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Social Networks and Factor Markets: Panel Data Evidence from Ethiopia

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In the absence of well-established factor markets, the role of indigenous institutions and social networks can be substantial for mobilizing factors for agricultural production. We investigate the role of an indigenous social network in Ethiopia, the iddir, in facilitating factor market transactions among smallholder farmers. Using detailed longitudinal household survey data and employing a difference-in-differences approach, we find that iddir membership improves households' access to factor markets. Specifically, we find that joining an iddir network improves households' access to land, labor and credit transactions between 7 and 11 percentage points. Furthermore, our findings also indicate that iddir networks crowd-out borrowing from local moneylenders (locally referred as Arata Abedari), a relatively expensive credit source, virtually without affecting borrowing from formal credit sources. These results point out the roles non-market arrangements, such as social networks, can play in mitigating market inefficiencies in poor rural markets.

Key words: Social networks, *iddir* networks, factor market imperfections, factor market transactions, crowding-out

1. Introduction

Markets in developing countries are characterized by a broad range of failures that adversely affect the individual actors and challenge the institutions created to mediate their interactions (Stiglitz, 1989; Besley, 1994). Factor markets, like several other markets in developing countries, are subject to widespread inefficiencies resulting from incomplete information and imperfect contract enforcement, exacerbated by unclear property rights and subsequent high transaction costs (Stiglitz and Weis, 1981; Collier, 1983; Stiglitz, 1989; Hoff and Stiglitz, 1990; de Janvry et al., 1991; Barrett and Mutambatsere, 2008; Pender and Fafchamps, 2006).

Nowhere are these problems more critical than in land, labor, and rural credit markets of developing countries. These three types of markets are particularly thin and inhibited by problems of information asymmetry. As a result, moral hazard, adverse selection, and related opportunistic behaviors are common, since transactions in these markets require extensive information for screening, monitoring, and contract enforcement. Information asymmetry in these markets results in transaction costs that are high, as monitoring and penalizing opportunistic behavior is difficult. The failure of factor markets imply that "either the transactions simply do not occur, or substitute institutions emerge to allow the transaction to take place" (de Janvry et al., 1991). A vast amount of literature points to such failures in these markets giving rise to traditional institutional arrangements and social networks playing critical roles in filling the gaps in exchanges of goods, services, and factors of production that markets fail to deliver (Binswanger and McIntire, 1987; Rosenzweig, 1988; Udry, 1990). One line of literature studies the widespread use of land and labor sharing contracts in developing countries in the face of risk and missing insurance markets (e.g. Johnson, 1950; Cheung, 1969) and imperfect monitoring of labor efforts (e.g., Newbery, 1975). These studies point to incentives, risk pooling, and the production efficiency advantage of land and labor sharing arrangements. Pender and Fafchamps (2006) point out that social relationships – capitalizing on pre-existing trust and thereby reducing transaction costs of monitoring – play important roles in determining land and labor contract arrangements.

A similar line of literature studies how information asymmetry undermines the operations and effectiveness of rural credit markets in developing countries. Empirical evidence, following the seminal work by Stiglitz and Weiss (1981), points to such information asymmetry in rural credit markets limiting lenders from writing effective contracts because, in the absence of information regarding the characteristics and activities of their clientele, formal lenders find it difficult to discern their potential borrower types in these areas (Udry, 1990; Aryeetey and Udry, 1997). In the absence of formal credit, households often rely on credit from their informal networks to smooth consumption (Fafchamps, 2006; Rosenzweig, 1988; Townsend, 1995; Fafchamps and Lund, 1998). Informal credit often involves trust-based self-enforcing informal networks and relationships which are typically characterized by flexibility in credit allocation and repayment (Udry, 1990; Fafchamps, 2006). In most rural communities, these activities are organized in some form of traditional social networks that provide group-based informal insurance, like *iddirs* in Ethiopia. These institutions perform a crucial function for rural households in overcoming important market imperfections by expediting the flow of information within and beyond the village (Udry, 1990; Barr, 2000), reducing monitoring and enforcement costs (Sadoulet et al., 1997; Berhane et al., 2009; Fafchamps and Minten, 2002; Karlan, 2007), and developing trust among agents (Fukuyama, 1995; Fafchamps and Lund, 2003).

There is a large empirical literature on the formation, prevalence, and role of social networks in dealing with a wide spectrum of socio-economic problems, including risk and consumption smoothing (Udry, 1994; Fafchamps and Lund, 2003; Okten and Osili, 2004; Hoddinott et al., 2005; Hoddinott et al., 2009; Wydick et al., 2011; Kinnan and Townsend, 2012; Ali and Deininger, 2014; Ali et al., 2014); credit, saving and transaction costs (Dercon et al., 2006; De Weerdt and Dercon, 2006); and technology adoption, insurance, and productivity (Foster and Rosenzweig, 1995; Barr, 2000; Conley and Udry, 2002; Fafchamps and Lund, 2003; Fafchamps and Minten, 2002; Bandiera and Rasul, 2006; Krishnan and Sciubba, 2009). However, little is known about the explicit roles of social networks in mitigating factor market imperfections, and hence, their role in facilitating factor market transactions among smallholder farmers.

In this paper, we study the role of an indigenous social network in Ethiopia, *iddir* associations, in overcoming factor market imperfections, and hence facilitating factor market transactions among smallholder farmers. *Iddir* is the most inclusive and widespread social network in Ethiopia, commonly established by community members, neighbors, or among friends and families. The origin of *iddir* as a social network is to provide funeral services and to support bereaved family members morally and financially (see for instance, Dercon et al., 2006). However, a closer look at *iddir* networks reveals their scope to go beyond funeral associations, as they are involved in many socio-economic issues (Pankhurst and Mariam, 2000; Mariam, 2003; Dercon et al., 2006). By offering informal social insurance, information, and trust among members, *iddir* associations share the main micro-level properties of other networks (Caeyers and Dercon, 2012). *Iddir* networks are well-suited for facilitating factor input transactions among its members as they provide privileged access to key resources ranging from smooth flow of information among members, thereby building trust, to penalizing opportunistic behavior through provisions of strict rules and social sanctions. This privileged access can help buyers and sellers of factor inputs minimize their screening, monitoring, and enforcement costs. However, empirical evidences have yet to come to support the above contributions of *iddir* networks. Generally speaking, very little is known about how *iddir* networks contribute to the economic activity of their members. Dercon et al. (2006; 2008) studied the role of *iddir* networks as funeral and insurance institutions, while Hoddinott et al. (2005) investigated the role of *iddir* networks as risk coping mechanisms. Investigating the roles of social networks in ameliorating market imperfections in the Ethiopian case provides an interesting context given the coexistence of such social networks, and evidence of pervasive market failures and high transaction costs in rural Ethiopia (Deininger et al., 2008; Deininger and Jin, 2008; Ghebru and Holden, 2008).

We use longitudinal household survey data from Ethiopia to investigate the role of *iddir* networks in facilitating factor market transactions among farmers. As in other social networks, identifying the causal effects of *iddir* networks on factor market transactions is prone to at least two problems. First, *iddir* participation is potentially endogenous due to self-selection and omitted variable bias as we expect that a host of observable and unobservable characteristics of households which affect *iddir* participation may also influence factor market participation. We exploit the longitudinal feature of the data and use a difference-in-differences approach to circumvent time-invariant self-selection and unobserved effects while also controlling for a large set of observable time-varying variables. Second, *iddir* participation may be affected by participation in factor markets directly, thereby opening a room for potential reverse causality effects. This is particularly a serious problem if *iddir* participation decision is made considering future factor market transaction demands. While we cannot theoretically rule out the fact that households who have been sharing (or wish to share) labor or land may join (or form) *iddir* networks, *iddir* associations are far larger networks than this and beyond the influence of paired relationships among households. As a solution to minimize this problem, we investigate the trajectories of two groups of households (those who recently become members and those who recently opted-out of their *iddir*), compared to the base group (those who remained non-members throughout the study period). As a further robustness exercise, we also use matching estimators and hence estimate our difference-in-difference equations on a conservatively matched sample of households. Using the above identification strategies, we find that *iddir* membership improves household's access to factor market transactions in a range of 7 to 11 percentage points. Specifically, we find that *iddir* membership improves households' sharecropping and labor-sharing practices, as well as their access to credit. Interestingly, our findings also indicate that *iddir* networks crowd-out borrowings from village moneylenders (locally referred to as *Arata Abedari*), who often provide expensive credit due to the screening, monitoring, and contract enforcement problems that can be removed by social networks. However, our findings suggest that membership in these networks does not crowd-out borrowing from formal credit sources that offer both relatively cheaper and larger amounts of credit. These results are robust across several specifications and consistent for both treatment groups (households joining *iddir* network as well as those opting-out of their *iddir* networks.). We believe that these findings shed light on the role of indigenous social networks in overcoming market imperfections, thereby facilitating market transactions in rural economies. The results of this analysis are important in at least two ways. First, while much of economics continues to rely on assumptions of market-based solutions to imperfections (Fafchamps, 2004:3-21), these results suggest that non-market institutions can also play crucial roles in intermediating transactions whenever contracts are not perfectly enforceable due to lack of information or efficient court systems. Second, they further suggest that the outcomes of government intervention to improve market performance in these contexts is not straightforward. Care must be taken not to crowd-out the role these institutions are bound to play in facilitating local exchange (Dercon et al., 2006). The rest of the paper is organized as follows. Section 2 presents the institutional features of *iddir* networks in Ethiopia. Section 3 presents a brief exposition of factor markets in Ethiopia, while Section 4 discusses the data and empirical models used for this analysis. In section 5, we present and discuss the empirical results, while Section 6 provides concluding remarks and policy implications.

