1991; Pender and Fafchamps, 2005; Otsuka, 2007). Pre-existing social networks are thought to play an important role in alleviating these issues by increasing trust, decrease information asymmetries and therefore reduce transaction costs. Such markets are thus a good focus for our study. Land usage rights in rural Gambia are vested in the hands of the descendants of the ancestral settlers, and thus the distribution of land ownership rights is highly unequal. This results in an abundant practice of land exchange between households whereby temporary land usage rights are transferred on an annual basis. This makes The Gambia a suitable candidate for testing how pre-existing networks in the form of ethnicity, kinship and geographical proximity affect the efficiency properties of temporary land transfers.

We start by showing that land ownership and cultivated acreage are unequally distributed across farmers, with systematic differences between ethnic groups. We also show that transfers of temporary usage rights over land are a lot more common between households that are related or neighbors. We thus have the proverbial smoking gun. But is homophyly in land transfers contributing to land inequality? To answer this question, we apply the new methodology we propose to the land and labor transfer data from The Gambia. We find no evidence that ethnic or kinship groupings distort land transfers away from a more equal land distribution. The fact that land transfers are more frequent between related or neighbor farmers does not contribute to a more unequal distribution of cultivated land. In other words, the data reject the idea that preferential exchange between certain farmers contributes to land inequality. The main reason seems to be that a small number of land-rich households transfer land to non co-ethnic farmers in their village, and these transfers are sufficient to compensate for land transfers between proximate households. These findings are in agreement with the anthropological and historical literature about land settlement in sub-Saharan Africa, which emphasizes the redistributive role of pioneer lineages who control the village land that their ancestors cleared, but welcome newcomers into their community with transfers of usage rights over land (Platteau, 1992).

The paper contributes to the literature in several different ways. Our first contribution is methodological. Most evidence of network effects in markets does little more than document that exchange is more likely among agents with social ties. This kind of evidence does not, by itself, demonstrate that trade embedded in a social context necessarily leads to inefficient or unequal outcomes: by travelling along a network of pre-existing ties, goods can still end up in the right hands. This is, for instance, what takes place in well-sorted value chains. The method we propose and illustrate empirically resolves this difficulty by approaching exhaustive data on dyadic flows from an aggregate point of view.

This method is applicable well beyond factor markets in developing countries. It is potentially applicable to research questions as diverse as gravity models and international trade; labor markets; value chains; favor exchange; electrical power grid and diffusion of information on social networks. All these questions have in common that flows take place on a network of links that are partially shaped by the geographical and social context. The same question arises in all of them: do the restrictions on flows imposed by social structure lead to an inefficient or inequitable allocation of resources? The main constraint to its applicability is the availability of exhaustive information about dyadic flows, and sufficiently detailed information about the social structure. While such datasets have largely been lacking in the past, they are becoming increasingly available. The methodology can also be applied to study whether differences in prices, costs, access or opportunities are due to social, geographical, or regulatory obstacles to exchange. The empirical application presented in this paper illustrates how the method can be used to identify situations in which social structure is an obstacle to an efficient or equitable resource allocation.

Second, the paper contributes to the empirical literature on the importance of pre-existing social networks for offsetting the negative effects of market imperfections. We find some evidence to this effect – but perhaps not as much as we would have anticipated, based on the existing literature. Third, this paper provides empirical evidence on the efficiency properties of social networks in The Gambia, a country that is fairly representative of West African rural institutions. If pre-existing social networks are important for the selection of trading partners, this has direct implications for the prospects of reducing poverty and inequality as well as economic growth (Holden et al., 2009). This issue is particularly important in West Africa where access to land is an increasing concern as land scarcity increases due to population growth (World Bank, 2005). We provide evidence that land ownership is unequally distributed within villages of the Gambia, with some systematic advantage to members of the majority ethnic group in each village. Land transfers serve a modest but significant role in equalizing factor allocations between households, and they do so in a way that appears unimpeded by ethnic and kinship divisions. Geographical proximity, in contrast, appears to have a factor equalizing effect over and above that of village-level equalization.

The paper is organized as follows. In Section 2, we present our methodology and articulate a novel testing strategy aimed at identifying the role of social ties in shaping transfers. We start by showing how the method works for a single good. We then illustrate how it can be applied to study allocative efficiency in factors of production. In the rest of the paper we apply this method to agrarian factor markets in The Gambia. Section 3 describes the land tenure system in rural Gambia and the data used in the empirical analysis. In Section 4 we apply the testing strategy to the data and present the main results of the empirical analysis. Section 5 discusses alternative interpretations of the empirical findings and provides a number of robustness checks. Section 6 concludes.

# 2 Methodology

## 2.1 Conceptual framework

The purpose of this paper is to propose a method for testing whether social structure limits the free flow of goods or services. The common approach to this question is to test whether goods or services flow less freely between certain individuals than others – e.g., whether white landlords are less likely to rent to black tenants, or whether favors are exchanged primarily between friends and relatives. When evidence of this type is found, it is typically interpreted as suggesting that social structure makes the final allocation of the goods or services inefficient or inequitable. What this approach fails to recognize is that it is quite possible for allocation to be efficient even in the presence of friction caused by social structure. It is also possible for allocation to be inefficient even though social structure does not hinder exchange. More importantly, it is even possible for social structure to restrict exchange and for allocation to be inefficient or unequal without one causing the other. The purpose of the new method we propose is to overcome these difficulties.

To understand the nature of the difficulty, we take an example from high school physics: communicating vessels. Imagine a set of $N$ vessels linked to each other by pipes. Unequal amounts of water are poured in vessels, with $a_i$ denoting the water poured in vessel $i$. Vessels represent households and water is any good or service that is exchanged between them, either through market or non-market exchange. Water pipes represent social structure. From physics theory, we know that the water level will be equalized among all communicating vessels. This can be represented formally as a network or graph in which each vessel is a node and each pipe is a link $L_{ij}$ between two nodes $i$ and $j$. If all vessels are connected, either directly or indirectly, they all belong to the same component and water levels should equalize across all of them. Alternatively, the network may be divided into multiple components, that is, distinct subsets of nodes that are connected with other nodes in the same component, but not with any node in other components. In that case, water levels will equalize within components but not across components.

The immediate implication is that equalization does not depend on network density or clustering: links (and hence flows) may be more frequent within certain subsets of the network, e.g., between co-ethnic nodes; but all nodes within the same component have equal access to water. It is only when social structure precludes flows between components that access can be unequal – and even in this case water allocation can be equal if the total water endowment of each component is proportional to their number of nodes.

It is also possible that pipes only let some of the water go through.[2] Let $s_{ij} \geq 0$ be the maximum amount of water that can flow from $i$ to $j$, and let $S \equiv [s_{ij}]$ denote the matrix of all $s_{ij}$. If there is no pipe between $i$ and $j$, $s_{ij} = 0$. When flows are constrained, water level equalization may or may not be achieved within a component, depending on the shape of network $S$ but also on the distribution of water endowments $a_i$ across nodes. When water flows are constrained, it is difficult to determine a priori whether equalization can be achieved within components or even between any pair of nodes $i$ and $j$. For instance, it is not possible to predict whether equalization is achieved between any pair of nodes $i$ and $j$ simply from knowing $s_{ij}$, $a_i$ and $a_j$. On the one hand, even if $i$ and $j$ are not connected ($s_{ij} = 0$), water may flow between them through other nodes, equalizing water levels between them. On the other hand, even when the connection between them is sufficient to equally share their initial endowments $a_i$ and $a_j$, flows to and from other nodes may prevent pairwise equalization between them.[3] Hence it is not because flows are restricted between $i$ and $j$ that equalization cannot be achieved, and it is not because flows between $i$ and $j$ are fairly unconstrainted that equalization will be achieved between them. The same reasoning applies to other distributed networks, e.g., electric power grid, value chains, and the like.

Several lessons can be drawn from the above discussion. First, observing that flows are shaped by social structure does not imply that allocation is unequal. The reverse is also true: the fact that social structure does not shape flows does not imply equal access – there can be

[2] An electrical power grid is another example of such a network: the grid may be interconnected, but the flow of power between different points is often restricted by technological constraints. If one segment of the grid fails, it may not be possible to channel enough current from the rest of the grid to avoid a loss of service.

[3] To illustrate, consider a network with three nodes $\{1, 2, 3\}$ arranged in a line, with $s_{12} = 1$ and $s_{23} = 1$. Endowments are $\{0, 2, 2\}$. Consider nodes 1 and 2 first. Water equalization implies a transfer of 1 from node 2 to node 1, which is feasible since $s_{12} = 1$. Suppose this takes place. Node 1 now has 1 unit of water, and so does node 2. Now consider nodes 2 and 3: equalization between them leads to a transfer of 0.5 units of water from node 3 to node 2, who now has 1.5 units of water. Since 1 unit of water has already been transferred from 2 to 1, further water equalization between them is impossible, and the final allocation is $\{1, 1.5, 1.5\}$: there is no water level equalization between 1 and 2 even though $s_{12}$ is large enough to equalize their respective endowments.

obstacles to flows that are not correlated with social structure. Secondly, observing that social structure shapes flows and that allocation is unequal does not, by itself, imply that one causes the other. This second point is important because much of the literature on discrimination and inequality typically focuses on documenting the effect of social structure on flows and interpret this evidence as responsible for unequal outcomes. The examples presented above illustrate the problems inherent in this approach. We need a better way of assessing when social structure is responsible for unequal outcomes.

To this effect, we propose a methodology to identify situations in which the pre-existing social structure may be responsible for unequal allocation. Given that the method is applied to land and labor transfers later in the paper, the testing strategy is framed in terms of factors of production. But it is in principle applicable to any good or service, and to any flows – whether they take place in a centralized manner, or through decentralized market or non-market exchange.

## 2.2 Testing stragegy

To illustrate how the proposed method works, we consider an economy with $N$ farming households observed during a single cropping season. Each household starts the season with $a_i$ units of a single factor of production, say land. The total supply of $a$ in the economy is denoted $A \equiv \sum_{i=1}^{N} a_i$. Each agent shares the same production function $q(x_i)$ where $x_i$ denotes the land available for cultivation by agent $i$. We assume that $q(x_i)$ exhibits decreasing returns to scale in $x_i$.[4] The efficient factor allocation is to set $x_i = \overline{a} = \frac{A}{N}$ to equalize the allocation of land across households. In the absence of frictions, we would expect this allocation to be realized through mutually beneficial exchange.[5] Given these assumptions, failure to equalize land across households signals the presence of frictions. We want to uncover the extent to failure to achieve an efficient allocation is associated with observable social structure.

We proceed as follows. Let $l_i$ be the net amount of $a$ that is transferred out by household $i$. Allocative efficiency requires that households have an equal amounts of land after transfers, i.e., that $a_i - l_i = \overline{a}$ which implies that $l_i = a_i - \overline{a}$ for all $i$. A regression of the following form can be employed to investigate whether the average factor transfer is efficiency-enhancing:

$$l_i = \alpha_0 + \alpha_1(a_i - \overline{a}) + u_i \tag{1}$$

Allocative efficiency requires $\alpha_1 = 1$. Land transfers are efficiency-enhancing if $0 < \alpha < 1$. This occurs when, on average, land-rich households transfer land out and land-poor households receive land transfers.

While easily implementable, regression (1) does not allow testing the effect of pre-existing

[4] We discuss this assumption more in detail later.

[5] The reallocation of land among households can be organized in a variety of market (e.g., sale, rental or sharecropping) and non-market ways (gift exchange, exchange of usage rights or squatting). Since our focus is on allocative efficiency, we only consider the transfers themselves, not the mechanisms by which land is transferred and the gains from trade shared between households.

networks on the efficiency properties of factor transfers. To do so, we must move the analysis to the dyadic level, i.e., the pairwise level. Factor transfers between households can be represented by a weighted directed graph in which agents are nodes and transfers are links. Let $w_{ij}$ denote a net transfer of $a$ from agent $i$ to agent $j$ with $w_{ji} = -w_{ij}$ by definition. Let the transfer matrix $W \equiv [w_{ij}]$ denote the set of all pairwise transfers. Simple accounting implies that transfers satisfy:

$$\begin{aligned} x_i &= a_i - \sum_{j \neq i} w_{ij} \\ \sum_i x_i &= A \end{aligned}$$

subject to feasibility conditions of the form:

$$x_i \geq 0 \text{ for all } i$$

Let $W^*$ denote a transfer matrix that satisfies the feasibility conditions and achieves efficiency, i.e., such that $x_i = \overline{a}$ for all $i$. We call such matrices efficient. There is a very large number of efficient matrices $W^*$, which means that the specific factor transfers that are needed to achieve efficiency are undetermined. The reason is simple. Say that a necessary condition for efficiency is that $i$ transfers 3 units of land to others. This can be achieved in a myriad of ways, e.g., by giving 1 to $j$ and 2 to $k$, or 1.5 to $j$ and 1.5 to $k$, or 3 to $m$, etc.