2. Institutional Features of *Iddir* Networks In Ethiopia

Iddir is the most inclusive and widespread type of social network in Ethiopia, prevalent both in rural and urban settings and inclusive of gender, wealth, education, religion, and ethnicity (Pankhurst, 2008). Originally, *iddir* networks were established to provide financial (cash) and other types of support (in kind) when a family member dies. These networks also assume a key role in facilitating the burial and funeral of the deceased member. However, a close look at *iddir* networks reveals that they go beyond funeral associations as they are involved in many socio-economic issues. *Iddirs* provide small credit for their members, often without collateral (Dercon et al., 2006); help unemployed members (Pankhurst and Mariam 2000); finance their members' health care expenditures (Mariam, 2003); provide financial assistance when their members suffer from other shocks (Dercon et al., 2006); and in recent years, some *iddirs* provide insurance for death of key livestock, such as oxen.

Iddir networks often have well-defined and written rules (Dercon et al., 2006). Membership is on a voluntary basis and is commonly open to all members living in a village (Hoddinott et al., 2005; Dercon et al., 2006; Mariam, 2003).[1] Hoddinott et al. (2005) and Mariam (2003) report that the majority of *iddirs* in Ethiopia have no restrictions on membership and that all villages in their study samples hosted at least one *iddir* that was open to anyone living in the village. Members are required to pay a monthly contribution, while new members may also have to pay an entrance fee. Membership fees in most *iddirs* are relatively small and provide some flexibility in payment due dates, and hence, most interested potential members are able to join. Dercon et al. (2006) report that the average monthly household contribution to *iddirs* in their sample amounted to 1.64 Birr (0.08 USD), which is too small to dictate participation in these networks. In addition, most *iddirs* have flexible conditions for the membership of the very poor, accepting non-monetary contributions and sometimes allowing people to become members free of charge (Pankhurst and Mariam, 2000; Mariam, 2003).

Previous studies show that individual and household wealth indicators have insignificant effects on *iddir* membership. For example, Dercon et al. (2006) find that, while demographic attributes of households including age and household size affect *iddir* participation, wealth, land, and livestock holdings had no effect. Richer households could obtain better coverage against risk by joining multiple

[1] See Pankhurst and Mariam (2000) for an exhaustive list of types of *iddir* associations in Ethiopia.

iddir networks, and perhaps by joining *iddir* associations established in rich neighborhoods. As suggested by Hoddinott et al. (2005), the income and wealth status of a household could affect the intensity of participation in *iddirs*, but not the extensive margin of participation in these egalitarian associations. This evidence sets an interesting context to evaluate the effectiveness of such an inclusive social network in facilitating factor market transactions among households.

Like many other social networks, *iddir* associations provide informal social insurance and information that can strengthen trust among members of the association (Caeyers and Dercon, 2012). Besides providing linkages among members, *iddirs* reduce transaction costs and provide security against shirking or defection in the absence of formal contractual agreements. Rigorous empirical evidence as to whether these qualities of *iddir* networks are important to facilitate factor market transactions among smallholder farmers is not yet available.

3. Factor Markets and the Potential of *Iddir* Networks in Ethiopia

As in many other developing countries, rural areas of Ethiopia are characterized by imperfect or missing factor markets (Deininger et al., 2008; Deininger and Jin, 2008; Ghebru and Holden, 2008). In Ethiopia, land belongs to the state and landlords are only entitled to user rights. Under this form of ownership, landowners are not entitled to sell, transfer, or mortgage their land. Pender and Fafchamps (2006) point out that, in the absence of land redistribution, the only means of acquiring access to land in Ethiopia is through gifts, borrowing, fixed-rental, or sharecropping. They find that the latter is the most prevalent form of securing access to land. Sharecropping is a tenancy agreement between landowners and their tenants. It evolves on the premise that tenants share a portion of the harvested production with the landowner depending on their agreement, usually half or two-third of gross production (see, Pender and Fafchamps, 2006). In some cases, landowners contribute some production inputs, generally draft-animal (oxen) or labor. In contrast, in fixed land rentals, the tenant pays a fixed amount of money, commonly in advance and assumes ownership of the land and the harvested production for the agreed production season.

Similarly, the agricultural labor market in Ethiopia lacks formality. Labor transactions depend on traditional labor-sharing practices, which mainly involve paired-borrowing of labor between farming households in return for similar labor on another day. As discussed in Krishnan and Sciubba

(2009), labor-sharing practices in Ethiopia may also involve large-scale labor borrowing from a large number of households, which may be returned when a similar event is organized by contributing households. These practices sometimes exploit the seasonal variation in demand for labor among households in the crop planting, growing, and harvesting periods. For instance, if a household's crops are not ready for harvest, the household continues to credit labor to other households who are in demand for it and gets the labor back when its crops are ready for harvest.

Such traditional arrangements in land and labor markets also extend to rural credit markets in Ethiopia. Despite recent progress, Ethiopia's agricultural credit market is not yet well developed. Rural credit is predominantly covered by informal loan arrangements, including moneylenders, and shares the same screening, incentive, and enforcement problems found in many rural credit markets in developing countries (Hoff and Stiglitz, 1990; Udry, 1990).

To sum up, factor markets in Ethiopia are incomplete and are dominated by traditional arrangements. Most of these arrangements or transactions do not involve formal contractual agreements. Thus, their validity hinges on informal relationships and trust among agents. In the presence of these imperfect factor markets, investigating the role of *iddir* networks is crucial in designing alternative policy measures that aim at improving factor markets in agriculture. Social networks play a key role in trust formation (Fukuyama, 1995; Fafchamps and Lund, 2003) and information sharing (Barr, 2000). These qualities of social networks offer an interesting context to reduce information asymmetry among agents of rural factor markets, and hence, facilitate factor market transactions among farmers.

In this paper, we empirically investigate the role of *iddir*, an indigenous social network in Ethiopia, in easing factor market imperfections in rural economies. We are specifically interested in investigating households' factor market transaction dynamics when they join *iddir* networks. We hypothesize that *iddir* networks can improve poorly functioning factor markets in rural Ethiopia, and hence, improve smallholder farmers' access to these markets. When information asymmetry is binding and lack of trust limits potential efficiency improvements in factor markets, *iddir* networks can serve as information hubs where households can exchange information relevant to their input endowments. Furthermore, and most importantly, the network built through *iddir* associations serves as a safety net (insurance) and a basis for stronger reciprocity among members.

More specifically, we hypothesize that *iddir* networks can bridge the information and reputation related gaps between those who would like to acquire access to land or labor and those who would like to provide these factors through land or labor sharing agreements. *Iddir* avails a large and flexible pool of labor, which offers the possibility of exploiting different planting and harvesting periods of members. Likewise, *iddir* networks can also improve households' access to credit specifically from other *iddir* members by minimizing information asymmetry. Furthermore, through their informational resource advantage, *iddir* members may even enjoy better access to factor markets that involve transactions with non-members. Since *iddirs* are formed among residents of (and often limited to) the same village, we expect that *iddir* membership may specifically improve households' access to credit from neighbors and friends, who are more likely to be from the same village. In contrast, we expect that *iddir* membership could potentially crowd-out access to credit from moneylenders who, on account of the relatively high risk and transaction cost involved, charge higher interest rates. *Iddir* offers borrowers with information on potential creditors and access to 'quasi-credit', where borrowers are able to get flexible borrowing terms such as low/zero interest rate and flexible repayment period. Similarly, it offers lenders with better screening, monitoring, and enforcement mechanisms through access to information on the status of borrowers and social sanctions on opportunistic behavior. Although *iddirs* may not have a clearly defined legal basis to enforce market transactions, they are observed to be guided by sound set of rules to which members can appeal in case of default, even if loans are made one-to-one without the institutional involvement of the *iddir*. In addition, these rules are strengthened through the social leverage that *iddirs* and their leaders are bestowed from members. These include group pressure and social penalties on individuals that fail to comply with agreed terms between members, similar to the roles played by community leaders in northern Nigeria to overcome loan enforcement problems (Udry, 1990).

4. Data and Econometric Method

4.1 Data source and sample description

The data we use for this study comes from a longitudinal household survey collected to evaluate the Productive Safety Net Program (PSNP) in Ethiopia. The data is collected from 68 food-insecure *woredas* (districts) randomly drawn from the 153 food-insecure *woredas* where the program operates in Ethiopia. These 153 food-insecure *woredas* are found in the four main regions of Ethiopia.[2] From each *woreda*, 2 to 3 PSNP beneficiary *kebeles* (villages) were randomly drawn as Enumeration Areas (EAs) from a pool of PSNP beneficiary *kebeles*. From each EA, 15 PSNP beneficiaries and 10 non-beneficiaries households were randomly selected from an exhaustive list of beneficiaries and non-beneficiaries in each EA. Four rounds of interviews (2006, 2008, 2010, and 2012) were conducted with the sample households with two-year gaps. A more detailed exposition on the sampling design is given in Berhane et al. (2011).

Table 1 presents the distribution of *iddir* membership across the surveys from the four main regions covered in the longitudinal survey. Some previous studies that focus on specific regions where *iddir* networks are particularly more prevalent report higher *iddir* participation than are seen in our sample (Hoddinott et al., 2005; Dercon et al., 2006).[3] A closer look at Table 1 suggests that *iddir* membership increases across the surveys, ranging from 51 percent in the first (2006) survey to 66 percent in the third (2010) survey. This generally increasing trend may be attributed to the increasing demand for the services that these networks provide and the concurrent expansion of these networks. This is not surprising given the increase in the recurrence of drought and other idiosyncratic shocks in rural Ethiopia in recent years, coupled with the fact that membership in an *iddir* network can directly or indirectly mitigate such shocks for a household. The increment is particularly large between the two middle surveys. These two middle surveys also cover larger balanced sample with complete information on our outcome variables of interest. In terms of timing, both middle surveys were conducted at similar times: the 2008 survey was fielded between late May and early July, while the 2010 survey was fielded in June and July. For these reasons, we focus on these two middle surveys in this study. However, we also use information from the first (2006) and fourth (2012) surveys to corroborate and test our identification strategy. Detailed descriptive statistics of the variables in these two surveys is given in Table A1 in the Appendix.

(Table 1 about here)

[2] The four main regions are Tigray, Amhara, Oromia, and Southern Nations, Nationalities, and Peoples (SNNP).
[3] For instance, if we only consider the two regions (Amhara and SNNP region) in our sample where *iddir* associations are very common, we can see substantially higher rate of *iddir* subscription in the sample.