### 2.2.1 Testing aggregate allocative efficiency

While it is not possible to determine which specific trades take place without introducing additional assumptions,[6] it is possible to provide some characterization of *average* trade flows if they serve to improve allocative efficiency within a village $v$ with average landholdings $\overline{a}_v$ and population $N_v$.

The logic is best illustrated with an example. Starting from an unequal factor distribution in village $v$, allocative efficiency requires that those with an above-average endowment transfer out $a_i - \overline{a}_v$ and that those with a below-average endowment receive in $\overline{a}_v - a_i$.[7] Although there are many transfers $w_{ij}$ that can achieve this result, allocative efficiency requires that, for each $i$, the *sum* of $i$'s out-transfers satisfies $\sum_j w_{ij} = a_i - \overline{a}_v$. Similarly, the sum of in-transfers is $\sum_j w_{ij} = \overline{a}_v - a_j$. Thus if we observe all net transfers $w_{ij}$ in village $v$, we can estimate a

[6] E.g., one could ask which transfer matrix $W$ minimizes the number of separate transfers needed to achieve efficiency. Since it is unclear how these trades could be implemented in a decentralized manner, we do not discuss this further.

[7] Let $N_1$ and $N_2$ denote the number of agents with an above and below average endowment, i.e., with $a_i - \overline{a}_v > 0$ and $a_j - \overline{a}_v < 0$, respectively. The $N - N_1 - N_2$ others have an allocatively efficient endowment such that $a_k = \overline{a}_v$. Allocative efficiency requires that $N_1$ agents collectively transfer out $\sum_{i \in N_1} a_i - \overline{a}_v$ and $N_2$ agents collectively transfer in $\sum_{j \in N_2} \overline{a}_v - a_j$.

regression of the form:

$$w_{ij} = \alpha_0 + \alpha_1 \frac{a_i - \overline{a}}{N_v} + \alpha_2 \frac{\overline{a} - a_j}{N_v} + u_{ij} \tag{2}$$

over all $N_v(N_v - 1)$ dyads. Since $w_{ij} = -w_{ji}$ by construction, it follows that $\alpha_0 = 0$ and $\alpha_1 = \alpha_2$ always.

If land transfers achieve an efficient allocation, it must be that $\alpha_1 = 1 = \alpha_2$. Simulation results confirm this property in Appendix A. We also show that $\alpha_1$ provides an estimate of how far actual transfers are from efficient transfers: if we take any set of efficient transfers $w^*_{ij}$ and multiply them by a shrinking factor $\tau < 1$ such that $w_{ij} = \tau w^*_{ij}$ then $\alpha_1 = \tau = \alpha_2$. Hence the closer $\alpha_1$ is to zero, the less efficiency gains are achieved by land transfers.

### 2.2.2 Testing group-wise efficiency

Now suppose that transfers can only take place between certain pairs of nodes – e.g., because social ties are needed to mitigate information asymmetries and enforcement problems. To fix ideas, let $S \equiv [s_{ij}]$ denote, as before, the set of maximum socially feasible flows such that:

$$|w_{ij}| \leq s_{ij} \text{ for all } ij \tag{3}$$

We do not observe $S$ directly. Instead we use pre-existing social links thought to reduce frictions as proxy variables for $s_{ij}$: if the absence of a particular type of social link between $i$ and $j$ precludes factor transfers, then we expect $w_{ij} = s_{ij} = 0$.

Can efficiency be achieved? This depends on whether there exists an efficient transfer matrix $W^*$ that satisfies the set of constraints (3). If such a matrix exists, allocative efficiency can be achieved even though transfers can only occur along existing social ties. If it does not, restrictions imposed by matrix $S$ prevent allocative efficiency from being reached. When this is true, we say that social structure prevents allocative efficiency.

As discussed earlier, allocative efficiency may be prevented when the network is segmented into distinct components. Formally, this means that the set of nodes $N$ can be partitioned into mutually exclusive sets $\{N_1, ...N_p\}$ such that (1) there is a path in $S$ leading from any node in $N_k$ to any other node in $N_k$; and (2) there is no path in $S$ leading from a node in $N_k$ to a node in $N_{m \neq k}$. In this case, allocative efficiency is only possible within each component. Applying model (2) separately to each compoment yields:

$$w_{ij} = \alpha_0 + \alpha_3 \frac{a_i - \overline{a}_k}{N_k} D_{ij} + \alpha_4 \frac{\overline{a}_k - a_j}{N_k} D_{ji} + u_{ij} \tag{4}$$

where $N_k$ is the size of the component $k$, $\overline{a}_k \equiv \frac{1}{N_k} \sum_{i \in N_k} a_i$ is the average endowment in component $k$, and $D_{ij} = 1$ if $i$ and $j$ belong to the same component $k$ and 0 otherwise. As before, $\alpha_0 = 0$ and $\alpha_3 = \alpha_4$ always. Allocative efficiency within components requires $\alpha_3 = 1 = \alpha_4$, and the magnitude of $\alpha_3$ captures the extent to which transfers achieve within-component equalization of land available for cultivation. See Appendix for illustrative examples.

An extreme case of this is when transfers are only possible across pairs of agents. In this case, the regression model simplifies to:

$$w_{ij} = \alpha_0 + \alpha_5 \frac{a_i - a_j}{2} L_{ij} + u_{ij} \tag{5}$$

where $L_{ij} = 1$ if there is a direct link between $i$ and $j$ in $S$, and 0 otherwise. If allocative efficiency is only achieved across isolated linked pairs of agents, then $\alpha_0 = 0$ and $\alpha_5 = 1$. An illustration is provided in Appendix A.

### 2.2.3 Testing social structure

To investigate the role of social structure in allocative efficiency, we combine the estimation of individual models (2), (4) and (5) with various joint models discussed below. From model (2) we obtain an estimate $\widehat{\alpha}_1$ of how far transfers are from being allocatively efficient on average; if $\widehat{\alpha}_1 < 0$ it means that transfers move land allocation away from efficiency. By comparing $\widehat{\alpha}_1$ to $\widehat{\alpha}_3$ in model (4), we see whether more efficiency is achieved within components than in aggregate. If we do find that $\widehat{\alpha}_3 > \widehat{\alpha}_1$, this indicates that the lack of social links between components hinders aggregate efficiency. Similarly, if we find that $\widehat{\alpha}_5 > \widehat{\alpha}_1$, we can conclude that more efficiency gain is achieved within pairs than in aggregate.

These results can be confirmed and refined by estimating joint models of the form:

$$\begin{aligned} w_{ij} \quad &= \quad \alpha_0 + \alpha_1 \frac{a_i - \overline{a}_v}{N_v} + \alpha_2 \frac{\overline{a}_v - a_j}{N_v} \\ &\quad + \alpha_3 \frac{a_i - \overline{a}_k}{N_k} D_{ij} + \alpha_4 \frac{\overline{a}_k - a_j}{N_k} D_{ij} + u_{ij} \end{aligned} \tag{6}$$

$$w_{ij} = \alpha_0 + \alpha_1 \frac{a_i - \overline{a}_v}{N_v} + \alpha_2 \frac{\overline{a}_v - a_j}{N_v} + \alpha_5 \frac{a_i - a_j}{2} L_{ij} + u_{ij} \tag{7}$$

Let us focus on (6) first. In this model, two types of differences can arise between $\frac{a_i - \overline{a}_v}{N_v}$ and $\frac{\overline{a}_v - a_j}{N_v}$ on the one hand, and $\frac{a_i - \overline{a}_k}{N_k} D_{ij}$ and $\frac{\overline{a}_k - a_j}{N_k} D_{ij}$ on the other: $\overline{a}_v \neq \overline{a}_k$; and $D_{ij} = 0$ for some pairs. If average endowments differ across components, convergence towards the village average can take the allocation of land away from allocative efficiency within components. When this occurs, we find that $\widehat{\alpha}_3 = \widehat{\alpha}_4 < 0$ while at the same time the estimates of $\alpha_1$ and $\alpha_2$ in (6) are larger than in (2). In contrast, if transfers serve to equalize land within components more than across components, then $\widehat{\alpha}_3 = \widehat{\alpha}_4 > 0$ and $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$ tend to zero.

A similar reasoning applies to (7): if improvements in allocative efficiency are achieved solely through transfers across linked pairs, $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$ tend to zero while $\widehat{\alpha}_5$ remains positive. In contrast, if individual pairwise links place no restrictions on aggregate efficiency gains, we should find that $\widehat{\alpha}_5$ tends to zero while $\widehat{\alpha}_1 = \widehat{\alpha}_2 > 0$.

### 2.3 Extensions

To explain our testing strategy we have focused on a simple case in which returns to scale are decreasing and there is a single traded factor. The advantage is that this case closely ressembles the communicating vessels example: allocative efficiency requires land equalization, and we can investigate the role of social structure by testing whether transfers equalize land available for cultivation across all households, or within components, or across individually linked pairs. Before taking this testing strategy to the data, however, we have to ask ourselves whether assuming decreasing returns to scale and a single traded factor makes sense for the context of our study. While our data do not contain specific information about yields, it is well known that, in the kind of traditional farming area that we study, yields fall with farm size. This has been well documented in the literature (e.g. Ali and Deininger 2015).[8] Hence it is not unreasonable to assume that returns to farm size are decreasing for the purpose of our study. As we document in the next section, for our study villages, trade in labor is much less prevalent than land transfers, suggesting that, at least as a first approximation, assuming a single traded factor is not entirely unreasonable either.

What we cannot rule out is that farmers differ in terms of productivity – e.g., because of differences in agricultural knowledge, business acumen, or household labor mobilization. So far we have assumed that all households share the same decreasing returns to scale production function $q(x_i)$. In this case, allocative efficiency requires equalization of land across all farms. If households differ in productivity, however, land equalization is no longer efficient. Our method can nonetheless be applied if productivity differences across farmers are multiplicative (i.e., Hicks-neutral). In this case, allocative efficiency requires equalization of factor ratios. We show in Appendix B how models (2), (4), (5), (6) and (7) can be modified for this case by replacing the land endowment $a_i$ with factor ratios throughout.[9]

## 3 Data

To illustrate the testing strategy outlined in the previous section, we rely on a unique dataset, the *Gambia Networks Data 2009,* which were collected in six out of eight Local Government areas between February and May 2009. A sample of 60 villages was randomly selected among villages with between 300 and 1000 inhabitants in the 2003 census. Restricting the sample to small villages is motivated by the desire to obtain complete dyadic data on factor transfers for each entire village. Collecting similar data in larger villages would have been impractical. For more detailed information on the data collection strategy, see Jaimovich (2015). The sample

[8] The few cases of increasing returns to farm size that have been documented in the literature seem to coincide with large differences in technological know-how between farmers, and may in fact signal high returns to human capital combined with the presence of readily available technological innovations. See also Allen and Lueck (1998) and Deininger and Feder (2001). For The Gambia, see Kargbo (1983)and von Braun and Webb (1989).

[9] This Appendix also contains an in-depth discussion of other possible models and their predictions regarding efficiency-enhancing reallocation of factors.

is representative of smaller villages of The Gambia, which account for 20 percent of villages in the country (Arcand and Jaimovich, 2014). Data was collected on each household in each village using a structured group interview approach. Information is available on the land $a_i$ and labor $l_i$ endowments of each household, as well as on all land and labor transactions $w_{ij}$ within each village for an entire agricultural year. The data also contains information on pre-existing social links.

Six villages are dropped from the analysis presented here because of missing household-level information. Given that our empirical focus is on factor transfers in agriculture, we drop three semi-urban villages[10] and we restrict the analysis to households whose main activity is farming.[11] The sample we use for the empirical analysis consists of 1,625 households across 50 villages, corresponding to 54,144 within-village dyads.