Though the data is not collected for the purpose of investigating the role of *iddirs*, the sampling design is well-suited for our purpose for the following reasons: First, *iddir* participation is unrelated to PSNP selection and its targeting criteria (or determinants). We perform some empirical exercises to investigate whether *iddir* participation is associated with PSNP participation or observable livelihood characteristics that define PSNP participation. Thus, we explore the association between *iddir* membership and PSNP participation as well as other observable characteristics that may affect PSNP participation, including wealth status, income, food security status, and other observed socio-economic variables. Table 2 presents these results. In the first column, we regress the propensity to join an *iddir* on different observable characteristics of households, including wealth, income, and other socio-demographic variables. The second and third columns extend this specification by including *zone*-level and *woreda*-level fixed effects, respectively.[4] The results indicate that self-reported wealth, income, food security status, and PSNP participation are not statistically correlated with *iddir* participation. Rather, as expected, households' socio-demographic characteristics, such as education, household size, and household's social status in the village, are correlated with *iddir* participation. This is in line with findings presented in Hoddinott et al. (2005) and Dercon et al. (2006). Furthermore, recent studies that evaluated the PSNP point out that PSNP selection is largely based on assets, income, and food security status, which we tried to control for using observable household characteristics in our regressions (Andersson et al., 2009; Gilligan et al., 2009; Berhane et al., 2011; Berhane et al., 2014). As expected, the results in Tale 2 suggest that there is substantial regional, *zonal* and *woreda*-level variation in the intensity of *iddir* participation. This is revealed through the substantial variation across regions detected as well as the differences with-in regions with and without controlling for *zonal* and *woreda*-level fixed effects.

Second, though indigenous social networks such as *iddirs* are not well-researched in Ethiopia, the few existing studies indicate that *iddir* networks are inclusive and open to all interested members of the community (Hoddinott et al., 2005; Dercon et al., 2006; Mariam, 2003). The fact that *iddir* networks are inclusive and uncorrelated with household wealth indicators has important implications for our identification strategy.

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[4] Controlling for these spatial fixed-effects is crucial because we expect significant regional, zonal and *woreda*-level variation in the intensity of *iddir* practices.

(Table 2 about here)

The share of *iddir* membership for the balanced longitudinal sample of 2,293 households for both middle surveys estimated in Table 2 is almost identical to the full sample figures in Table 1.[5] In 2008, 59.6 percent of sample households were members of *iddir* networks, while the corresponding rate in 2010 is 67.5 percent. Other details and trends of the variables across both surveys are given in Table A1 in the Appendix. The identification strategy exploits the switching in membership status of households who were not *iddir* members in 2008, by following their *iddir* membership status in the next survey (2010). Out of the 2,293 sample households in 2008, 345 households joined *iddir* networks after the 2008 survey (but before the 2010 survey), 165 households lost their *iddir* membership, 1,202 continued as members of *iddir* network in 2010,while 581 households remained non-members in both surveys. In this study, we are interested in estimating the trajectory of the first two groups of households, compared to those households who remained non-members in both surveys. While we mainly focus our comparison between those who joined (after 2008) *iddir* networks and those who remained non-members, we also compare the trajectory in factor market transaction between those households who lost their *iddir* networks with those households who remained non-members in both surveys. Observing the increasing trend in Table 1 and simple correlations in Table 2, we expect that this switching is either exogenous to our outcomes of interest or driven by factors that are dealt within our estimation strategy. This comparison enables us to remove any time-invariant selection into *iddir* membership. Furthermore, in some of our specifications we employ time-varying controls that may induce *iddir* participation. For convenience, we label the 345 households who joined *iddir* networks after 2008 as our main *treatment* group, while those 581 households who remained non-members in both surveys are *control* group households. But we also use those households who lost their *iddir* membership (after 2008) to strengthen our inference on the main *treatment* group.

[5] The sample size in Table 2 is smaller than Table 1 because we consider those households who are in both surveys. We also exclude those households without adequate labor, so that they are beneficiaries of the direct support part of the PSNP program in Ethiopia.

4.2 Outcome variables of interest

We are interested in investigating the role of *iddir* networks in complementing poorly functioning agricultural land, labor, and credit markets. We are particularly interested in investigating households' factor market (land, labor, and credit) transaction dynamics when they join social networks that provide them information, linkages, and social capital. As discussed in Section 3, we hypothesize that *iddir* networks can improve households' access to sharecropping land. Similarly, we are also interested in examining the impact of *iddir* networks in facilitating labor-sharing practices. As discussed in Krishnan and Sciubba (2009), there are different types of labor-sharing practices in Ethiopia that involve varying numbers of participants. Here our focus is on a specific type of labor-sharing practice that commonly involves symmetric reciprocation of labor among parties involved in the network, commonly two or three households reciprocating labor each other. It is crucial to emphasize that our focus here is on a labor-sharing practice that commonly involve paired-borrowing of labor between farming households in return for similar labor on another day (or season). These practices are different than those labor-sharing practices that involve larger-scale borrowing of labor from a large number of households, a practice locally called ''*debo*'' (see Krishnan and Sciubba, 2009). This distinction has some implication for our identification strategy, because the latter type of practice may easily lead to *iddir* formation while the former is unlikely due to the limited number of households which cannot form *iddir*.

Finally, we aim to estimate the impact of *iddir* networks in facilitating credit transactions among farmers, and hence, their role in easing liquidity constraints of smallholder farmers. We are particularly interested in estimating how *iddir* networks affect credit flow from friends and neighbors, those individuals who are expected to be members of the *iddir* network.[6] Furthermore, we investigate whether *iddir* networks crowd-out expensive credit sources. By providing alternative sources of credit, we expect that *iddir* networks may crowd-out households' credit from local moneylenders who charge high interest rates.[7] Table 3 provides a list of the outcome variables of interest in this study and their

[6] Although some *iddir* associations provide soft loans to their members, this accounts for less than 1 percent in our data. Thus, our focus is restricted to the indirect role of *iddir* networks in facilitating credit access from neighbors and friends.
[7] If *iddir* associations also include relatives, the effect of *iddir* membership on households' credit access from relatives may improve. However, in practice, *iddir* formation is heavily affected by neighborhood and friendship, rather than familial relationships.

summary statistics measured at the pre-treatment period (2008). Consistent with the literature on social networks, we generally expect that the potentially untapped role of *iddir* networks in factor market exchanges mainly works through trust formation, information sharing, and reducing enforcement costs that can instrumentally smooth the flow of transactions. Furthermore, these networks involve social support that enables them to impose strong social sanctions on households who defect, which is an effective tool and guarantee for members of the network.

Table 3 compares factor market participation level of two groups of households at the baseline (2008). Panel A compares those households who joined (after 2008) *iddir* network (treatment group) with those who remained non-members (in both surveys). This comparison shows that both treatment and control group households have statistically similar pre-treatment factor market transactions for many of our outcome variables. Before households in the treatment group joined an *iddir*, the degree of involvement in factor market transactions for both the treatment and control group households was fairly similar. Panel B of this table compares factor market participation of those households who opted-out of their *iddir* network (after 2008) with those remaining non-members in both surveys. This comparison also shows statistically similar level of intensity in factor market participation among those recently losing their network and those remain non-members. This helps our identification strategy, ensuring that we are comparing similar households. More specifically, focusing on the first treatment group, around 7 percent of the treatment group households sharecropped-in land in the base year (2008), while the corresponding rate for those control group households is 10 percent. Similarly, Table 3 shows that more than 50 percent of households borrowed at least 20 Birr in the previous 12 months.[8] The most common source of credit was relatives, friends and neighbors, micro-finance institutions, and informal moneylenders (*Arata Abedari)*. The distributions of these sources of credit are statistically comparable across the treatment and control group households, except for credit from informal sources.

(Table 3 about here)

[8] Around 25 percent of this borrowing is for consumption purposes, while 13 percent is drawn for purchasing farm inputs.

4.3 Econometric method and identification strategy

As discussed in Section 4.1, we exploit the variation in *iddir* membership across both surveys (2008 and 2010) to empirically identify the effect of this indigenous network in facilitating factor market exchanges. We use a difference-in-differences approach and compare factor market transactions of households that joined *iddir* networks (treatment group) with those non-member households (control group), before and after the former joined *iddir* networks. Such an identification strategy helps us to cancel out time-invariant selection into *iddir* membership based on some time-invariant unobservable factors. To strength our causal inference on these treatment group households, we also estimate the trajectory of factor market transaction for those households who opted-out of their *iddir* networks. Furthermore, to capture some time-varying factors that might induce *iddir* participation and factor market participation, we control for a large set of households' time-varying demographic and socio-economic characteristics, as well as their exposure to shocks. Note that *iddir* networks are formed with the aim of supporting members in case of death in the household or other types of idiosyncratic shocks. These shocks can generate some dynamics in factor market transactions and those households who recently suffered death of a family member or other type of shock might be more likely to join these networks. Thus, we need to explicitly control for shocks that may induce *iddir* participation. We introduce both idiosyncratic and covariate shocks and their lags in our empirical specification. Finally, we also control for variables that may capture general trend of the household economic status, compared to last year's status, for the purpose of capturing potentially left-over time-varying unobserved factors.[9] More explicitly, we estimate the following difference-in-differences (DID) equation:

$$Y_{it} = \beta_0 + \beta_1 joining_{it} + \beta_2 losing_{it} + \beta_3 after + \beta_4 (joining_{it} * after) + \beta_5 (losing_{it} * after) + \beta_6 X_{it} + \alpha_v + \varepsilon_{it} \quad \text{(Equation 1)}$$

where Y_{it} is a binary variable that stands for the households' participation in land, labor, and credit transactions. *joining* is a dummy variable for households joining *iddir* networks after 2008 (equal to one if the household became an *iddir* member after the 2008 survey, zero otherwise), while *losing* is an indicator variable for those households losing their *iddir* networks (after 2008). *after* stands for a period

[9] This variable might be potentially endogenous to some of our outcomes, and hence associated estimates should be interpreted with some caution.

after the treatment households joined *iddir* networks (a dummy that takes a value equal to one for 2010, zero otherwise). β_1 *and* β_2 capture pre-treatment potential differences in factor market transactions between the treatment group households (those joining and losing *iddir* membership) and control group households (those who remained non-members in both surveys). Our main parameter of interest, β_4, captures the interaction effect between *iddir* membership and the latter survey year (2010). Similarly, β_5 measures the factor market trajectory of those households who lost their *iddir* network (after 2008) compared to those who remained non-members in both surveys. B_6 captures the effect of other time-varying and time-invariant covariates, while α_v absorbs village-level fixed effects. ε_{it} captures other unobserved factors that may induce heterogeneity in factor market transactions.

Our main parameter of interest, β_4, measures the effect of change in *iddir* membership status on the change in household's participation in factor market transactions across both surveys. Identifying β_4 hinges on the common trend assumption. This assumption implies that in the absence of *iddir* participation those households who joined *iddir* networks (after 2008) would have had, on average, a similar growth pattern in their factor market transactions as those households who did not join. This assumption is not directly testable, but the implication of the assumption can be tested using pre-treatment survey data. We have access to pre-treatment data from the 2006 and 2008 surveys for many of our outcome variables. Thus, we estimate equation (1) using the pre-treatment surveys (2006 and 2008), assuming placebo treatment for those households who joined an *iddir* after 2008. We know that those households joining *iddir* networks after 2008 were non-members in the years 2006 and 2008, thus, estimating equation (1) using the 2006 and 2008 survey should yield a treatment effect close to zero. Our placebo regression results (see Table A2 in Appendix) unambiguously confirm this argument. These estimates suggest that our treatment effects are not driven by differential trend in factor market participation between the treated and control group households.

Along with the common trend assumption, there are other related challenges to properly identify the causal effects of social networks on factor market transactions. The first concern is related to self-selection and omitted variable bias that may lead to potential endogenetiy problems. as well as failure of the common trend assumption. While time-invariant selection effects are less of a concern, we are cognizant that there might be other time-varying unobserved factors that may induce *iddir* and factor market participation simultaneously. To minimize such heterogeneity between treatment households (those joining or losing *iddirs*) and non-members, heterogeneities that may induce differential trend in factor market participation, we also estimate equation (1) on a conservatively matched sample of households. We employ propensity score matching and balance the covariates of treatment and control group households at the baseline (2008). Our propensity score equation mimics the regression in Table 2 but excludes potentially endogenous variables. First stage probit estimates and balancing tests are given in Tables A3 and A4, respectively. A second concern associated with identifying β_4 is related to reverse causality as *iddir* membership may be directly affected by market participation. Households who have been involved (or wish to be involved) in labor, land, or credit sharing are more likely to join (or form) *iddir* networks. While we cannot rule out this possibility, there are two reasons that justify that this is less likely. First, *iddir* networks are large traditional networks that may cover up to hundreds of households that are unlikely to be affected by small group of land and labor-sharing groups. Second, our identification strategy strengths our causal inference by comparing the trajectories of two groups of households: those who joined *iddir* and and those who left *iddir* membership as compared to the base group (non-members in both periods). One implication of this approach is a decrease in factor market outcomes for those who opted-out of *iddir* network support the claim that *iddir* participation is driving the correlation between *iddir* membership and factor market participation.

Since all our outcome variables of interest are binary response outcomes, we estimate equation (1) using linear panel data models and probit models.[10] We rigorously attempt different specifications of the covariates, including some non-linear effects of the variables. As mentioned earlier, the intensity and prevalence of *iddir* networks can vary across *woredas*, and perhaps across villages. Thus, we also control for village-level fixed effects in some of our specifications. For each factor market (land, labor, and credit), we estimate equation (1) without any control, with controls, and with village-level fixed effects. We estimate equation (1) for two land transaction outcomes of interest: probability of sharecropping-in and sharecropping-out of land in the main (*meher*) season. Similarly, we estimate equation (1) for households' tendency to participate in labor-sharing practices in the main season. Finally, we estimate equation (1) for modeling households' credit access from neighbors and friends, as

[10] Not surprisingly, the treatment effects from the linear regression models are very comparable with the implied marginal effects from the probit models. For this reason the latter estimates are not reported but available from the authors up on request.

well as their credit access from local moneylenders. In all regressions, we cluster standard errors at the household level, the level of variation in the variables of interest.

5. Estimation Results and Discussion

In this section, we present and discuss the main results. Table 4 presents the estimation results for the land transactions of households: sharecropping-in and sharecropping-out practices. Columns 1 to 3 present the estimation results for household's propensity to participate in sharecropping-in practices considering different specifications. In the first column, we present estimates without controls, while in the second column we control for demographic, socio-economic variables and village level-fixed effects. In the third column we estimate equation (1) for a matched sample of households. Similarly, columns 4 to 6 of Table 4 present the estimation results for households' participation in sharecropping-out practices.[11]

(Table 4 about here)

Consistent with our hypothesis, *iddir* membership improves households' probability to participate in land markets through share tenancy, particularly by enabling them to enter into sharecropping arrangements, the most common and vibrant forms of land tenancy contracts in Ethiopia (Pender and Fafchamps, 2005). Specifically, joining *iddir* networks improves households' probability to acquire access to land through sharecropping-in by about 9 percentage points, while also symmetrically improving landlords' probability to sharecrop/loan-out their land by around 6 percentage points. These results are quantitatively strong and stable over alternative specifications. Particularly, these estimates are robust to the inclusion of many covariates and village level-fixed effects. On the other hand, the treatment effects are insignificant for those households opting-out of *iddir* associations. Losing *iddir* network may imply losing access to key resources, thereby limiting factor market transactions.[12] Overall, these estimates suggest that *iddir* networks do indeed bridge the gap between those who would like to offer their land for others to cultivate and those who would like to acquire

[11] Full set of estimates for all variables in the various specifications are given in Table A5 in the appendix.

[12] One could also argue it is possible that market participation for those households opting-out of *iddir* associations may remain stable in case these households kept exploiting their previous network. While this is possible, a key factor determining market participation for this group could be why they lose their membership in the first place. If households lose their *iddir* membership because they are expelled due to misconduct, this may explain why their market participation deteriorates.

access to land lease through share tenancy. This is particularly appealing in the Ethiopian context where formal land markets are inhibited by legal restrictions on land sales market, and alternative tenancy mechanisms are subject to production risk, shirking on labor effort, and high cost of monitoring. These estimates can plausibly be attributed to the role of *iddir* networks in reducing factor market inefficiency resulting from information asymmetry between demanders and suppliers of land, as well as to their role as a safety net by providing security and trust for agents interested in land transactions. As discussed in Section 2, *iddir* members meet regularly for general meetings or when members face idiosyncratic shocks. These kinds of events allow members to discuss their general activities and share information, including those relevant to their demand and supply of factor markets. *Iddir* networks thus play a crucial role in reducing transaction costs in relation to the screening and enforcement of land transactions. The fact that such networks strengthen friendship and trust among members implies that farmers reduce their screening cost as they have inside information about potential tenants and landlords. Furthermore, *iddir* networks reduce potential enforcement problems through strict *iddir* rules and the social stigma and social disapproval through which these networks punish rule-breakers.

Table 5 presents difference-in-differences estimates on the effect of *iddir* membership on labor-sharing practices of households. Column 1 presents estimation results without controls. Column 2 extends this specification by controlling socio-economic, demographic variables as well village level-fixed effects. Column 3 provides treatment effects based on a matched sample of households.[13]

(Table 5 about here)

The estimates in Table 5 indicate that *iddir* membership improves households' probability of participation in labor-sharing arrangements by about 10 percentage points. These estimates remain stable even after controlling for households' observable characteristics and regional and village level-fixed effects. Interestingly, the treatment effects are negatively signed for those households who opted-out of *iddir* networks, although the effects are not significant. This strengthens our causal inference that attribute *iddir* networks to be the sources of these correlations. Conceptually, these treatment effects represent a remarkable improvement in households' demand for labor and allocation of excess agricultural labor supply. Intuitively, *iddir* networks are well-suited institutions for creating paired

[13] Full set of estimates for all variables in the various specifications are given in Table A6 in the Appendix.

partnerships and reciprocal group labor exchange through their frequent meetings and group level discussions. *Iddir* networks not only can provide access to potential members who would like to engage in labor-sharing, but they also provide the needed labor at the right time by exploiting the seasonal variation in demand for labor among members of the network. Recalling previous studies on the effect of labor-sharing practices on farmers' productivity (Krishnan and Sciubba, 2009), our results indirectly indicate that *iddir* networks can boost smallholder farmers' productivity by generating social capital. In this sense, our results complement previous studies on the effect of labor-sharing networks on economic performance.

Finally, in Table 6 we present the estimation results associated with the effect of *iddir* membership on households' credit access from different sources. Columns 1 to 3 present the estimation results for households' credit access from neighbors and friends, those households who are expected to be members of the *iddir* network. In the first column, we present estimates without controls, while the second column presents results with additional controls and village level-fixed effects. In the third column, we present the estimation results using a matched sample of households. Similarly, columns 4 to 6 present difference-in-differences estimates for households' credit access from local moneylenders (*Arata Abedari*).[14]

(Table 6 about here)

The estimation results in Table 6 show that *iddir* membership, in the same fashion as the analyses of other factors presented earlier, improves households' access to credit from friends and neighbors by about 7 percentage points. These estimates tell a consistent story in the sense that friends and neighbors are commonly members of the *iddir* network, and hence the flow of credit from these members in the village should increase. These findings support previous studies in Ethiopia which argue that membership in social networks by smallholder farmers affect their credit access from semi-formal institutions (Berhane et al., 2009; Ali and Deininger, 2014). Intuitively, this implies that *iddir* networks play an important role in overcoming households' liquidity constraints by availing potential lenders.[15] This, in turn, suggests that *iddir* networks can play a potential role in overcoming some of

[14] Full set of estimates for all variables in the various specifications are given in Table A7 in the appendix.
[15] One possible question here is whether the three factor markets are interlinked and instead one market (e.g., credit market) is deriving the other market (e.g., land market) as discussed in Ray (1998:561). To investigate this, we compute simple associations (cross-correlations) among the outcome variables of interest in this study. We found insignificant correlation among the different outcomes in the three different factor markets. More specifically, we compute simple associations

the prevalent high transactions costs in rural credit markets by providing information and security against defections in credit transactions.