Rural villages in The Gambia are organized around compounds. A compound is a group of buildings, used for housing, storage and other purposes, that are located in relative proximity to each other, typically around a central courtyard. Most often, a compound has a single household head that makes decisions regarding production and other daily activities. Sometimes a compound has several decision makers. In such cases, independent production units (*dabadas*) can exist within the compound and independent consumption and cooking units (*sinkiros)* can exist within a single compound or within a single *dabada* (von Braun and Webb, 1989; Webb, 1989). Since we are interested in production decisions, the *dabada* is used as the unit of observation. If several *dabadas* reside within the same compound, the data contain information about the social links between them. Fourteen percent of household heads in our sample are not heads of the compound in which they live.

Descriptive statistics for the variables of interest are presented in Table 1. They paint a picture typical of rural Gambia. The largest households in the sample have more than 50 members, but they only account for 0.01 percent of the total sample. These large households arise as the result of polygamous marriages, which are frequent in our data: fifty percent of household heads have more than one wife. The household head is on average 54 years of age. Sample households are predominately headed by poorly educated men: only 8.7 percent have any formal education and nearly half are illiterate; the rest have received Koranic education providing basic literacy in Arabic. [12] In the analysis we take as pre-determined the number

[10]In terms of network activity, 2 percent of the households in the semi-urban villages participate in the land market, while 10 percent participate in the labor market. The main reason for the absence of land sharing is probably the very small landholdings in these areas (0.24 hectares per household compared to 10.28 in the rural villages), and the much higher availability of employment opportunities outside the village.

[11]Village level averages such as $\bar{a}$ and $\bar{r}$ are calculated for farmers only.

[12]The high incidence of polygamy, low education level, and advanced age of household heads are unusual compared to other parts of Africa. But they tally with what is known about The Gambia. According to the nationally representative Multiple Indicator Cluster Survey (MICS) from 2010, 41 percent of women aged 14-49 are in a polygamous marriage. More than two-thirds of the women aged 14-49 are currently married (The Gambia Bureau of Statistics (GBOS), 2011). MICS also reports that 68.4 percent of household heads have no education. This share is higher in our dataset due to the rural nature of the sample. The official report on the 2003 Gambian census, which constitutes the sampling frame for the survey, lists the mean age of household heads to be 46 (The Gambia Bureau of Statistics (GBOS), 2008).

Table 1: Household-level descriptive statistics

| | Mean | Std. Dev. |
|---|---|---|
| Household size | 14.1 | 15.0 |
| Age of head | 54.3 | 16.2 |
| Female headed household | 5.7% | |
| Head has some formal education | 8.7% | |
| Head is illiterate | 48.9% | |
| Income per capita (in 2009 PPP US$) | 282 | 285 |
| Share of income from crop sales | 16.1% | 0.271 |
| Receive remittances | 45.5% | |
| Relative wealth level (=1 (low), 2, 3 or 4 (high)) | 1.75 | 0.81 |
| Observations | 1,625 | |

Source: Author's own calculations on the Gambia Networks Data 2009.

of working adults available to the household for work on the farm, and we focus on factor transfers made during a single cropping season.

The average monetary income per capita is 2,750 Gambian Dalasis a year, which is equivalent to 282 USD a year in PPP terms.[13] The share of monetary income that comes from crop sales is 16 percent, which appears low but is probably due to the fact that crops are mostly consumed or bartered and, as a result, their contribution to income is under-reported. More than 45 percent of households receive remittances, reflecting a substantial incidence of migration abroad and to urban centers in The Gambia.[14]

### 3.1 Endowments and transfers of land and labor

In The Gambia, all land is nominally owned by the state, but usage rights are determined by the indigenous land tenure system (Freudenberger, 2000). Two principal types of usage rights exist, which are referred to as *primary* and *secondary.* A household with primary rights over a plot of land can not only decide which crops to grow but also whether to lend all or some of the land to another farmer – in which case this farmer gains secondary rights over that land. A household with secondary rights over a plot has full control over its agricultural management while they maintain secondary rights over it.

Landless and land-poor households can obtain secondary usage-rights to land in two ways (Freudenberger, 2000). First, households with surplus land have a moral obligation to transfer secondary rights over some of it to those in need. The village chief, in particular, often has a land reserve from which he can allocate land to households in need. Second, usage rights over

[13] Using Penn World Tables 7.1 PPP-adjusted exchange rate for 2009 (Heston et al., 2012). Note that consumption and bartering of own production is not included in this figure. The Gambia Integrated Household Survey of 2010 found that mean consumption of own production and gifts in The Gambia in 2010 amounted to 6,283 dalasis per household per year, or 776 dalasis per person, using the mean household size of 8.1 from that survey (GBS, 2011).

[14] According to the 2010 World Development Indicators, Gambia ranked second-highest in Sub-Saharan Africa in terms of international remittances as a share of GDP.

Table 2: Descriptive statistics on land and labor

| | Mean | Std. Dev. |
|---|---|---|
| Have primary usage rights to land | 81.9% | |
| Land owned with official rights (hectares) | 10.5 | 24.5 |
| Gini coefficient of land owned | 0.52 | |
| Ratio of land share to population share of main ethnic group | 1.2 | |
| Land-labour ratio (hectares land per active worker) | 2.76 | 7.39 |
| Participates in land transfers | 45.2% | |
| Land transfer (hectares) | 1.04 | 2.83 |
| Land transfer (% of donors' land endowment)* | 37.6% | 0.307 |
| Number of working adults | 5.4 | 10.4 |
| Participates in labor transfers (within the village) | 54.4% | |
| Labor transfer (days) | 5.3 | 15.4 |

* Conditional on transferring out land. Excludes observations where the donor is also a receiver.
Source: Author's own calculations on the Gambia Networks Data 2009.

land can be accessed through market-based transactions such as land rental. Sharecropping is not a common practice in The Gambia.[15] The questionnaire was designed to capture both monetary and non-monetary transfers of secondary usage rights. In practice, most transfers are non-monetary, although small payments in cash, kola nuts, or labor services sometimes are made to mark the fact that the secondary user continues to recognize the primary rights of the owner over the land (Eastman, 1990; Freudenberger, 2000; Jaimovich, 2011). This practice is common in African land tenure systems (e.g., Platteau 1992) and is confirmed by field observations made during the survey.[16]

Secondary usage rights are temporary in nature. Plots are borrowed on an annual or seasonal basis (Chavas et al., 2005). This means that households with few or no primary usage rights to land must secure or renew secondary usage rights every year. The overwhelming majority of land transfers recorded in the survey relate to annual or seasonal usage rights.

As shown in Table 2, 82 percent of farming household have some *primary* usage rights to land and their average land holding is 10.5 hectares per household. The distribution of primary usage rights is highly unequal, however, with some households having less than 0.5 hectares and others more than 100 hectares. The Gini coefficient of primary land rights, averaged over the 50 villages, is 0.52 and the share of land in the hands of the 10% most land-rich households is 34% on average. This unequal distribution is partly a result of the process of village settlement – which, in the case of much of sub-Saharan Africa, tend to be relatively recent.[17] According to African customs, village founders acquire primary usage rights over

[15] Dey (1982) describes how donor-supported sharecropping schemes in The Gambia were unsuccessful and quickly abandoned.

[16] We thank Dany Jaimovich, who participated in the data collection, for this observation.

[17] It is estimated that a hundred years ago, Africa had less than 100 million inhabitants, possibly as few as 50 million. This compares to the current population of approximately 1 billion. The offshoot of this reality is that the majority of African villages in existence today were probably created in the last century (See Arcand and Jaimovich, 2014, for more detail on the case of Gambia).

the land they clear. Upon their death, these rights are passed on to their descendents. As the village grows by attracting new members from other lineages and ethnic groups, descendents of the village founders tend to retain rights over more of the village land.

The unequal ownership of land is reflected in the social structure: members of the founder lineages have intermarried and tend to belong to the same ethnic group. Therefore, owners of much of the land tend to come from the same ethnic group and to all be related to each other: as shown in Table 2, a village's main ethnic group typically own more land than its share of the population – the ratio between the two exceeds 1 on average. Similarly, households in the village's largest kinship group on average own more than three times more land that households outside that group. There is therefore much scope for increasing allocative efficiency by transferring secondary land usage rights from descendants of the village founders to relative newcomers. Efficiency-enhancing transfers of land should thus flow primarily from founder lineages to other ethnic and kinship groups. It is nonetheless unclear whether moral obligations to transfer usage rights to land-poor households are sufficiently strong to extend across ethnic and kinship lines.

We also have information about labor endowments. Households have an average of 5.4 working-age adults. The corresponding land–labor ratio is 2.8 hectares per working adult on average among the farming households in the sample. While this indicates that land is relatively abundant on average, land endowments are inequitably distributed, so that the median land–labor ratio is 1 hectare per working adult.

These observations form the main motivation for our empirical investigation: the settlement history of Gambian villages has generated a highly unequal distribution of primary land rights that partly coincides with ethnic and kinship divides. Hence our research question: are transfers of secondary land rights hindered by social structure, thereby hindering allocative efficiency?

Table 3 provides descriptive statistics on participation in land and labor transfers, in the sample as a whole, and separately by land–labor ratios. Around 45 percent of households engage in land transfers, and households that export land typically transfer land to more than one household. Land transfers amount to 38 percent of the initial land endowments of the land-exporting households. At the receiving end, 36 percent of landless households in the sample receive secondary land rights from other households.[18]

A large proportion of households participate in labor transfers (54 percent). But the average household head only spends 5.4 days working on someone else's farm. This is small compared to land transfers, which amount to more than one hectare of land per household, or around 10 percent of their average land endowment. One possible interpretation, often proposed in the literature (e.g., Ali and Deininger 2015) is that transaction costs are higher for labor than land transfers – possibly because of supervision difficulties.[19] For this reason,

[18] The 2 percent of landless households who transfer out land also transfer land in – and thus end up with a nonnegative amount of land.

[19] The relatively small geographical size of the villages means that soil quality is fairly uniform within each

Table 3: Land and labor market participation rates by initial land–labor ratios

| | All | Landless | 0.1-0.6 ha/w | 0.6-1.6 ha/w | 1.6-3.0 ha/w | 3.0 ha/w |
|---|---|---|---|---|---|---|
| *Land transfers:* | | | | | | |
| Participates | 45.2 | 36.1 | 42.4 | 41.1 | 53.8 | 56.5 |
| Land sender | 21.0 | 2.0 | 14.9 | 19.0 | 30.1 | 40.5 |
| Land receiver | 28.9 | 35.7 | 33.3 | 26.2 | 30.5 | 21.4 |
| *Labor transfers:* | | | | | | |
| Participates | 54.4 | 42.5 | 49.8 | 56.6 | 64.3 | 57.5 |
| Labor sender | 36.9 | 30.6 | 34.1 | 39.5 | 43.6 | 34.7 |
| Labor receiver | 32.3 | 23.8 | 27.5 | 30.6 | 41.0 | 39.8 |
| Observations | 1,625 | 294 | 255 | 516 | 266 | 294 |

Note: ha/w corresponds to the number of hectares per working adult.

Source: Author's own calculations on the Gambia Networks Data 2009.

labor markets in subsistence agriculture are very thin throughout most of West Africa (Otsuka, 2007; Holden et al., 2009).[20] Since land transfers by definition take place before labor transfers, transfers of secondary land rights serve to reduce differences in land-labor ratios across households ex ante, so as to obviate the need for ex post adjustment through labor transactions. As a result, the primary role of labor transactions is to deal with shocks in household manpower availability, e.g., through illness.

A cursory look at the data reveals that, as anticipated, households with a higher initial land–labor ratio are more likely to transfer-out land and less likely to transfer-in land. The same pattern is not evident for labor: land abundant households are not more likely to transfer in labor, suggesting that labor transfers do not serve to equalize land-labor ratios across households. For these reasons, the empirical analysis is largely focused on transfers of secondary land rights.

### 3.2 Social proximity

The data contain information on three distinct aspects of pre-existing social structure: ethnicity, kinship (family ties), and geographical proximity. We use this data to construct two group-wise $D_{ij}$ and two pairwise $L_{ij}$ variables.

The sample is representative of the ethnic diversity in The Gambia. As shown in Table 4, the largest ethnic group (Mandinka) accounts for 54.1 percent of households in the sample. Four other ethnic groups each account for at least 5 percent of the households.[21] Since, by definition, ethnicity is shared by all the members of a group, it is captured using a group-wise

village. Hence information asymmetries and moral hazard are probably less severe in land transactions than in labor transactions.