The estimation results in columns 4 to 6 of Table 6 show the effect of *iddir* networks in crowding-out credit sources that charge high interest rates. These results show that *iddir* membership crowds-out credit from local moneylenders (*Arata Abedari*) who are often blamed for being exploitative by charging very high interest rates. Households who joined *iddir* networks reduced their reliance on local moneylenders for credit by around 4 to 5 percentage points. These results highlight the potential of indigenous rural institutions and networks, such as *iddir* associations, for crowding-out other informal lenders that charge higher interest rates. This is in contrast to the ineffectiveness of formal credit institutions in driving out informal moneylenders (Hoff and Stiglitz, 1990; Bell, 1990). This result potentially arises because, unlike formal credit institutions, *iddir* members have better access to local information useful for dealing with problems of screening, monitoring, and enforcement, to which formal banks do not have access. This implies that *iddir* member lenders have lower transactions costs than moneylenders. This has crucial implications for the supply of credit and the level of interest rates charged, which may drive moneylenders out of the market. For instance, Aleem (1990) argues that one reason why moneylenders charge high interest rates is that they have high average costs related to screening and enforcement. On the other hand and interestingly, the treatment effects for those households opting-out of *iddir* network is in contrast to those joining these networks. While the latter reduced their reliance on informal moneylenders, the former increase their reliance on these lenders, potentially due to lack of alternative credit sources. This is very intuitive and supports our claim that it is *iddir* that is driving these correlations and not the factor market transactions. We also attempt to estimate the effect of *iddir* networks on crowding-out credit from formal government sources and micro-finance institutions, but the treatment effects were statistically insignificant.[16] This is of course not unexpected, given the low interest rate these institutions charge and their supply of reliable and substantially larger loans. This provides interesting policy implications for countries like Ethiopia, which are striving to provide formal credit access to smallholder farmers.

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between our credit market transactions indicators and land market transactions indicators for the whole sample in Table 2 and note that there is no significant association among the transactions in different markets. This is in line with the previous literature which generally show that direct credit linkages between landowners and tenants are rare in Ethiopia.

[16] These results are available from the authors on request.

To summarize, the overall empirical results presented above are quite intuitive. The results generally highlight that informal indigenous networks can help the formation of physical and social capital that can improve factor market transactions among smallholder farmers.

5.1. Robustness Exercises

We rigorously attempt to check alternative model specifications and explanations that we think may affect our identification strategy. First, some of the existing sociological literature on *iddir* networks in Ethiopia (for instance, Mariam, 2003), which focused on specific regions and very few villages, suggests that households who are not *iddir* members are commonly new arrival immigrants. If such behavior somehow prevails in our data, it may confound the effect of joining *iddir* networks with some immigration or family (network) formation effect. To rule out such confounding effects, we estimate our models restricting the sample to those households whose household head was born in the village where he or she is currently living. Table A8 in the appendix presents these results. All estimates are similar in magnitude to the main estimates presented in Tables 4, 5 and 6.

Second, as mentioned in Section 4.3, we also test the implication of our common trend assumption using pre-treatment surveys. This assumption implies, that in the absence of *iddir* networks, both treatment and control group households would share identical time trends in factor market transactions. Our placebo estimation results (see Table A2 in the Appendix) indicate that both treatment and control group households share identical pre-treatment time trend in factor market transactions, as indicated by the insignificant and almost zero treatment effect estimates.[17] This evidence suggests that the treatment effects estimated, and hence our main results, are not driven by potential differential time trend between the treatment and control group households. Third, one could also argue that some of the relationships and networks already built in labor-sharing and land transactions might lead to *iddir* formation, thereby suggesting reverse causality. As we discussed above, while we cannot theoretically rule out the fact that individuals who share (or wish to share) labor or land join (or form) *iddir* networks, *iddir* associations are far larger than this and beyond the influence of paired-labor and land sharing arrangements. However, we also probe this claim using

[17] Since some of the households joined the survey at a later stage (at 2008), the sample size in these placebo regressions is slightly lower than the sample used for our main estimations.

several robustness exercises. In addition to estimating the treatment effects for those households who recently joined *iddir* networks, we also compare the trajectory of households who lose their *iddir* membership), with the base group (those who remained non-members). Accordingly, we find thatfactor market outcomes of those who leave *iddir* network either decreases or remains stable as compared to the base group. These pieces of evidence reinforce our causal inference which attributes the correlations to be driven by *iddir* participation. Fourth, our matching estimators strengthens our causal inference by comparing the factor market trajectory of very comparable households.

Fifth, we also use the fourth survey (2012 survey) instead of the third (2010 survey) in estimating our difference-in-differences equations for some of our outcome variables. We specifically assess the path of factor market performance of those treated (those joining *iddir* networks) households compared to the control group households even at later years. More generally, many of the results for the outcomes for which we have data are similar to the main estimates given in Tables 4, 5 and 6.[18] This results show that once households join *iddir* networks, they continue enjoying the benefits of the network as measured in the relative growth in factor market participation. Furthermore, these results also avoid concerns on the timing of the measurement of some of our outcomes. For instance, the question related to credit access spans the last 12 months. However, we do not know exactly when the households joined these networks, only that they joined after the 2008 survey and before the 2010 survey. Thus, these estimates confirm that the effects of *iddir* networks persist even if we assume that the treatment group households joined the *iddir* networks at the onset of the 2010 survey.

Finally, compared to Amhara and SNNP regions, *iddir* networks are not widely practiced in Tigray region. To assess if such heterogeneity can confound some of the results, we estimate all our models excluding sample households from Tigray region, and confirm the results do not change.[19] Although many of our explanatory variables do not vary much across the years, we also attempt to control for some background characteristics such as land, labor, and livestock assets of households from previous surveys to capture inertia effects and initial differences among the treated and control group households. However, doing this did not affect any of our estimates, perhaps because these assets did not exhibit substantial dynamics across the surveys. Finally, we attempt to assess if the effect of

[18] The results for this exercise are not reported to conserve space. But they are available from the authors up on request.
[19] These results are available from the authors on request.

iddir networks varies across different types of households. However, we are slightly constrained in performing this exercise because we only know whether the household is a member of an *iddir* in the village. We cannot identify if they subscribe to more than one *iddir* network.[20] As pointed out in Hoddinott et al. (2005) and Dercon et al. (2006), households (particularly richer households) may subscribe to more than one *iddir*, which suggests that the heterogeneous effect of *iddirs* cannot be ruled out. However, our sampling and identification strategy helps us to minimize such heterogeneity as we are comparing households who have just joined with those who have not. It is less likely that households would suddenly subscribe to many *iddirs* in such a short time.

6. Concluding Remarks and Policy Implications

Using a detailed longitudinal household survey data from Ethiopia, we empirically show that indigenous social networks such as *iddir* associations can play a crucial role in facilitating factor market transactions. *Iddir* networks are the most popular and widely available social networks both in urban and rural areas of Ethiopia. The fact that these networks are inclusive, offers interesting context and perspective to investigate their role in overcoming some of the factor market imperfections in rural economies. While studies such as Krishnan and Sciubba (2009) investigate the compositional and architectural impact of social networks on economic performance (or agricultural output), we investigate the role of *iddir* networks in facilitating factor market transactions, which are key inputs for improving the economic performance of smallholder farmers. To circumvent the selection of households into *iddir* networks, we rely on a difference-in-differences approach by comparing the growth in factor market transactions between those households who joined *iddir* networks and those who did not, before and after the former joined the networks. We further strengthen our identification strategy and causal inference by following factor market participation trajectory of those households opting-out of *iddir* networks. These comparisons are strengthened by matching estimators that enables us to focus on observationally comparable sample of households.

The fact that *iddir* networks avail information, strengthen trust, and reduce enforcement costs has important implications in view of the binding factor market imperfections in rural economies.

[20] Note also that we lack data to assess whether these transactions are intra-*iddir* or otherwise.

Owing to these qualities, *iddir* networks can substantially reduce transaction costs and information asymmetry among agents of factor markets, facilitating smooth transactions within factor markets. For instance, in countries like Ethiopia where land insecurity is a limiting factor in land transactions (Deininger et al., 2008; Ghebru and Holden, 2008; Deininger and Jin, 2008), understanding the role of *iddir* associations is crucial. In this context, our results indicate that *iddir* networks offer alternative ways to overcome land market imperfections by bridging the gap between those farmers who own excess land (in excess of their draft power), and those with excess draft power (in excess of their land endowment).[21] Similarly, we find that *iddir* networks can improve agricultural labor market imperfections by facilitating labor-sharing practices among households. While Krishnan and Sciubba (2009) find that social capital generated through labor-sharing arrangements matters for agricultural output, our results show that indigenous social networks, such as *iddir* associations, generate social capital by facilitating labor-sharing arrangements.

Another important implication of *iddir* networks relates to credit markets and their role in easing liquidity constraints of smallholder farmers. Access to credit is a central factor in transforming smallholder farming of the Ethiopian type. Dercon and Christiaensen (2011) emphasize that credit constraints and uninsured agricultural production are key factors that keep smallholder farmers in poverty. In this context, our results show that *iddir* networks boost the credit access of households from potential members of the *iddir* association. *Iddir* networks improve households' credit access from friends and neighbors. Interestingly, our findings also indicate that *iddir* networks crowd-out expensive and inefficient credit sources, including informal local moneylenders (*Arata Abedari*) without virtually affecting formal credit sources such as microfinance institutions. This is intuitively expected, because *iddir* members (both borrowers and lenders) have privileged access to information, which lowers the transaction costs associated with their credit transactions. Thus, households' access to alternative, and perhaps, cheaper credit sources through these networks can drive high cost informal lenders out of the credit market. This is particularly appealing in view of the fact that formal credit markets are commonly thought to be ineffective at crowding-out informal moneylenders in rural areas (Hoff and Stiglitz, 1990; Udry, 1990).

[21] However, the efficiency of these transactions has to be investigated, which is a potential future avenue of research.

To summarize, given the direct and indirect roles that *iddir* networks can play in factor markets and other development initiatives, new thinking regarding ways of supporting these networks is needed. As suggested by Dercon et al. (2006), policy makers may focus on scaling up the institutional capacity of these networks without diluting their institutional strength. Although our results highlight the potential of indigenous social networks, such as *iddirs*, in facilitating factor market transactions, further investigation into how to exploit the potential of these networks is needed. One possible dimension might be forming partnerships between *iddir* networks and other government and non-government organizations as suggested by Pankhurst (2008). Such partnerships may be vital in expanding formal credit institutions by combining the desirable qualities of *iddir* networks with the institutional capacity of the formal organizations. Whichever direction is considered, there needs to be an initiative to tap the potential that these networks offer.

However, this study is not without limitations. First, it is understood that we are estimating a reduced form equation where the mechanics and channels through which *iddir* networks affect factor markets are not clearly visible. Further theoretical and empirical studies on the channels through which these social networks affect market participation are required. Second, while we attempt various empirical approaches to circumvent selection, reverse causality and omitted variable bias further empirical studies based on a plausible source of exogenous variation in *iddir* membership would strengthen our study. While we were not successful on our search for a convincing instrument variable, this is a potential strategy to confirm the results in this study. Third, we only know whether the households are members of an *iddir* in the village. There might be heterogeneity among the services given by different *iddirs*, and hence, households subscribing to different *iddirs* might be subject to heterogeneous treatment effects. Though not expected in such a short time span, households may also subscribe to more than one *iddir* association simultaneously. It would be interesting to investigate the heterogeneous effects of these networks and their policy implications.[22] Uncovering these heterogeneities may also answer bigger theoretical questions including ‘‘why do not all households join *iddir* if these associations are beneficial’’ or why some members opted-out of *iddir* while others stay members and whether these can be attributed to heterogeneous benefits from these associations.

[22] For instance, Krishnan and Sciubba (2009) emphasize that the impact of social networks on economic performance heavily depends on the size and type of the network.

Finally, although *iddir* networks facilitate factor market transactions, further research on the efficiency of such transactions is worth considering. More generally and as also argued in Fafchamps (2006), social networks present both positive and negative externalities emanating from the complicated attributes of these networks; thus, further research on the potential of these indigenous networks would help in designing better policy interventions.

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Tables and Figures

Table 1: Overall distribution of *iddir* membership across sample households of PSNP surveys

	Survey			
	2006	**2008**	**2010**	**2012**
Iddir-members	1,629	2,157	1,974	2,453
Non-members	1,569	1,534	1,024	1,383
Share of *iddir* members, %	51	58	66	64

Table 2: Correlates of *iddir* participation

Variables considered	(1)	(2)	(3)
Age of household head	0.002***	0.001	0.001
	(0.001)	(0.000)	(0.000)
Female headed household	-0.004	-0.012	0.007
	(0.019)	(0.016)	(0.017)

Household head attended school	0.088***	0.055***	0.063***
	(0.012)	(0.012)	(0.012)
Household size	0.010***	0.013***	0.011***
	(0.004)	(0.003)	(0.003)
Oxen	-0.028***	-0.009	-0.007
	(0.008)	(0.007)	(0.007)
Land size (in hectare)	-0.018**	-0.010	-0.009
	(0.007)	(0.007)	(0.007)
Equib-member[23]	0.136***	0.128***	0.112***
	(0.019)	(0.019)	(0.018)
Subjective wealth status: ''Rich''	0.015	-0.000	0.025
	(0.031)	(0.028)	(0.028)
Subjective wealth status: ''Average''	0.001	0.002	-0.001
	(0.016)	(0.015)	(0.015)
Subjective income status: ''More than adequate''	0.009	0.003	0.001
	(0.060)	(0.059)	(0.061)
Subjective income status: ''Adequate''	0.014	0.005	-0.004
	(0.015)	(0.014)	(0.014)
Food insecure household	-0.012	-0.016	-0.015
	(0.012)	(0.011)	(0.011)
PSNP beneficiary household	-0.005	-0.002	0.005
	(0.014)	(0.012)	(0.013)
Father of household head respected in village	0.068***	0.054***	0.012
	(0.016)	(0.015)	(0.016)
Idiosyncratic shocks[24]	-0.029*	-0.014	-0.026*
	(0.016)	(0.015)	(0.015)
Idiosyncratic shocks last year	0.028	0.037*	0.036*
	(0.021)	(0.019)	(0.020)
Covariate shocks	-0.005	-0.006	0.007
	(0.014)	(0.013)	(0.014)
Covariate shocks last year	-0.012	-0.015	-0.033**

[23] *Equib* is a form of ''rotating credit and saving association'' (ROSCA) in Ethiopia. ROSCAs function as a source of informal finance in developing countries where "each member agrees to pay periodically into a common pool a small sum so that each, in rotation, can receive one large sum" (Hoff and Stiglitz, 1990). Although both *equib* and *iddir* are social networks that operate through powerful social pressures, *equib* has distinct features, compared to *iddir*, as *equib* mainly functions as a financial intermediary, rather than as an inclusive social network of broader purpose.

[24] We categorize shocks into idiosyncratic and covariate shocks considering whether these events affect specific households or communities living in a similar area. Idiosyncratic shocks include death and illness of family members as well as other similar events that specifically affect a specific household. Covariate shocks are those spatially covariant natural bad events whose effects go beyond a specific household and these include drought, flood, pests, crop diseases and others.

	(0.015)	(0.014)	(0.015)
Rain was sufficient	0.033***	0.008	0.028**
	(0.012)	(0.012)	(0.012)
Amhara region	0.548***	0.658***	0.337***
	(0.023)	(0.022)	(0.033)
Oromiya region	0.417***	0.744***	0.401***
	(0.027)	(0.041)	(0.027)
SNNP	0.627***	0.763***	0.617***
	(0.024)	(0.028)	(0.030)
Constant	0.000	-0.539***	-0.075
	(0.041)	(0.047)	(0.048)
R-squared	0.231	0.379	0.381
Number of individuals	2293	2293	2293
Number of observations	4586	4586	4586

Notes: In the first column of this table we regress the propensity to join an *iddir* on observable socio-demographic and -economic characteristics of households. The second and third columns extend this specification by including *zone*-level and *woreda*-level fixed effects, respectively. Robust and clustered (at household level) standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table 3: Factor market transaction comparison between treatment and control groups in base year (2008 survey)

	Treatment group	Control group	Difference
Panel A: Treatment group households are those joining *iddir* networks after 2008			
Land transactions: sharecropping-in	0.070 (0.255)	0.098 (0.298)	-0.029
Sharecropping-out	0.110 (0.314)	0.157 (0.364)	-0.046**
Labor transactions: labor-sharing-main season	0.278 (0.449)	0.289 (0.454)	-0.011
Credit transactions and sources: friends and neighbors	0.125 (0.331)	0.129 (0.336)	-0.004
Relatives	0.151 (0.358)	0.158 (0.365)	-0.008
MFI and government sources	0.148 (0.355)	0.364 (0.364)	-0.009
Informal lender (*Arata Abedari*)	0.099 (0.298)	0.041 (0.199)	0.057***
Other sources	0.055 (0.228)	0.043 (0.203)	0.012
Panel B: Treatment group households are those opting-out of *iddir* networks after 2008			
Land transactions: sharecropping-in	0.097(0.297)	0.098 (0.298)	-0.001
Sharecropping-out	0.176(0.382)	0.157 (0.364)	0.019
Labor transactions: labor-sharing-main season	0.236(0.426)	0.289 (0.454)	-0.064
Credit transactions and sources: friends and neighbors	0.121(0.327)	0.129 (0.336)	-0.008
Relatives	0.127(0.334)	0.158 (0.365)	-0.031
MFI and government sources	0.200(0.401)	0.364 (0.364)	0.043
Informal lender (*Arata Abedari*)	0.012(0.110)	0.041 (0.199)	-0.029*
Other sources	0.030(0.172)	0.043 (0.203)	-0.013

Notes: Column 1 and 2 present the mean factor market transactions for the treatment and control group households in the base year (2008) (with standard deviations in parentheses), while column 3 presents mean differences between both groups. In Panel A, we compare factor market transactions between those households who recently joined *iddir* networks with those remaining non-members, while Panel make a similar comparison between those households who recently opted-out of *iddir* network and those non-members in both surveys. ***, **, * indicate that differences are significantly different from zero at the 0.01, 0.05 and 0.10 levels, respectively.