[20]Seasonal migrant workers typically referred to as 'strange farmers' were a relatively common phenomenon in rural Gambia in the past (Swindell, 1987). They were not commonly found in the studied villages in 2009, however, and they do not appear in the data.

[21]Using the Herfindahl index to measure ethnic diversity, we find that ethnic fragmentation inside villages ranges from 0 (completely homogeneous) to 0.84, with a mean of 0.28.

Table 4: Descriptive statistics on ethnicity and kinship links

| | Mean |
|---|---|
| Ethnicity: Mandinka | 54.1% |
| Ethnicity: Fula | 18.6% |
| Ethnicity: Wollof | 10.1% |
| Ethnicity: Jola | 6.5% |
| Ethnicity: Sererr | 5.6% |
| Household head has family links in the village | 85.0% |
| Wife of household head has family links in the village | 50.8% |
| Household have marriage links in the village | 64.2% |
| Household has family links in the village | 95.8% |
| Observations | 1,625 |

Source: Author's own calculations on the Gambia Networks Data 2009.

variable $D_{ij}^E$ equal to 1 if $i$ and $j$ share the same ethnicity. In this case, each ethnic group forms a component.

Kinship, in contrast, defines a symmetric network in which a link $L_{ij}^K$ between two households $i$ and $j$ is defined to exist if they are related, either through the household head, the wife(s) of the head, or through marriage. Unlike in other African contexts (e.g., Barr et al., 2012), kinship networks are relatively dense in our sample. As shown in Table 4, 85 percent of household heads and 51 percent of their wives have relatives in the village. Similarly, 64 percent of households have marriage ties in the village. In total, 95.8 percent of households have at least one of these kinds of links. This means that the largest component of the kinship network is often large: in the majority of villages, most (though not all) households are connected, directly or indirectly, through consanguinity and marriage, and thus belong to the same network component. Component membership defines a second group-wise variable $D_{ij}^K$.

We also have information on whether two households reside in neighboring compounds. We use this information to define a pairwise variable $L_{ij}^D$ equal to 1 if $i$ and $j$ are neighbors, and 0 otherwise. Given that households live relatively close to each other, there is no natural partition of households into components, and we do not attempt to define a group-wise variable $D_{ij}^D$. Data on geographical proximity were only collected in 25 of the villages, containing 624 households in total. In the reduced sample on which proximity data is available, almost 10 percent of the households are compound neighbors.

Kinship, ethnicity, and geographical distance are the dimensions of social proximity for which we have data. They offer the advantage of being immutable or pre-determined and are thus reasonably exogenous to the factor transfers taking place within an agricultural season. We nonetheless expect that factor transfers between two households are often embedded in long-term relationships of favor exchange that we do not observe. From the available literature, it is likely that these favor exchange relationships are shaped, as least partially, by kinship, ethnicity, and geographical distance. If gift exchange transcends pre-determined social categories such that they do not matter, this will show up in our analysis as zero $\alpha_3, \alpha_4$

and $\alpha_5$ coefficients on network regressors. Even in this case, gift exchange may still not achieve efficiency. For instance, even if people choose their network links so as to maximize gains from factor exchange, they may not be able to sustain a number of links that is sufficient to ensure equalization of factor endowments or factor ratios in all circumstances. This situation will manifest itself in the form of $\alpha_1$ and $\alpha_2$ being less than 1. These observations form the basis for our testing strategy.

## 4 Empirical results

Before launching into the estimation of our model, we look at the available evidence regarding the redistribution of land among farming households through transfers. The Gini coefficient on after-transfer household land is 0.47, compared to 0.52 for before-transfer land endowments. More than 75 percent of villages have a more equal factor distribution after land transfers than before. The proportion of after-transfer land in the hands of the 10% most land-rich households is 31% – down from 34% on average. Land transfers also tend to equalize differences in endowments across ethnic groups: after transfers, the largest ethnic group controls 1.12 times more land than members of other ethnic groups, compared to 1.2 before transfers. From this we conclude that transfers have, on average, an equalizing effect on the allocation of cultivable land. But the distribution of land after transfers remains fairly unequal.

To provide an initial check on the idea that inequality is mitigated by social structure, we estimate in Table 5 a set of regressions of village-level land inequality on measures of social network density. To facilitate interpretation, network density is normalized by its standard deviation. Inequality measures are calculated both before and after land transfers. The results show a negative association between village network density and land inequality before transfers: more socially connected villages are more equal both before and after land transfers. This is true for both the kinship network as well as neighbor links, but this association does not hold for the ethnic components. This is somewhat surprising, and something we return to in the link-level analysis. The effects are qualitatively unchanged if we instead consider inequality after land transfers, althoug the significance level is reduced. [22] The estimated coefficients are small, but economically meaningful: a one standard deviation increase in either the kinship or neighbor density measure is associated with a decrease in the Gini coefficient of between four and eleven points, depending on the network density measure used.

We also investigate whether land transfers are more common between socially proximate households. To this effect we regress $|w_{ij}|$ on the five measures of social proximity described earlier: co-ethnicity $D_{ij}^E$, membership in the same kinship component $D_{ij}^K$, being directly related $L_{ij}^K$, and being neighbors $L_{ij}^D$. Results, shown in Table 4, show that $D_{ij}^E$ and $D_{ij}^K$ do not predict land transfers, but $L_{ij}^K$ and $L_{ij}^D$ do, suggesting homophyly in land transactions

[22] This is perhaps not surprising: the same underlying factors that facilitate short-term land transfers may also facilitate permanent land transfers between households – e.g., through inheritance and transfers inter vivos at the time of marriage.

Table 5: Village land inequality and social network density

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Before land transfers | | | After land transfers | | |
| | Kinship | Ethnicity | Neighbor | Kinship | Ethnicity | Neighbor |
| Density / SD | -0.068*** | -0.019 | -0.107** | -0.038* | 0.005 | -0.071* |
| | (0.021) | (0.023) | (0.041) | (0.020) | (0.020) | (0.035) |
| Constant | 0.645*** | 0.572*** | 0.662*** | 0.542*** | 0.457*** | 0.557*** |
| | (0.043) | (0.066) | (0.077) | (0.041) | (0.059) | (0.066) |
| Observations | 50 | 50 | 24 | 50 | 50 | 24 |

Note: The dependent variable are gini coefficients at the village level and can vary between zero and one.
Source: Author's own calculations on the Gambia Networks Data 2009.

along those two dimensions.[23]

The situation can thus be summarized as follows: an essential resource is not allocated equitably between small producers, a situation we have reasons to suspect to be inefficient; the dominant ethnic group in a village owns more land; inequality in land and factor ratios is lower in more socially connected villages; and farmers who are neighbors or directly related share more land with each other. To many, this type of evidence is a smoking gun suggesting that preferential transfers between members of the land-rich dominant ethnic group contribute to the unequal land allocation. The purpose of our testing strategy is to put this 'smoking gun' reasoning to the test.

We start by estimating the various models outlined in section 2 on land transfers alone. The main reason for focusing on land is that, as noted above, land transfers are much more important than labor transfers in terms of the proportion of traded factors.

A fair approximation of our data is that land transfers are used to determine the size of one's farm ex ante, while labor transfers are used to deal with temporary surpluses and deficits in labor ex post – e.g., in response to unforeseen shocks in the production process (Fafchamps, 1993). To verify the robustness of our findings, in the next sub-section we replicate the analysis in terms of land–labor ratio. As discussed in the conceptual section and demonstrated in Appendix B, our methodology can similarly be applied using land-labor ratios in lieu of land endowments to allow for possible trade in labor.

## 4.1 Land transfers

We first test whether land transfers eliminate differences in land endowments. This is achieved by estimating our simplest model (2). The average land endowment $\overline{a}$ is calculated as the sum of all land endowments divided by the number of households in the village.[24] Since the

[23] Virtually identical results are obtained if we replace the dependent variable by a dummy equal to 1 is $|w_{ij}| > 0$ and 0 otherwise.

[24] The dataset also includes information about land transfers to and from households outside the village. To avoid biasing our testing strategy, these transfers are netted out before calculating $\bar{a}$.

Table 6: One factor model: Do social components equalize farm size?

| Regressor | Coefficient | (1) | (2) Ethnicity | (3) Kinship | (4) Ethnicity | (5) Kinship |
|---|---|---|---|---|---|---|
| $\frac{(a_i - \overline{a})}{N_v}$ | $\alpha_1$ | 0.024** | | | 0.032*** | 0.0510*** |
| | | (0.009) | | | (0.011) | (0.016) |
| $\frac{(\overline{a} - a_j)}{N_v}$ | $\alpha_2$ | 0.024** | | | 0.032*** | 0.051*** |
| | | (0.009) | | | (0.011) | (0.016) |
| $\frac{(a_i - \overline{a}_k)}{N_v} D_{ij}$ | $\alpha_3$ | | 0.015** | 0.017** | -0.009* | -0.029*** |
| | | | (0.006) | (0.007) | (0.005) | (0.010) |
| $\frac{(\overline{a}_k - a_j)}{N_v} D_{ij}$ | $\alpha_4$ | | 0.015** | 0.017** | -0.009* | -0.029*** |
| | | | (0.006) | (0.007) | (0.005) | (0.010) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 | 0 |
| Observations | | 54,144 | 54,144 | 54,144 | 54,144 | 54,144 |

Note: The dependent variable is the amount of land transferred from $i$ to $j$ measured in hectares. Standard errors clustered by village are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

regression is dyadic, standard errors must be corrected for non-independence across observations. To deal with this issue, we cluster standard errors at the village level. This allows for any correlation structure between errors within each village, including the type of network error correlation discussed in Fafchamps and Gubert (2007).

Results are presented in the first column of Table 6. The statistically positive coefficient $\alpha_1$ imply that land abundant farmers on average transfer out land, while land-poor households import land from others. But these transfers are not sufficient to equalize land across households within each village: the test $\alpha_1 = \alpha_2 = 1$ is strongly rejected with $p < 0.0001$. This particular finding is vulnerable to measurement error in $a_i$, which is expected to generate attenuation bias. It follows that $\widehat{\alpha}_1$ and $\widehat{\alpha}_1$ should probably best be seen as as a lower bound on the true coefficients. Still, point estimates are only a small percentage what would be required for land equalization, suggesting that attenuation bias is unlikey to account for the rejection of perfect equalization.

Next we examine whether there are more equalizing land transfers between members of the same ethnic group or kinship component, i.e., for $D^E_{ij}$ and $D^K_{ij}$, respectively. Estimation results for regression model (4) are presented in the columns 2 and 3 of Table 6. Results indicate that transfers achieve less equalization of land area within ethnic groups (column 2) or kinship components (column 3) than they achieve across the villages as a whole: $\widehat{\alpha}_3 < \widehat{\alpha}_1$ in both cases. This is our first indication that land transfers do not operate primarily within ethnic or kinship groupings.

In Columns 4 and 5, we combine both sets of regressors and estimate the joint model (6), repeated below for convenience:

$$
\begin{aligned}
w_{ij} \quad = \quad & \alpha_0 + \alpha_1 \frac{a_i - \overline{a}_v}{N_v} + \alpha_2 \frac{\overline{a}_v - a_j}{N_v} \\
& + \alpha_3 \frac{a_i - \overline{a}_k}{N_k} D_{ij} + \alpha_4 \frac{\overline{a}_k - a_j}{N_k} D_{ij} + u_{ij} \qquad (8)
\end{aligned}
$$

We obtain positive coefficient estimates for $\alpha_1$ (and $\alpha_2$) but negative coefficient estimates for $\alpha_3$ (and $\alpha_4$). As shown in the simulation results presented in Appendix A, this outcome arises when transfers serve to equalize land across the whole village.[25] This confirms that there is no more land equalization within ethnic or kinship groups than across the entire village. In other words, ethnicity and kinship are not what drives the lack of land equalization in the village. This is consistent with Arcand and Jaimovich (2014) who also conclude that ethnic divisions do not reduce land transfers in the Gambia Networks Data 2009.