Table 4: **Effect of *iddir* networks on land transactions, difference-in-differences estimates**

	Sharecropping-in			**Sharecropping-out**		
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
β_1 *(joining)*	-0.029	-0.056**	-0.062***	-0.046**	-0.053**	-0.057**
	(0.018)	(0.022)	(0.023)	(0.023)	(0.025)	(0.025)
β_2 *(losing)*	-0.001	-0.036	-0.046*	0.019	0.002	-0.006
	(0.026)	(0.025)	(0.027)	(0.033)	(0.035)	(0.036)
β_3 *(after)*	-0.034**	-0.047***	-0.057***	0.003	0.000	-0.001
	(0.015)	(0.016)	(0.017)	(0.019)	(0.022)	(0.023)
β_4 *(joining*after)*	0.092***	0.087***	0.097***	0.057*	0.054*	0.057*
	(0.024)	(0.025)	(0.026)	(0.030)	(0.031)	(0.032)
β_5 *(losing*after)*	0.040	0.041	0.050	-0.046	-0.050	-0.044
	(0.029)	(0.030)	(0.031)	(0.040)	(0.041)	(0.043)
Regional dummies (4)	No	Yes	Yes	No	Yes	Yes
Village fixed effects	No	Yes	Yes	No	Yes	Yes
Constant	0.098***	0.113**	0.139**	0.157***	0.195***	0.187***
	(0.012)	(0.052)	(0.061)	(0.015)	(0.064)	(0.066)
R-squared	0.006	0.230	0.248	0.003	0.207	0.229
Number of observations	2182	2182	1984	2182	2182	1984

Notes: Each column presents difference-in-differences estimations of equation (1) for household's involvement in land transactions. Except the first and fourth columns, all estimations include four regional dummies and village (*kebele*)-level fixed effects. Robust and clustered (at household level) standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table 5: **Effect of *iddir* networks on labor transactions, difference-in-differences estimates**

	Labor-sharing (Main season)		
Explanatory variables	(1)	(2)	(3)
β_1 *(joining)*	-0.017	0.009	0.006
	(0.031)	(0.041)	(0.041)
β_2 *(losing)*	-0.064*	-0.055	-0.035
	(0.038)	(0.046)	(0.047)
β_3 *(after)*	0.027	0.035	0.052*
	(0.026)	(0.029)	(0.031)
β_4 *(joining*after)*	0.109***	0.096**	0.088*
	(0.042)	(0.044)	(0.045)
β_5 *(losing*after)*	-0.045	-0.059	-0.074
	(0.051)	(0.052)	(0.054)
Regional dummies (4)	No	Yes	Yes
Village fixed effects	No	Yes	Yes
Constant	0.301***	0.344***	0.323***
	(0.019)	(0.099)	(0.105)
R-squared	0.015	0.214	0.225
Number of observations	2126	2126	1958

Notes: Each column presents difference-in-differences estimations of equation (1) for household's involvement in labor transactions. Except the first column, all estimations include four regional dummies and village (*kebele*)-level fixed effects. Robust and clustered (at household level) standard errors are in parentheses. Robust standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table 6: Effect of *iddir* networks on credit access, difference-in-differences estimates, full model results

	Credit from neighbors and friends			**Credit from informal lenders *(Arata Abedari)***		
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
β_1 *(joining)*	-0.004	-0.050*	-0.043	0.057***	0.058***	0.058***
	(0.023)	(0.029)	(0.030)	(0.018)	(0.019)	(0.019)
β_2 *(losing)*	-0.008	-0.047	-0.044	-0.029**	-0.065***	-0.070***
	(0.029)	(0.033)	(0.035)	(0.012)	(0.018)	(0.018)
β_3 *(after)*	-0.010	-0.018	-0.008	-0.003	-0.013	-0.013
	(0.018)	(0.023)	(0.025)	(0.011)	(0.013)	(0.013)
β_4 *(joining*after)*	0.074**	0.070**	0.061*	-0.046**	-0.037*	-0.034*
	(0.030)	(0.031)	(0.033)	(0.020)	(0.020)	(0.020)
β_5 *(losing*after)*	0.022	0.024	0.011	0.046**	0.053**	0.056**
	(0.035)	(0.036)	(0.038)	(0.023)	(0.023)	(0.024)
Regional dummies (4)	No	Yes	Yes	No	Yes	Yes
Village fixed effects	No	Yes	Yes	No	Yes	Yes
Constant	0.129***	0.010	-0.000	0.041***	0.065***	0.067**
	(0.014)	(0.046)	(0.053)	(0.008)	(0.025)	(0.026)
R-squared	0.005	0.153	0.153	0.012	0.184	0.189
Number of observations	2182	2182	1984	2182	2182	2098

Notes: Each column presents difference-in-differences estimations of equation (1) for household's access to credit from different sources. Except the first and fourth columns, all estimations include four regional dummies and village (*kebele*)-level fixed effects. Robust and clustered (at household level) standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Appendix

Table A1*:* **Descriptive statistics of the explanatory variables considered**

Explanatory variables considered	2008 survey	2010 survey
Age of household head	44.806	45.756
Female headed household	0.193	0.210
Head attended school	0.291	0.581
Number of adults	5.555	5.621
Number of oxen	0.890	0.914
Land (in hectare)	1.099	1.290
Equib member	0.038	0.059
Subjective wealth status: ‘‘Rich’’	0.048	0.036
Subjective wealth status: ‘‘Average’’	0.220	0.227
Subjective income status: ‘‘More than adequate’’	0.006	0.003
Subjective income status: ‘‘Adequate’’	0.231	0.246
Food insecure household	0.733	0.476
PSNP beneficiary household	0.513	0.480
Father of household head respected in village	0.493	0.493
Idiosyncratic shocks	0.162	0.203
Idiosyncratic shocks last year	0.049	0.114
Covariate shocks	0.529	0.527
Covariate shocks last year	0.640	0.843
Rain was sufficient	0.517	0.313
Improvement in economic status	0.164	0.376
Amhara region	0.331	0.331
Oromiya region	0.259	0.259
SNNP region	0.143	0.143
Number of observations	1091	1091

Table A2: Placebo regression on pre-treatment sample using 2006 and 2008 surveys

	Sharecropping-in		**Sharecropping-out**		**Labor-sharing (main-season)**	
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
β_1 (joining)	-0.011	0.020	-0.064***	-0.015	0.061*	0.043
	(0.018)	(0.023)	(0.025)	(0.031)	(0.034)	(0.041)
β_2 (after)	-0.002	0.006	-0.010	-0.008	0.164***	0.149***
	(0.013)	(0.014)	(0.018)	(0.019)	(0.028)	(0.027)
*β_3 (joining*after)*	-0.015	-0.018	0.019	0.021	-0.048	-0.068
	(0.023)	(0.023)	(0.032)	(0.032)	(0.048)	(0.045)
Other controls	No	Yes	No	Yes	No	Yes
Regional dummies (4)	No	Yes	No	Yes	No	Yes
Village-level fixed effects	No	Yes	No	Yes	No	Yes
Constant	0.059***	0.118***	0.121***	0.157**	0.209***	0.371***
	(0.009)	(0.049)	(0.013)	(0.065)	(0.018)	(0.089)
R-squared	0.002	0.115	0.006	0.136	0.015	0.167
No. of observations	1,434	1,434	1,434	1,434	1,434	1,434

Notes: Each column presents difference-in-differences estimations for household's involvement in factor market transactions. In this table we are using pre-treatment surveys to estimate placebo treatment effects. We did this exercise only for the outcome variables where we have complete information in both pre-treatment surveys. Estimates in the second, fourth, and sixth columns include village (*kebele*)-level fixed effects. Robust standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table A3: First stage probit regression (Propensity score) for treatment at the baseline

Explanatory variables	Coefficients (s.e are in brackets)
Age of household head	0.004
	(0.003)
Female headed household	-0.224**
	(0.113)
Head attended school	0.126
	(0.095)
Number of adults	-0.021
	(0.037)
Number of oxen	0.032
	(0.052)
Land (in hectare)	-0.064
	(0.052)
PSNP beneficiary	0.100
	(0.086)
Idiosyncratic shocks	-0.137
	(0.115)
Idiosyncratic shocks last year	0.071
	(0.193)
Covariate shocks	0.190**
	(0.096)
Covariate shocks last year	-0.335***
	(0.099)
Weather (enough rain)	0.053
	(0.090)
Improvement in living standard	0.216*
	(0.116)
Amhara region	1.488***
	(0.126)
Oromiya region	1.351***
	(0.137)
SNNP region	1.614***
	(0.160)
Constant	-1.639***
	(0.170)
Pseudo R-squared	0.147
Number of observations	1091

Notes: ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table A4. Balance of household characteristics, two-sample t-test

	$E(X_{non-members})$	$E(X_{members})$	t-test
Age of household head	44.433	44.441	-0.010
Female household head	0.165	0.165	0.010
Head attended school	0.294	0.295	-0.040
Number of adults	2.793	2.847	-0.660
Number of oxen	0.893	0.854	0.710
Land (in hectare)	1.093	1.109	-0.310
PSNP beneficiary	0.471	0.487	-0.520
Idiosyncratic shocks	0.161	0.183	-0.920
Idiosyncratic shocks last year	0.050	0.054	-0.270
Covariate shocks	0.600	0.601	-0.030
Covariate shocks last year	0.670	0.675	-0.170
Weather (enough rain)	0.481	0.450	0.970
Improvement in economic status	0.157	0.189	-1.340
Amhara-region	0.427	0.400	0.860
Oromiya-region	0.304	0.316	-0.400
SNNP-region	0.191	0.206	-0.600

Table A5: **Effect of *iddir* networks on land transactions, difference-in-differences estimates, full model results**

	Sharecropping-in			**Sharecropping-out**		
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
β_1 *(joining)*	-0.029	-0.056**	-0.062***	-0.046**	-0.053**	-0.057**
	(0.018)	(0.022)	(0.023)	(0.023)	(0.025)	(0.025)
β_2 *(losing)*	-0.001	-0.036	-0.046*	0.019	0.002	-0.006
	(0.026)	(0.025)	(0.027)	(0.033)	(0.035)	(0.036)
β_3 *(after)*	-0.034**	-0.047***	-0.057***	0.003	0.000	-0.001
	(0.015)	(0.016)	(0.017)	(0.019)	(0.022)	(0.023)
β_4 *(joining*after)*	0.092***	0.087***	0.097***	0.057*	0.054*	0.057*
	(0.024)	(0.025)	(0.026)	(0.030)	(0.031)	(0.032)
β_5 *(losing*after)*	0.040	0.041	0.050	-0.046	-0.050	-0.044
	(0.029)	(0.030)	(0.031)	(0.040)	(0.041)	(0.043)
Age of household head		-0.001**	-0.001*		-0.001**	-0.001*
		(0.000)	(0.000)		(0.001)	(0.001)
Female headed household		-0.062***	-0.064***		-0.025	-0.038**
		(0.012)	(0.013)		(0.019)	(0.019)
Head attended school		0.017	0.024*		-0.005	0.001
		(0.013)	(0.014)		(0.017)	(0.018)
Number of adults		0.009*	0.008		-0.002	-0.005
		(0.005)	(0.005)		(0.006)	(0.006)
Number of oxen		0.018**	0.015**		0.000	0.004
		(0.007)	(0.007)		(0.009)	(0.008)
Land (in hectare)		0.002	0.006		0.016*	0.016**
		(0.007)	(0.008)		(0.008)	(0.008)
PSNP beneficiary		-0.023*	-0.033**		-0.018	-0.027*
		(0.013)	(0.013)		(0.016)	(0.016)
Idiosyncratic shocks		-0.039***	-0.037***		-0.022	-0.011
		(0.013)	(0.014)		(0.020)	(0.021)
Idiosyncratic shocks last year		0.008	0.007		-0.011	-0.010
		(0.021)	(0.022)		(0.028)	(0.030)
Covariate shocks		-0.004	-0.011		-0.019	-0.024
		(0.014)	(0.015)		(0.017)	(0.018)
Covariate shocks last year		0.022	0.024		0.007	0.012
		(0.015)	(0.016)		(0.020)	(0.021)
Rain was sufficient		0.006	-0.003		-0.008	-0.010
		(0.013)	(0.013)		(0.017)	(0.017)
Improvement in economic status		0.002	-0.003		0.019	0.016
		(0.013)	(0.013)		(0.018)	(0.018)