One possible interpretation of these findings is that lineage heads, who are entrusted with the land of their lineage, choose to co-opt newcomers into the village by granting them secondary or temporary rights on land. Since these newcomers often are from a different ethnic and kinship group, this means that sizable land transfers take place across ethnic and kinship boundaries. If we ignore land transfers from these outliers, we may find more evidence of land equalization within ethnic and kinship groups.

To verify this interpretation, we reestimate the regressions without land-rich outliers. In practice, we winsorize these outliers by replacing values of $(a_i - \bar{a}_k)/N_k$ and $(\bar{a}_k - a_j)/N_k$ below the first percentile and above the 99th percentile with the value of the first and the 99th percentile, respectively. Results are shown in Table 7. Two findings come out of this exercise. First, when estimating regression model (4) (columns 1 and 2), point estimates for $\alpha_3$ and $\alpha_4$ increase markedly: they more than double for ethnicity and nearly double for kinship. This suggests that, when transfers from outliers are omitted from the analysis, the rest of the transfers within co-ethnic or kin farmers serve a more effective role in within-group land equalization. However, when we estimate model (6), we again find negative estimates for $\alpha_3$ and $\alpha_4$ (albeit not significantly so in the case of co-ethnicity) and positive estimates for $\alpha_1$ and $\alpha_2$. This indicates that the negative coefficients found in Table 6 are not purely due to large land owners: even smaller land owners share land across ethnic or kinship boundaries.

Next, we introduce direct kinship links between households $L_{ij}^K$ and estimate model ((5)). Results, reported in column 1 of Table 8, show that $\widehat{\alpha}_5$ is positive and statistically significant, suggesting that land transfers between directly related households tend to equalize their respective land areas. The point estimate is very small, however: approximately 0.2% of the transfers that would be necessary to equalize landholdings between related households. Once we add village regressors $\frac{a_i - \overline{a}_v}{N_v}$ and $\frac{\overline{a}_v - a_j}{N_v}$, the finding disappears, as shown in column 2. Again, the interpretation is that land transfers are better predicted by differences from the

[25] Point estimates $\alpha_3$ and $\alpha_4$ turn negative in this case because average land endowments differ across ethnic groups, and land equalization within the village means moving away from land equalization within ethnic or kinship groupings.

Table 7: Robustness to outliers of component results

| Regressor | Coefficient | (1) Ethnicity | (2) Kinship | (3) Ethnicity | (4) Kinship |
|---|---|---|---|---|---|
| $\frac{(a_i - \overline{a})}{N_v}$ | $\alpha_1$ | | | 0.046** | 0.083*** |
| | | | | (0.021) | (0.024) |
| $\frac{(\overline{a} - a_j)}{N_v}$ | $\alpha_2$ | | | 0.046** | 0.083*** |
| | | | | (0.021) | (0.024) |
| $\frac{(a_i - \overline{a}_k)}{N_v} D_{ij}$ | $\alpha_3$ | 0.038*** | 0.032*** | -0.004 | -0.043*** |
| | | (0.012) | (0.011) | (0.017) | (0.016) |
| $\frac{(\overline{a}_k - a_j)}{N_v} D_{ij}$ | $\alpha_4$ | 0.038*** | 0.032*** | -0.004 | -0.043*** |
| | | (0.012) | (0.011) | (0.017) | (0.016) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 |
| Outlier method | | Winsorization | Winsorization | Winsorization | Winsorization |
| Observations | | 54,144 | 54,144 | 54,144 | 54,144 |

Note: The dependent variable is the amount of land transferred from $i$ to $j$ measured in hectares. Standard errors clustered by village are shown in parentheses. *** p<0.01, ** p<0.05, * p<0.1

village average than by pairwise differences across related households.

In the last two columns of Table 8 we consider geographical proximity $L_{ij}^D$. As explained earlier, data on compound neighbors only exist for a subset of households, hence the drop in the total number of observations. When the only regressor is the pairwise land difference between neighbors, we find a positive and significant $\alpha_5$ estimate, suggesting that land transfers between neighbors on average go in the direction of equalizing their respective land areas. Unlike in the case of related households, this finding survives adding village regressors $\frac{a_i - \overline{a}_v}{N_v}$ and $\frac{\overline{a}_v - a_j}{N_v}$: point estimates for $\alpha_1$ and $\alpha_2$ remain large and comparable to those obtained in column 2, but they are not statistically significant. In contrast, $\widehat{\alpha}_5$ remains statistically significant, weakly suggesting that land transfers serve more the role of land equalization between neighbors than land equalization within the village. We cannot, however, reject the hypothesis that $\alpha_1$ and $\alpha_2$ are equal to the estimates reported in column 2. Furthermore, point estimates remain well below 1 throughout, indicating that perfect equalization is far from achieved.

To conclude, we find that land transfers on average go in the direction of equalizing land across all households in the village, although the effect is small in magnitude – a result that is in agreement with our earlier finding that the Gini coefficient of land drops from 0.52 to 0.47 after transfers, a modest improvement. We find no evidence that there is more equalization of land area within ethnic or kinship group than across the village as a whole. This finding remains even when we remove large landowners whose social role includes welcoming newcomers into the village by offering them some land to cultivate on a temporary basis. This implies that land transfers generally occur across ethnic and kinship boundaries. When we look more closely at close links between neighbors and between directly related households, we find

Table 8: One factor model: Do direct social links equalize farm size?

| Regressor | Coefficient | (1) Kinshipy | (2) Kinship | (3) Neighbor | (4) Neighbor |
|---|---|---|---|---|---|
| $\frac{(a_i - \overline{a})}{N_v}$ | $\alpha_1$ | | 0.021** | | 0.025 |
| | | | (0.010) | | (0.022) |
| $\frac{(\overline{a} - a_j)}{N_v}$ | $\alpha_2$ | | 0.021** | | 0.025 |
| | | | (0.010) | | (0.022) |
| $\frac{(a_i - a_j)}{2} L_{ij}$ | $\alpha_5$ | 0.002** | 0.001 | 0.007* | 0.005* |
| | | (0.001) | (0.001) | (0.004) | (0.003) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 |
| Observations | | 54,144 | 54,144 | 21,266 | 21,266 |

Note: The dependent variable is the amount of land transferred from $i$ to $j$ measured in hectares. Standard errors clustered by village are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

evidence that land transfers go in the direction of equalizing landholdings between them. But for direct kinship links, the effect disappears once we control for village-level regressors. In contrast, we do find evidence that land transfers between neighbors serve to equalize their respective landholdings over and above their role in equalizing landholdings at the village level. Coefficient estimates are well below 1 in all cases, however, indicating that equalization is far from achieved in any of the cases we consider.

### 4.2 Factor ratios

As explained in the conceptual section, land equalization need not be efficient if farmers differ in productivity. If productivity differences are Hicks-neutral and labor is tradable, however, factor ratios should be equalized across farms. To investigate this possibility, we test whether land transfers serve to equalize the land-labor ratio $r_i$ across farms and, more importantly, whether social structure is an impediment to such equalization at the village level. To this effect we repeat the same analysis using land-labor ratios $r_i$ in lieu of land endowments $a_i$.

The first set of results is presented in Table 9, which mirrors Table 6. Results are qualitatively similar, but point estimates are larger – albeit still well below 1. As before we find that equalization within villages trumps equalization within ethnic or kinship groups: point estimates $\alpha_3$ and $\alpha_4$ become negative once we include village level regressors $\frac{r_i - \overline{r}_v}{N_v}$ and $\frac{\overline{r}_v - r_j}{N_v}$. In results not shown here to save space, we repeat the winsorization exercise of Table 7, and find qualitative identical results, albeit with larger point estimates. Table 9 mirrors Table 8, with the inclusion of direct kinship or neighbor links between household pairs. Results are again similar to those presented earlier.

To conclude, results regarding factor ratio equalization are quite similar to those of land equalization: land transfers on average go in the direction of factor ratio equalization but fall far short of achieving it in full. We do not, however, find that this failure is driven by

Table 9: Two factor model: Do social components equalize farm size?

| Regressor | Coefficient | (1) | (2) Ethnicity | (3) Kinship | (4) Ethnicity | (5) Kinship |
|---|---|---|---|---|---|---|
| $\frac{(r-\bar{r})}{N_v}$ | $\alpha_1$ | 0.065*** | | | 0.089*** | 0.152*** |
| | | (0.021) | | | (0.029) | (0.037) |
| $\frac{(\bar{r}-r_j)}{N_v}$ | $\alpha_2$ | 0.065*** | | | 0.089*** | 0.152*** |
| | | (0.021) | | | (0.029) | (0.037) |
| $\frac{(r_i-\bar{r}_k)}{N_v}D_{ij}$ | $\alpha_3$ | | 0.037*** | 0.045*** | -0.026* | -0.090*** |
| | | | (0.013) | (0.015) | (0.013) | (0.023) |
| $\frac{(\bar{r}_k-r_j)}{N_v}D_{ij}$ | $\alpha_4$ | | 0.037*** | 0.045*** | -0.026* | -0.090*** |
| | | | (0.013) | (0.015) | (0.013) | (0.023) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 | 0 |
| Observations | | 54,144 | 54,144 | 54,144 | 54,144 | 54,144 |

Note: The dependent variable is the amount of land transferred from $i$ to $j$ measured in hectares. Standard errors clustered by village are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

Table 10: Two factor model: Do direct links equalize farm size?

| Regressor | Coefficient | (1) Kinship | (2) Kinship | (3) Neighbor | (4) Neighbor |
|---|---|---|---|---|---|
| $\frac{(r-\bar{r})}{N_v}$ | $\alpha_1$ | | 0.061** | | 0.058 |
| | | | (0.023) | | (0.070) |
| $\frac{(\bar{r}-r_j)}{N_v}$ | $\alpha_2$ | | 0.061** | | 0.058 |
| | | | (0.023) | | (0.070) |
| $\frac{(r_i-r_j)}{2}L_{ij}$ | $\alpha_5$ | 0.005** | 0.002 | 0.017* | 0.014* |
| | | (0.002) | (0.003) | (0.010) | (0.008) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 |
| Observations | | 54,144 | 54,144 | 21,266 | 21,266 |

Note: The dependent variable is the amount of land transferred from $i$ to $j$ measured in hectares. Standard errors clustered by village are shown in parentheses.*** p<0.01, ** p<0.05, * p<0.1

a propensity to equalize factor ratios primarily within ethnic or kinship groups, or between directly related households. We do, however, find some evidence that neighbors share land to even out their factor ratio differences over and above what is explained by village-wide equalization.

### 4.3 Labor transfers

Land transfers are not the only margin that can be used to equalize factor ratios across households. Another option is to adjust the amount of labor during the cropping season. To formally examine this, we use labor transfers of household heads as dependent variable $w_{ij}$ and estimate a model of the form:

$$w_{ij} = \beta_0 + \beta_1 \frac{(r_i - \overline{r})}{N_v} + \beta_2 \frac{(\overline{r} - r_j)}{N_v} + u_{ij} \tag{9}$$

This model can be extended similarly to models (4) and (5). Labor transfers that improve allocative efficiency requires negative parameter estimates: labor $l$ should on average to flow from agents with a low land-labor endowment ratios $r_i$ to agents with high land-labor ratios relative to the village average $\overline{r}$. Estimation results are reported in Table 11. We find no evidence that labor transfers equalize factor ratios: The only parameter of statistical significance is the kinshop link parameter, and it is of the opposite sign (positive), than what is required for family links to positively impact the factor-equalizing properties of labor transfers. These findings suggest that labor transfers do not help equalize ex ante factor ratios in the studied villages. Given the timing of labor transfers – i.e., after cultivation rights have been allocated and planting has begun – the logical conclusion is that labor transfers primarily serve as an ex post adjustment to labor shocks.[26]

If labor transfers are only used as an ex post adjustment to labor shocks during peak season, cultivated land can be taken as pre-determined at the time these transfer takes place. Given this, it may be useful to reestimate model (9) using land-labor ratios calculated using cultivated land in lieu of owned land. In results not shown here, we have investigated this possibility.[27] Results are very similar to those reported in Table 11.

[26] We do not show results of the combined models (6) and (7) in order to save space. Results closely resemble the reported results: Labor does not appear to play a factor-equalizing role.

[27] We investigate this possibility by defining $\tilde{r}_i \equiv \frac{\tilde{a}_i}{l_i}$ where $\tilde{a}_i$ is the land in the hands of farmer $i$ after all land transfers have taken place. If labor transfers serve to equalize factor rations ex post, labor should on average flow from agents with a low $\tilde{r}_i$ to those with a high $\tilde{r}_i$ relative to the village average $\overline{r}$.

Table 11: Do labor transfers equalize farm size?

| Regressor | Coefficient | (1) | (2) Ethnicity | (3) Kinship | (4) Kinship | (5) Neighbor |
|---|---|---|---|---|---|---|
| $\frac{(r-\bar{r})}{N_V}$ | $\alpha_1$ | 0.000 | | | | |
| | | (0.000) | | | | |
| $\frac{(\bar{r}-r_j)}{N_v}$ | $\alpha_2$ | 0.000 | | | | |
| | | (0.000) | | | | |
| $\frac{(r_i-\bar{r}_k)}{N_v}D_{ij}$ | $\alpha_3$ | | 0.000 | 0.000 | | |
| | | | (0.000) | (0.000) | | |
| $\frac{(\bar{r}_k-r_j)}{N_v}D_{ij}$ | $\alpha_4$ | | 0.000 | 0.000 | | |
| | | | (0.000) | (0.000) | | |
| $\frac{(r_i-r_j)}{2}L_{ij}$ | $\alpha_5$ | | | | 0.005** | -0.000 |
| | | | | | (0.001) | (0.000) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 | 0 |
| Observations | | 54,144 | 54,144 | 54,144 | 54,144 | 21,266 |

Note: The dependent variable is the amount of household head labor transfered from $j$ to $i$, measured in working days. Standard errors clustered by village are shown in parantheses.
*** p<0.01, ** p<0.05, * p<0.1

## 5 Discussion

We have examined whether social structure affects the equalization of factors and factor ratios across farming households. Provided some additional assumptions, the absence of equalization can be seen as implying a failure to allocate factors of production efficiently. How convincing is this conclusion? As noted in the conceptual section, whether or not inequality in cultivated acreage or factor ratios signals allocative inefficiency hinges on two maintained assumptions that we cannot substantiate with the data at hand: decreasing returns to scale; and unobserved productivity differences. We discuss them in turn.

We do not dispute the possible existence of increasing returns to scale in tropical farming, and indeed a number of tropical countries have (or have had) large successful commercial farms – including Liberia, which lies in West Africa like The Gambia. These commercial farms, however, rely on technological and organizational innovations that are out of the reach of the predominantly illiterate farmers residing in our study villages. Successful use of animal traction requires a minimum scale of production, but this scale is well within the realm of the smallholder farmers in our study. Using a simple replication argument, one may conclude that traditional farming is characterized by constant returns to scale in land and labor. While this argument is not without merit, it is widely recognized that hired labor is subject to various moral hazard considerations which create a wedge between the productivity of labor on one's own farm or someone else's. This particularly true in West Africa because agrarian sharing norms tend to delegitimate efforts to hire large number of agricultural laborers (Platteau et al., 1998). In the context of our study population, decreasing returns to scale thus are a reasonable assumption, substantiated by much existing data on smallholder farming in African and elsewhere (e.g., Deininger and Feder 2000, Ali and Deininger 2015).

To circumvent the possible existence of unobserved productivity differences, we applied our methodology to factor ratios which, if productivity differences are Hicks-neutral, should be equalized to achieve allocative efficiency. We showed that land transfers do not equalize ex ante land-labor ratios, and that labor transfers do not equalize ex ante or ex post factor ratios. The conclusion that follows from this evidence is that factors of production are not effiently allocated so as to match possible Hicks-neutral differences in productivity across farmers.

There remains the possibility that productivity differences across farmers are factor-biased. If some farmers have a higher land productivity than others[28], we would expect them to have a higher land-labor ratio. We suspect that unobservable productivity differences matter more in modern agriculture, and less in traditional subsistence agriculture which is fairly undifferentiated and follows simple heuristic rules of behavior. In our study area, factor-biased productivity differences would have to be large to explain a Gini coefficient of 0.47 in land available for cultivation – given how thin agricultural labor markets are in the study area. Furthermore, unless land and labor are near perfect substitutes in production – which is unlikely – we should observe much larger labor transactions from land-poor to land-rich (and presumably highly productive) farmers. This is not what we observe: labor flows hardly respond to differences in ex ante or ex post factor ratios. Finally, Chavas et al. (2005) find evidence that technical inefficiency among Gambian farmers is modest and that differences in factor mix are not driven by technological differences. The authors nonetheless find substantial allocative inefficiency in farm input allocation, which motivates the focus of the present paper.

While these arguments militates against the idea that productivity differences account for our data, we cannot fully rule it out. To provide evidence about the possible extent of the issue, we reestimate our regression models (2), (4) and (5) with additional controls for possible differences in factor-biased productivity across farmers. Village fixed effects can control for possible differences in land quality across villages. However, in the dyadic system that we estimate where $w_{ij} = -w_{ji}$, village fixed effects are perfectly collinear with the main variables of interest and differences across villages are de facto already accounted for. The territory of each individual village is fairly small so that within-village differences in land quality are likely to be small. Household-specific controls are added to proxy for differences in farm management and labor supervision capabilities between farmers. The list of controls, which is limited by the available data, is household size; age of the household head; literacy of the household head; whether the household head has any formal education; whether the household head is female; a dummy for whether the household receives remittances; and a wealth-level indicator. These controls are included for both the sending and receiving

[28] And land and labor are strong substitutes, i.e., the elasticity of substitution between them is more than 1. If the production function is (approximately) Cobb-Douglas, factor-specific productivity shifters factor out of the land and labor aggregates and are observationally equivalent to Hicks-neutral productivity diffferences.

Table 12: Including controls in the one-factor model

| Regressor | Coefficient | (1) | (2) Ethnicity | (3) Kinship | (4) Kinship | (5) Neighbor |
|---|---|---|---|---|---|---|
| $\frac{(a_i-\overline{a})}{N_v}$ | $\alpha_1$ | 0.023** | | | | |
| | | (0.009) | | | | |
| $\frac{(\overline{a}-a_j)}{N_v}$ | $\alpha_2$ | 0.023** | | | | |
| | | (0.009) | | | | |
| $\frac{(a_i-\overline{a}_k)}{N_v}D_{ij}$ | $\alpha_3$ | | 0.014** | 0.016** | | |
| | | | (0.006) | (0.007) | | |
| $\frac{(\overline{a}_k-a_j)}{N_v}D_{ij}$ | $\alpha_4$ | | 0.014** | 0.016** | | |
| | | | (0.006) | (0.007) | | |
| $\frac{(a_i-a_j)}{2}L_{ij}$ | $\alpha_5$ | | | | 0.002** | 0.007* |
| | | | | | (0.001) | (0.004) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 | 0 |
| Controls | | YES | YES | YES | YES | YES |
| Observations | | 54,144 | 54,144 | 54,144 | 54,144 | 21,266 |

Note: The dependent variable is the amount of land transferred from $i$ to $j$ measured in hectares. Standard errors clustered by village are shown in parentheses.*** $p<0.01$, ** $p<0.05$, * $p<0.1$

household. If village fixed effects and household controls capture part of the variation in land and labor productivity, we expect transfers to respond more closely to our model, and thus our earlier estimates should increase. Results of the one factor model with village fixed effects and household characteristics are reported in Table 12. Our main findings do not change, and point estimates are comparable in magnitude to those reported earlier. This is also the case when the controls are added to the two factor model (results not shown). Taken all together, the evidence fails to provide support for the conjecture that productivity differences is the primary driver of variation in land endowment across households in the study area.[29]

# 6 Conclusion

In this paper we have examined whether observable dimensions of social structure hinder or facilitate factor equalization in the rural Gambia. Land ownership is highly unequal in our study in spite of being populated by largely illiterate smallhorders practicing a traditional form of agriculture. Furthermore, labor transactions, though common, only represent a small share of total available labor. In this context, we expect a relative equalization of factors and factor ratios through factor transactions to improve the efficiency of factor allocation across farms.

It is widely believed that frictions caused by lack of trust or observability explain why

[29]Again, in order to preserve space, we do not show results of the combined models (6) and (7). Results of these models do also not change when including controls.

many economic transactions take place along more socially proximate households. This is indeed what we find in our data. It is therefore easier to equalize factor allocations within social groupings or between kin and neighbors. The question we investigate is whether the restrictions on factor transfers imposed by social structure restrict factor equalization across socially distant households and groups.

To our knowledge, this paper constitutes the first attempt to formally investigate this issue. We introduce a novel way of testing whether social and geographical distance reduces the likelihood of equalizing factor transfers. The data requirements for this approach are severe: we need exhaustive pairwise information about all factor transfers, and sufficiently rich data on relevant aspects of the social structure. Using such data for a large number of villages in The Gambia, we implement the approach empirically.

The results support the hypothesis that land transfers lead to a more equal distribution of land and to more comparable factor ratios across farms. But complete equalization is far from achieved. Contrary to expectations, we do not find that equalizing transfers of land are more likely within ethnic groups or kinship groups – if anything, we find the opposite result. This finding survives when we omit land transfers originating from a small number of households with large landholdings, whose social role is to welcome newcomers with some land. We also find some evidence that land transfers between neighbors perform a factor equalizing function over and above that occurring at the village-level, suggesting that land-poor households may benefit from their proximity to land-rich households. In contrast, we find no evidence that labor transfers serve to equalize factor allocation, either ex ante or ex post. Their role is probably to deal with unanticipated shocks – on which we have no data.

The methodology we present in this paper has many other potential applications to study the extent to which the absence of equalization – e.g., in prices, costs, access, or opportunities – is due to preferential linking or its converse, discrimination. The method requires exhaustive information about dyadics flows and sufficient information about social structure. Until not so long ago this type of information would have been hard to come by, in which case a 'smoking gun' approach would have the best available option. Today, however, exhaustive datasets on flows and links are becoming more commonly available, extending the relevance of our method.

The method does have some limitations, at least in its current form. The focus is on flows and obstacles to flows, not on the form that flows take (e.g., market or non-market exchange) or on the motivation for these flows (e.g., mutual assistance or self-interest). For instance, our empirical results do not imply that the perceived motive for land transfers is to equalize factor ratios or to increase efficiency. It is more likely that transfers are seen as a way of helping poor households and are given out of a sense of civic duty (Beck and Bjerge, 2015),[30] or because it is more cost-effective to transfer land to a poor household ex ante rather than transfer food and cash ex post (Fafchamps 1992). No matter the intent behind land transfers, the end result

[30] Using the same dataset, Jaimovich (2011) finds that differences in realized income inequality across villages are correlated with transfers of inputs and credit - though not of land.

is the same: transferring land to a land-poor household leads to a more egalitarian allocation of factors which, in a world of decreasing returns to scale, increases allocative efficiency.

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# Appendix A. Extended conceptual section

In this Appendix, we extend the modeling and testing strategy approach adopted in the conceptual Section. We start by briefly discussing models that make predictions at odds with the data. We then consider what happens if there are two factors of production. Finally we examine the testable implications of unobserved heterogeneity. We conclude with a summary of the lessons learned from this discussion. Some production function/transaction costs configurations make factor allocation predictions that cannot be tested by the data at hand. We nonetheless identify an important and empirically relevant subset that makes testable predictions regarding the reallocation of factors between farmers. For these configurations, our method can be applied to test whether efficiency-enhancing factor transfers are shaped by the structure of social networks.

## A.1 Constant and increasing returns to scale

If the single-factor production function exhibits constant returns to scale in $x_i$, any allocation of factors across households is efficient. Given this, we should not observe any factor transfers if, as is likely, there is any transaction cost in transferring factors across households. Since we do observe factor transfers in the data, we do not consider it further. Similarly, increasing returns to scale implies the concentration of all factors into a single production unit, which is not what we observe either. Hence we ignore it here.

## A.2 Two factor models

Let us assume two factors of production, say, $x$ and $y$. The production function is now of the form $q(x_i, y_i)$ where $y_i$ is a second factor of production. Each agent is endowed with a factor vector $\{a_i, l_i\}$ while the agent's factor usage is denoted $\{x_i, y_i\}$. The total supply of factors in the economy is denoted $A \equiv \sum_{i=1}^{N} a_i$ and $L \equiv \sum_{i=1}^{N} l_i$.