Regional dummies (4)	No	Yes	Yes	No	Yes	Yes
Village fixed effects	No	Yes	Yes	No	Yes	Yes
Constant	0.098***	0.113**	0.139**	0.157***	0.195***	0.187***
	(0.012)	(0.052)	(0.061)	(0.015)	(0.064)	(0.066)
R-squared	0.006	0.230	0.248	0.003	0.207	0.229
Number of observations	2182	2182	1984	2182	2182	1984

Notes: Each column presents difference-in-differences estimations of equation (1) for household's involvement in land transactions. Except the first and fourth columns, all estimations include four regional dummies and village (*kebele*)-level fixed effects. Robust and clustered (at household level) standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table A6: **Effect of *iddir* networks on labor transactions, difference-in-differences estimates, full model results**

	Labor-sharing (Main season)		
Explanatory variables	(1)	(2)	(3)
β_1 *(joining)*	-0.017	0.009	0.006
	(0.031)	(0.041)	(0.041)
β_2 *(losing)*	-0.064*	-0.055	-0.035
	(0.038)	(0.046)	(0.047)
β_3 *(after)*	0.027	0.035	0.052*
	(0.026)	(0.029)	(0.031)
β_4 *(joining*after)*	0.109***	0.096**	0.088*
	(0.042)	(0.044)	(0.045)
β_5 *(losing*after)*	-0.045	-0.059	-0.074
	(0.051)	(0.052)	(0.054)
Age of household head		-0.001*	-0.001*
		(0.001)	(0.001)
Female headed household		0.040	0.018
		(0.027)	(0.027)
Head attended school		-0.045**	-0.053**
		(0.022)	(0.023)
Number of adults		0.012	0.014*
		(0.008)	(0.008)
Number of oxen		0.023*	0.025*
		(0.013)	(0.014)
Land (in hectare)		0.027**	0.023*
		(0.013)	(0.014)
PSNP beneficiary		-0.029	-0.012
		(0.022)	(0.023)
Idiosyncratic shocks		0.053*	0.056*
		(0.029)	(0.030)
Idiosyncratic shocks last year		0.077*	0.059
		(0.042)	(0.043)
Covariate shocks		0.010	0.011
		(0.022)	(0.023)
Covariate shocks last year		-0.052**	-0.056**
		(0.026)	(0.027)
Rain was sufficient		0.003	0.010
		(0.023)	(0.024)
Improvement in economic status		0.007	-0.020
		(0.025)	(0.026)

Regional dummies (4)	No	Yes	Yes
Village fixed effects	No	Yes	Yes
Constant	0.301***	0.344***	0.323***
	(0.019)	(0.099)	(0.105)
R-squared	0.015	0.214	0.225
Number of observations	2126	2126	1958

Notes: Each column presents difference-in-differences estimations of equation (1) for household's involvement in labor transactions. Except the first column, all estimations include four regional dummies and village (*kebele*)-level fixed effects. Robust and clustered (at household level) standard errors are in parentheses. Robust standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table A7: Effect of *iddir* networks on credit access, difference-in-differences estimates, full model results

	Credit from neighbors and friends			Credit from informal lenders (*Arata Abedari*)		
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
β_1 *(joining)*	-0.004	-0.050*	-0.043	0.057***	0.058***	0.058***
	(0.023)	(0.029)	(0.030)	(0.018)	(0.019)	(0.019)
β_2 *(losing)*	-0.008	-0.047	-0.044	-0.029**	-0.065***	-0.070***
	(0.029)	(0.033)	(0.035)	(0.012)	(0.018)	(0.018)
β_3 *(after)*	-0.010	-0.018	-0.008	-0.003	-0.013	-0.013
	(0.018)	(0.023)	(0.025)	(0.011)	(0.013)	(0.013)
β_4 *(joining*after)*	0.074**	0.070**	0.061*	-0.046**	-0.037*	-0.034*
	(0.030)	(0.031)	(0.033)	(0.020)	(0.020)	(0.020)
β_5 *(losing*after)*	0.022	0.024	0.011	0.046**	0.053**	0.056**
	(0.035)	(0.036)	(0.038)	(0.023)	(0.023)	(0.024)
Age of household head		0.000	0.000		-0.001*	-0.001**
		(0.001)	(0.001)		(0.000)	(0.000)
Female headed households		-0.003	-0.007		-0.006	-0.008
		(0.021)	(0.023)		(0.012)	(0.012)
Head attended school		0.024	0.022		0.018*	0.018*
		(0.018)	(0.019)		(0.010)	(0.010)
Number of adults		0.005	0.007		-0.003	-0.004
		(0.006)	(0.007)		(0.004)	(0.004)
Number of oxen		-0.018**	-0.019*		-0.010**	-0.011**
		(0.009)	(0.010)		(0.004)	(0.005)
Land (in hectare)		-0.003	-0.004		0.004	0.005
		(0.008)	(0.008)		(0.006)	(0.006)
PSNP beneficiary		0.012	0.017		0.013	0.012
		(0.017)	(0.018)		(0.010)	(0.010)
Idiosyncratic shocks		0.025	0.025		-0.022*	-0.023*
		(0.021)	(0.022)		(0.012)	(0.012)
Idiosyncratic shocks last year		0.010	0.002		0.028	0.030
		(0.031)	(0.032)		(0.020)	(0.021)
Covariate shocks		-0.034**	-0.027		-0.024**	-0.025**
		(0.016)	(0.017)		(0.011)	(0.012)
Covariate shocks last year		0.013	0.004		0.024**	0.029**
		(0.019)	(0.021)		(0.011)	(0.012)
Rain was sufficient		0.011	0.013		-0.021**	-0.019*
		(0.016)	(0.017)		(0.011)	(0.011)

Improvement in economic status		-0.012	-0.014		-0.032***	-0.034***
		(0.017)	(0.019)		(0.010)	(0.011)
Regional dummies (4)	No	Yes	Yes	No	Yes	Yes
Village fixed effects	No	Yes	Yes	No	Yes	Yes
Constant	0.129***	0.010	-0.000	0.041***	0.065***	0.067**
	(0.014)	(0.046)	(0.053)	(0.008)	(0.025)	(0.026)
R-squared	0.005	0.153	0.153	0.012	0.184	0.189
Number of observations	2182	2182	1984	2182	2182	2098

Notes: Each column presents difference-in-differences estimations of equation (1) for household's access to credit from different sources. Except the first and fourth columns, all estimations include four regional dummies and village (*kebele*)-level fixed effects. Robust and clustered (at household level) standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.

Table A8: Difference-in-differences estimates for households whose head was born in the village

	Sharecropping-in			**Sharecropping-out**		
Explanatory variables	(1)	(2)	(3)	(4)	(5)	(6)
β_4 *(joining*after)*	0.101***	0.096***	0.097***	0.068**	0.063*	0.066*
	(0.027)	(0.029)	(0.030)	(0.033)	(0.035)	(0.035)
β_5 *(losing*after)*	0.038	0.039	0.041	-0.026	-0.030	-0.027
	(0.034)	(0.034)	(0.036)	(0.047)	(0.048)	(0.050)
Regional dummies (4)	No	Yes	Yes	No	Yes	Yes
Village fixed effects	No	Yes	Yes	No	Yes	Yes
Constant	0.100***	0.106*	0.068	0.166***	0.184**	0.162**
	(0.014)	(0.062)	(0.068)	(0.017)	(0.072)	(0.081)
Number of observations	1834	1834	1648	1834	1834	1648

	Labor-sharing (Main season)		
	(1)	(2)	(3)
β_4 *(joining*after)*	0.116***	0.111**	0.114**
	(0.045)	(0.047)	(0.049)
β_5 *(losing*after)*	-0.019	-0.029	-0.028
	(0.057)	(0.058)	(0.061)
Regional dummies (4)	No	Yes	Yes
Village fixed effects	No	Yes	Yes
Constant	0.304***	0.272***	0.304**
	(0.021)	(0.103)	(0.121)
Number of observations	1810	1810	1670

	Credit from neighbors and friends			**Credit from informal lenders**		
	(1)	(2)	(3)	(4)	(5)	(6)
β_4 *(joining*after)*	0.079**	0.070**	0.064*	-0.037*	-0.029	-0.020
	(0.033)	(0.034)	(0.036)	(0.021)	(0.021)	(0.022)
β_5 *(losing*after)*	0.034	0.038	0.027	0.064**	0.071***	0.073***
	(0.039)	(0.041)	(0.042)	(0.026)	(0.026)	(0.026)
Regional dummies (4)	No	Yes	Yes	No	Yes	Yes
Village fixed effects	No	Yes	Yes	No	Yes	Yes
Constant	0.119***	0.042	0.014	0.045***	0.074***	0.086***
	(0.015)	(0.050)	(0.045)	(0.009)	(0.026)	(0.029)
Number of observations	1834	1834	1648	1834	1834	1648

Notes: Each column presents difference-in-differences estimations of equation (1) for household's access to factor market transaction. Except the first and fourth columns, all estimations include four regional dummies and village (*kebele*)-level fixed effects. Robust and clustered (at household level) standard errors are in parentheses. ***, **, * indicates significance level at 1, 5 and 10 percent, respectively.