Allocative efficiency again depends on whether production is characterized by decreasing, constant, or increasing returns to scale. If the function $q(x_i, y_i)$ has increasing returns to scale in $x$ and $y$, the efficient allocation of factors is to have a single production unit concentrating all available factors – e.g., a plantation. Since this is not at all what we observe in our data, we do consider this case further. With constant returns to scale, there is no specific efficient scale of production. But efficiency requires that marginal rates of substitution between factors be equalized across households:

$$\frac{\frac{\partial q(x_i,y_i)}{\partial x_i}}{\frac{\partial q(x_i,y_i)}{\partial y_i}} = \frac{\frac{\partial q(x_j,y_j)}{\partial x_j}}{\frac{\partial q(x_j,y_j)}{\partial y_j}} \text{ for all } i \text{ and } j \tag{A.1}$$

If we further assume that the production function is homothetic in $x$ and $y$, an efficient factor allocation must satisfy:[31]

$$\frac{x_i}{y_i} = \frac{x_j}{y_j} = \overline{r} \text{ for all } i \text{ and } j \tag{A.2}$$

where $\overline{r} \equiv \frac{A}{L}$ is the average factor ratio in the economy. Hence, for transfers of factors across households to improve production efficiency, they must flow so as to equalize factor ratios across all households in a given village.[32]

This observation provides a partial characterization of factor transfers that can be used to test the role of social networks. Agents that have a factor ratio endowment $r_i \equiv \frac{a_i}{l_i} > \overline{r}$ should on average transfer out part of their $a_i$ endowment such that their factor usage ratio $x_i/y_i$ is equal to $\overline{r}$. This can be tested by estimating a regression model of the form:

$$w_{ij} = \alpha_0 + \alpha_1 \frac{r_i - \overline{r}}{N_v} + \alpha_2 \frac{\overline{r} - r_j}{N_v} + u_{ij} \tag{A.3}$$

where $w_{ij}$ as before denotes out-transfers of $a$. If factor transfers improve allocative efficiency, we should find that $\alpha_1 > 0$ and $\alpha_2 > 0$: on average, factor $a$ flows from agents relatively rich in that factor to agents poor in that factor.[33]

We are now ready to introduce limits to transfers imposed by social matrix $S$. The testing logic remains the same as before. If transfers are not feasible across components, we expect convergence in factor ratios within components only. The estimating equation becomes:

$$\begin{aligned} w_{ij} \quad = \quad & \alpha_0 + \alpha_1 \frac{r_i - \overline{r}}{N_v} + \alpha_2 \frac{\overline{r} - r_j}{N_v} \\ & + \alpha_3 \frac{r_i - \overline{r}_k}{N_k} D_{ij} + \alpha_4 \frac{\overline{r}_k - r_j}{N_k} D_{ij} + u_{ij} \end{aligned} \tag{A.4}$$

where $\overline{r}_k \equiv \frac{\sum_{i \in N_k} a_i}{\sum_{i \in N_k} l_i}$. The testing strategy is similar as before: if factors only flow within components of the social network, we should find $\alpha_1 = \alpha_2 = 0$ and $\alpha_3 > 0$ and $\alpha_4 > 0$. Other regression models presented in the conceptual Section similarly extend to this case, and need not be discussed further.

[31] The first part of the equality follows from the fact that homothetic production functions have linear expansion paths (or scale line). The second part follows from equilibrium conditions on factor markets. Homotheticity is likely to hold in this study, at least approximately, given the small range of farm sizes observed in our data.

[32] Equalization of factor ratios does not require transfers of both factors across households; trade in one factor is sufficient. It follows that, in the CRS case, efficiency can be achieved even with one non-traded factor.

[33] In an efficient factor allocation we should have:

$$\begin{aligned} \frac{r_i + \sum_j [w_{ij} - w_{ji}]}{l_i} &= \overline{r} \\ \frac{r_j + \sum_i [w_{ij} - w_{ji}]}{l_j} &= \overline{r} \end{aligned}$$

If returns to scale are decreasing, allocative efficiency requires that:

$$\begin{aligned}
\frac{\partial q(x_i,y_i)}{\partial x_i} &= \frac{\partial q(x_j,y_j)}{\partial x_j} \text{ for all } i \text{ and } j \\
\frac{\partial q(x_i,y_i)}{\partial y_i} &= \frac{\partial q(x_j,y_j)}{\partial y_j} \text{ for all } i \text{ and } j
\end{aligned}$$

which implies that each household should use the same quantity of $x$ and $y$. The above also implies that:

$$\frac{\frac{\partial q(x_i,y_i)}{\partial x_i}}{\frac{\partial q(x_i,y_i)}{\partial y_i}} = \frac{\frac{\partial q(x_j,y_j)}{\partial x_j}}{\frac{\partial q(x_j,y_j)}{\partial y_j}} \text{ for all } i \text{ and } j \tag{A.5}$$

and hence efficiency requires an equalization of factor ratios across farms, as in the CRS case. We thus have, for the DRS case, two available testing strategies: to apply model (2) to an individual factor; or to apply model (A.3) to factor ratios. Both strategies should yield similar results in the DRS case. In the CRS case, only model A.3 can be used; model (2) is not identified since farm size is undetermined.

### A.3 Unobserved heterogeneity

Identifying efficiency-enhancing factor flows becomes more difficult if agents differ in their unobserved productivity – or, equivalently, in an unobserved fixed factor (e.g., management capacity). In an efficient allocation, more productive agents should attract more factors of production for the marginal productivity of factors to be equalized across agents. If we do not know who is more productive, we cannot test whether the *absolute* allocation of factors is efficient.

To illustrate the difficulty, let the production of agent $i$ be written $\theta_i q(x_i)$ where $\theta_i$ denote the total factor productivity of agent $i$ and $x_i$ is a single factor of production.[34] With decreasing returns to scale,[35] allocative efficiency requires that:

$$\theta_i \frac{\partial q(x_i)}{\partial x_i} = \theta_j \frac{\partial q(x_j)}{\partial x_j} \text{ for all } i \text{ and } j$$

The above implies that $x_i > x_j$ if $\theta_i > \theta_j$: more productive agents use more $x$. Since we do not observe $\theta_i$, identification fails in all the regression models discussed so far: without knowing who is most productive, we cannot test whether the allocation of the single factor $x_i$ across farmers is efficient. By extension, the same conclusion applies in the CRS case if there are two factors of production but only one is traded.

[34] Unobserved individual productivity $\theta_i$ can be thought of as a total factor productivity shifter. If we posit a Cobb-Douglas production function, $\theta_i$ can also represent a fixed unobserved factor (e.g., management capacity) or factor-biased productivity differentials: in a Cobb-Douglas production function, both factor out as a multiplicative constant.

[35] If returns to scale are constant in $x_i$, it is efficient to allocate all the supply of $x$ to the most productive producer. Since we do not observe such cases in our data – far from it – we do not consider this case any further.

Some identification can be recovered if we observe not one but two traded factors, $x$ and $y$. The production function is now of the form $\theta_i q(x_i, y_i)$. We continue to assume DRS in $x$ and $y$.[36] Allocative efficiency now requires that:

$$\begin{aligned} \theta_i \frac{\partial q(x_i, y_i)}{\partial x_i} &= \theta_j \frac{\partial q(x_j, y_j)}{\partial x_j} \text{ for all } i \text{ and } j \\ \theta_i \frac{\partial q(x_i, y_i)}{\partial y_i} &= \theta_j \frac{\partial q(x_j, y_j)}{\partial y_j} \text{ for all } i \text{ and } j \end{aligned}$$

which yields the same expression (A.1). If we continue to assume that the production function is homothetic in $x$ and $y$, an efficient factor allocation still must satisfy (A.2): factors should flow so as to equilibrate factor ratios among agents.

It follows that, unless factor endowments are perfectly correlated with productivity differentials, *on average* agents with $r_i \equiv \frac{a_i}{l_i} > \bar{r}$ should transfer out some of their excess factors to others, and vice versa. In the conceptual section, this property holds exactly for each farmer; here it only holds on average, and requires that factor endowments and productivity not be strongly positively correlated.[37] With these assumptions, it is possible to apply the same testing strategy as that outlined above. The strategy requires a strong maintained assumption about the distribution of factors and productivity. But the assumption is fairly reasonable in the context of our data, where land is mostly inherited from the household's lineage and its manpower endowment largely depends on where the household is in its life cycle. There is no compelling reason to expect these exogenous factors to be strongly positively correlated with $\theta_i$, even if some correlation may be present. Moreover, given the low technological level of the study population, it is unlikely that productivity differentials differ massively among them – or at least not as much as the very large differentials in land endowment. Hence it is not entirely unreasonable to give this approach a try.

### A.4 Summary

To summarize, we have devised a method for testing the role of social network structure in improving the efficiency of factor allocation in farming villages. This method does not work if production exhibits increasing returns to scale, or if constant returns to scale are combined with unobserved heterogeneity in productivity: in these cases, all factors should go to a single producer – which is not what we observe in the data. The method also fails when unobserved heterogeneity is combined with decreasing returns to scale and a single traded factor. In this case, we are unable to empirically characterize the efficient allocation of factors without information on individual heterogeneity, and hence we cannot test whether factor transfers serve to improve efficiency.

[36] If $q(x, y)$ is CRS, the optimal allocation is for all factors to go to the single most productive farmer. Again, this is not what we observe.

[37] If $\theta_i$ is strongly correlated with $r_i$, then it is possible that the efficient allocation is to give even more land to land-rich farmers. We rule this case out by assumption.

There remain several cases in which we can characterize the efficient allocation of factors, either in absolute terms or in terms of factor ratios. In these cases, the characterization can be used as basis for a test of the role of social network structure in permitting or curtailing efficiency gains in factor allocation. Table A.1 lists all the various configurations and their predictions. The testable cases include: decreasing returns to scale (DRS) with one traded factor and no unobserved heterogeneity; and DRS with two traded factors, with or without unobserved heterogeneity. In the first case, efficiency can be characterized in absolute terms and model (2) serve as starting point for our testing strategy. In the second case, we can characterize efficiency in terms of factor ratios and construct a testing strategy based on factor ratios. The latter method also applies to the CRS case with two factors but no unobserved heterogeneity, even if one factor is de facto not traded.

Table A.1: Summary table of model predictions

| Case | Heterogeneity? | No. of factors | No. of traded factors | Returns to scale? | Prediction of factor structure across farms | Model(s) |
|---|---|---|---|---|---|---|
| 1 | NO | 1 | 1 | DRS | Equality of factors. | (2), (5)-(8) |
| 2 | NO | 1 | 1 | CRS | Undetermined. If any tc, no trade. | Ruled out |
| 3 | NO | 2 | 1 | DRS | Unidentified. | - |
| 4 | NO | 2 | 1 | CRS | Equality of factor ratios. Cultivated land is multiple of ex ante labor. | (11), (12) |
| 5 | NO | 2 | 2 | DRS | Equality of both factors. | (5)-(8), (11), (12) |
| 6 | NO | 2 | 2 | CRS | Equality of factor ratios. If any tc, trade only in factor with lowest tc. | (11), (12) |
| 7 | YES | 1 | 1 | DRS | Unidentified. | - |
| 8 | YES | 1 | 1 | CRS | One plantation. | Ruled out |
| 9 | YES | 2 | 1 | DRS | Unidentified. | - |
| 10 | YES | 2 | 1 | CRS | Unidentified. | - |
| 11 | YES | 2 | 2 | DRS | If $\theta$ is not strongly correlated with $r$: Equality of factor ratios. | (11), (12) |
| 12 | YES | 2 | 2 | CRS | One plantation. | Ruled out |

# Appendix B. Simulations

The purpose of this Appendix is to demonstrate the validity of the testing strategy using simulations.We simulate an economy with a single asset $a$ shared unequally among $N$ farmers divided into two unequal-size groups or components. We also generate undirected links between pairs of farmers, with a random probability of linking $p$. We generate three types of transfers: globally efficient transfers $w_{ij}^e$ such that every farmer has $\overline{a} \equiv a/N$ cultivated acreage; group efficient transfers $w_{ij}^g$ such that each farmer in group $k$ has $\overline{a}_k = \sum_{j \in k} \frac{a_j}{N_k}$; and dyadic transfers $w_{ij}^d$ partially equalizing cultivated acreage between pairs of farmers. To illustrate the fact that efficiency does not require many pairwise transfers, we construct $w_{ij}^e$ and $w_{ij}^g$ so as to occur only over a small number of dyads – 95% of dyads have no transfers. To simulate inefficient aggregate or group-wise transfers, we multiply $w_{ij}^e$ and $w_{ij}^g$ by a fraction $\tau < 1$.[38] In the case of $w_{ij}^d$, dyadic efficiency is achieved for farmers that have a single link. Many farmers have more than one link, however. Because they must share land with several others, pairwise efficiency cannot be achieved with each of them since farmers cannot transfers out more than their land endowment $a_i$.[39]

Simulation results are presented in Tables B.1-B.3. We simulate 30 villages each with $N = 20$ farmers. In the main simulations, farmers are sorted by land endowment and divided into two groups, one with rich farmers and one with poor farmers. The two groups have size $N_1 = 11$ and $N_2 = 9$. We also simulate what happens when the two groups have similar endowment – more about this later. We set the linking probability $p = 0.1$, and the shrinking parameter $\tau = 0.3$. Villages differ systematically in total land endowment but these is no land transfer between villages. In all the reported regressions standard errors are clustered at the village level.

Table B.1 presents results for village-efficient transfers $w_{ij}^e$. The first five columns present results when the two groups have sharply different endowments. Column 1 report estimates from regression model (2). The estimated values of $\alpha_1$ and $\alpha_2$ are identically 1 while $\alpha_0$ is identically 0, as predicted. In column 2, the dependent variable $w_{ij}^e$ is replaced with 'shrunk' transfers $\tau w_{ij}^e$. Coefficient estimates $\alpha_1$ and $\alpha_2$ are equal 0.3, the value of the shrinking parameter. In column 3 we regress $w_{ij}^e$ on deviations from group average $\frac{a_i - \overline{a}_k}{N_k}$ and $\frac{\overline{a}_v - a_k}{N_k}$. Estimated coefficients are close to 0, although not identically so: village-wide land redistribution achieves a modicum of within-group redistribution as well, and this is what is picked up by $\alpha_3$ and $\alpha_4$. In column 4 $w_{ij}^e$ is regressed on the average dyadic difference $\frac{a_i - a_j}{2}$. The coefficient estimate $\alpha_5$ captures whatever dyadic redistribution is generated by $w_{ij}^e$, in this case 10%.

In column 5 we estimate model (6). We find that $\alpha_3$ and $\alpha_4$ are both negative while $\alpha_1$ and $\alpha_2$ are larger than 1. The first result arises because transfers that are village-efficient

[38]We also experimented with random shrinking. The results, not reported here, are similar except that estimated coefficient vary due to randomization error.

[39]In the simulations, this is captured by shrinking dyadic transfers when givers have more than one link, to ensure that they do not exhaust their own factor endowment.

Table B.1: Simulation results. Dependent variable is simulated village-efficient transfers

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|---|
| | | Endowment: Split according to rich and poor | | | | | Endowment: Similar across groups | |
| Regressor | Coefficient | $w_{ij}$ | $w_{ij} * \tau$ | $w_{ij}$ | $w_{ij}$ | $w_{ij}$ | $w_{ij}$ | $w_{ij}$ |
| $\frac{(a_i-\bar{a})}{N_v}$ | $\alpha_1$ | 1.00*** | 0.30*** | | | 1.24*** | | 1.02*** |
| | | (0.00) | (0.00) | | | (0.02) | | (0.07) |
| $\frac{(\bar{a}-a_j)}{N_v}$ | $\alpha_2$ | 1.00*** | 0.30*** | | | 1.24*** | | 1.02*** |
| | | (0.00) | (0.00) | | | (0.02) | | (0.07) |
| $\frac{(a_i-\bar{a}_k)}{N_v}D_{ij}$ | $\alpha_3$ | | | 0.11*** | | -0.54*** | 0.48*** | -0.03 |
| | | | | (0.02) | | (0.02) | (0.03) | (0.07) |
| $\frac{(\bar{a}_k-a_j)}{N_v}D_{ij}$ | $\alpha_4$ | | | 0.11*** | | -0.54*** | 0.48*** | -0.03 |
| | | | | (0.02) | | (0.02) | (0.03) | (0.07) |
| $\frac{(a_i-a_j)}{2}L_{ij}$ | $\alpha_5$ | | | | 0.08*** | -0.03 | | 0.02 |
| | | | | | (0.02) | (0.02) | | (0.02) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Observations | | 11,400 | 11,400 | 11,400 | 11,400 | 11,400 | 11,400 | 11,400 |

Note: Standard errors clustered by village are shown in parantheses. *** p<0.01, ** p<0.05, * p<0.1

take cultivated acreage away from what would be group efficient: since the two groups have different land endowments, achieving group efficiency would take farmers away from village efficiency. To cast more light on this finding, we present in columns 6 and 7 simulation results in which the two groups are equal in terms of land endowment. Columns 6 and 7 duplicate columns 3 and 5, respectively. The only difference is in $\bar{a}_k$. In column 6 we find that $\frac{a_i-\bar{a}_k}{N_k}D_{ij}$ and $\frac{\bar{a}_v-a_k}{N_k}D_{ij}$ predict village-efficient transfers much better than when groups have very different land endowments: $\alpha_3$ and $\alpha_4$ are nearly equal to 0.5. This is not surprising: since $\bar{a}_k$ is now close to $\bar{a}_v$, the main difference between the $\frac{a_i-\bar{a}_k}{N_k}D_{ij}$ and $\frac{\bar{a}_v-a_k}{N_k}D_{ij}$ terms and the $\frac{a_i-\bar{a}_v}{N_v}$ and $\frac{\bar{a}_v-a_v}{N_v}$ is $D_{ij}$, which is 0 when $i$ and $j$ do not belong to the same group. Given that the groups are of roughly equal size, it means that $\frac{a_i-\bar{a}_k}{N_k}D_{ij}$ and $\frac{\bar{a}_v-a_k}{N_k}D_{ij}$ cannot predict any transfer between individuals in different groups. Hence the coefficient estimates. This is confirmed in column 7 where we combine both sets of terms, and where $\frac{a_i-\bar{a}_v}{N_v}$ and $\frac{\bar{a}_v-a_v}{N_v}$ get coefficients clost to 1 and $\frac{a_i-\bar{a}_k}{N_k}D_{ij}$ and $\frac{\bar{a}_v-a_k}{N_k}D_{ij}$ have coefficients that are small in magnitude and not statistically significant.

In Table B.2 we present similar results for group-efficient transfers $w^g_{ij}$. In column 1, we obtain estimated coefficients $\alpha_3$ and $\alpha_4$ that are equal to 1, as predicted. In column 2, we shrink $w^g_{ij}$ to 30% of its original value. Coefficient estimates shrink by the same amount, as it should be. In column 3 we regress $w^g_{ij}$ on deviations from village average. Estimates for $\alpha_1$ and $\alpha_2$ are positive and significant. This is because within-group land redistribution does improve village-wide efficiency, although by much less than 100%. In column 4 we use $\frac{a_i-a_j}{2}$ as sole regressor. The estimated coefficient $\alpha_5$ is small by slightly above 0, capturing the fact

Table B.2: Simulation results. Dependent variable is simulated group-efficient transfers

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|---|
| | | Endowment: Split according to rich and poor | | | | | Endowment: Similar across groups | |
| Regressor | Coefficient | $w_{ij}$ | $w_{ij} * \tau$ | $w_{ij}$ | $w_{ij}$ | $w_{ij}$ | $w_{ij}$ | $w_{ij}$ |
| $\frac{(a_i - \bar{a})}{N_v}$ | $\alpha_1$ | | | 0.40*** | | -0.00 | 0.96*** | 0.00 |
| | | | | (0.02) | | (0.01) | (0.01) | (0.02) |
| $\frac{(\bar{a} - a_j)}{N_v}$ | $\alpha_2$ | | | 0.40*** | | -0.00 | 0.96*** | 0.00 |
| | | | | (0.02) | | (0.01) | (0.01) | (0.02) |
| $\frac{(a_i - \bar{a}_k)}{N_v} D_{ij}$ | $\alpha_3$ | 1.00*** | 0.30*** | | | 1.00*** | | 1.00*** |
| | | (0.00) | (0.00) | | | (0.00) | | (0.00) |
| $\frac{(\bar{a}_k - a_j)}{N_v} D_{ij}$ | $\alpha_4$ | 1.00*** | 0.30*** | | | 1.00*** | | 1.00*** |
| | | (0.00) | (0.00) | | | (0.00) | | (0.00) |
| $\frac{(a_i - a_j)}{2} L_{ij}$ | $\alpha_5$ | | | | 0.04*** | 0.00 | | -0.00 |
| | | | | | (0.01) | (0.01) | | (0.02) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Observations | | 11,400 | 11,400 | 11,400 | 11,400 | 11,400 | 11,400 | 11,400 |

Note: Standard errors clustered by village are shown in parantheses. *** p<0.01, ** p<0.05, * p<0.1

that some of the gain in group-wide efficiency is achieved through transfers between linked farmers. When we include all regressors, we again find $\alpha_3 = \alpha_4 = 1$ as in column 1.

In columns 6 and 7 we again consider groups with similar land endowments. In this case, group-efficient redistribution can achieve close to village-wide efficiency, as indicated by the $\alpha_1$ and $\alpha_2$ estimates reported in column 6. When we combine both sets of terms in column 7, $\alpha_3$ and $\alpha_4$ take value 1 while $\alpha_1$ and $\alpha_2$ become 0. This is because $\frac{a_i - \bar{a}_v}{N_v}$ and $\frac{\bar{a}_v - a_v}{N_v}$ are incapable of predicting why transfers only take place within groups.

Table B.3 presents equivalent results for dyadic transfers $w_{ij}^d$. Column 1 shows that, on average, $w_{ij}^d$ eliminate 53% of the $\frac{a_i - a_j}{2}$ difference across all linked dyads. As explained earlier, full pairwise efficiency is not achievable when farmers have more than one link on average, and have to accommodate multiple redistribution needs. Shrinking $w_{ij}^d$ by a factor $\tau$ reduces the $\alpha_5$ coefficient accordingly (see column 2), as expected. From column 3 we conclude that $w_{ij}^d$ transfers cause a sizeable reduction in factor allocation inefficiency: the gain is equivalent to what 45% of what is generated by village-efficient transfers. In column 4 we similarly note a reduction in within-group inefficiency, but the gain is much smaller since, as we have explained above, dyadic links are uncorrelated with group membership, and within-group efficiency would not eliminate across-group endowment differences. When we combine all regressors in column 5, results are dominated by $\alpha_5$ – the other coefficients are much smaller in magnitude.

To summarize, by estimating the different regression models discussed in Section 2, we have been able to estimate not only to what extent transfers on average increase efficiency in

Table B.3: Simulation results. Dependent variable is simulated dyadic transfers

| Regressor | Coefficient | (1) $w_{ij}$ | (2) $w_{ij} * \tau$ | (3) $w_{ij}$ | (4) $w_{ij}$ | (5) $w_{ij}$ |
|---|---|---|---|---|---|---|
| $\frac{(a_i - \bar{a})}{N_v}$ | $\alpha_1$ | | | 0.44*** | | -0.01 |
| | | | | (0.03) | | (0.01) |
| $\frac{(\bar{a} - a_j)}{N_v}$ | $\alpha_2$ | | | 0.44*** | | -0.01 |
| | | | | (0.03) | | (0.01) |
| $\frac{(a_i - \bar{a}_k)}{N_v} D_{ij}$ | $\alpha_3$ | | | | 0.23*** | 0.02 |
| | | | | | (0.03) | (0.02) |
| $\frac{(\bar{a}_k - a_j)}{N_v} D_{ij}$ | $\alpha_4$ | | | | 0.23*** | 0.02 |
| | | | | | (0.03) | (0.02) |
| $\frac{(a_i - a_j)}{2} L_{ij}$ | $\alpha_5$ | 0.49*** | 0.15*** | | | 0.49*** |
| | | (0.03) | (0.01) | | | (0.03) |
| Constant | $\alpha_0$ | 0 | 0 | 0 | 0 | 0 |
| Observations | | 11,400 | 11,400 | 11,400 | 11,400 | 11,400 |

Note: Standard errors clustered by village are shown in parantheses. *** p<0.01, ** p<0.05, * p<0.1

village-wide, group-wide or pairwise allocation of land, but also whether transfers are more common within groups or across linked dyads and whether group membership and dyadic links affect efficiency.