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IZA DP No. 14092

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ABSTRACT

Learning about Farming: Innovation and Social Networks in a Resettled Community in Brazil*

We study the role of social learning in the diffusion of cash crops in a resettled village economy in northeastern Brazil. We combine detailed geo-coded data on farming plots with dyadic data on social ties among settlers, and we leverage natural exogenous variation in network formation induced by the land occupation movement and the agrarian reform. By using longitudinal data on farming decisions over 15 years we find consistent evidence of significant peer effects in the decision to farm new cash fruits (pineapple and passion fruit). Our results suggest that social diffusion is heterogeneous along observed plot and crop characteristics, i.e. farmers growing water-sensitive crop are more likely to respond to the actions of peers with similar water access conditions.

JEL Classification: C45, D85, J15, O33, Q15

Keywords: technology adoption, agrarian reform, social networks, peer effects, Brazil

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1 Introduction

Knowledge diffusion and learning are major drivers of economic growth (Lucas, 1988; Durlauf and Fafchamps 2005; Acemoglu 2009; Banerjee et al. 2019). Information constraints to innovation and technological change have long been studied in the literature on economic development, and a great deal of attention has been given to the role of social networks in the uptake and diffusion of new and uncertain technologies, especially in agriculture (e.g. Feder et al. 1985; Conley and Udry 2010). Agricultural technology adoption involves a high degree of uncertainty and complexities that go beyond farm characteristics. The Green Revolution, which brought new high-yielding varieties (HYVs) to India in the 1960s, highlighted the importance of understanding why many farmers did not adopt new seeds despite suitable agronomic conditions and high returns (Foster and Rosenzweig 1995; Munshi 2004).[1]

While the importance of networks and peer experience in shaping the adoption of new technologies is largely recognized, especially in developing contexts, the identification of social learning effects remains a major challenge because peers are usually chosen endogenously (Manski, 1993; Brock and Durlauf, 2001; Moffitt, 2001; Fafchamps and Lund, 2003). If an individual's information network, e.g. the set of neighbors she learns from, is not random but shaped by some unobserved characteristics common to peers, the estimates of the social learning effect would be biased. In other words, when detecting a significant correlation between the outcomes of linked farmers, it is difficult to say whether this is due to authentic peer effects or simply to the process of social link formation along unobservable characteristics. Recently, field experiments have been used to generate exogenous variation in the timing and frequency of social interactions or in the degree of information supply about peers' behavior (see Feingenberg et al. 2010; Cai et al. 2015; Fafchamps and Quinn, 2018).

In this paper, we investigate the dynamics of social learning by exploiting the unique experience of an agrarian reform settlement in the poorest state in Brazil, where stranger households found themselves living in a newly created 'village' undergoing rapid economic

[1] By tracking farming households in rural India, Foster and Rosenzweig (1995) find that lack of knowledge is a main deterrent to adoption and that farmers whose neighbors had experience growing the new seeds adopted more HYVs on their own land. A large body of works have tested the role of other mechanisms such as credit and insurance constraints (e.g. Kondylis et al., 2017; Ben Yishay et al., 2019) but technology adoption oftentimes remains low even after some of these barriers are removed (e.g. Ambler et al., 2018; Karlan et al., 2014; Stifel and Minten, 2008).

and agricultural transformation they were not trained for. What makes this setting particularly attractive for our purposes is the *natural exogenous variation* in the farmers' network formation induced by the land occupation movement. The latter creates informal settlements or villages (*assentamentos*) where interpersonal ties are not driven by kinship or other endogenous traits, but by the location of vacant land.[2] By using individual–level data and exploiting the network structure of social interactions, we investigate peer effects in agricultural adoption decisions in a controlled link formation setting that allows us to overcome endogeneity concerns.

Agrarian reform in Brazil, which has controversially involved both civil society and political leaders since the 1990s, is one of the most powerful and globally renowned intervention to reduce long-lasting land inequalities and extreme poverty in the country. The distinctive aspect of Brazilian agrarian reform is the active role played by the landless workers' movements, among which the most widely known is the *Movimento Sem Terra* (MST), in pushing the state to expropriate unproductive land (Sigaud 2004; Wolford 2010). These movements mobilized alien (i.e. externally recruited) households to occupy land in order to put pressure on the governmental body (Instituto Nacional de Colonização e Reforma Agrária, or INCRA) to expropriate unproductive and vacant land.[3] After a process of occupation ('encampment') settlers are officially given the 'right' to cultivate their own plots such that, for the first time in some rural areas in Brazil, household residency and property overlap (Bergamasco 1997; Wanderley 2000). This means that, for the first time, household farming has become a relevant exchange activity in these communities, as opposed to landless wage labor in large estates *latifúndios*. These agrarian reform settlements become centers for technological change and socio-economic development, whereby landless farmers can be the driving force of a newly created village economy.

[2] Community-based networks are active throughout the developing world and, unlike in our setting, they are typically organized around close-knit communities that have been in place for long periods of time. Depending on the context, these groups may be based on kinship (including castes in India or clans in sub-Saharan Africa) or on geographical proximity (villages or neighborhoods) (see Munshi 2014, Barr 2003). However, communities based on either geography or kinship are likely to be formed endogenously (e.g. the former through location choice, the latter through marriage). For example, studying the American South in the decades of the late 19th century after Emancipation, Chay and Munshi (2014) show that Black spatial proximity varied substantially across southern counties, depending on the crops grown in the local area. Blacks worked (and lived) in close proximity to each other where labor-intensive plantation crops (such as tobacco, cotton and rice) were grown. They lived in a more dispersed fashion where less labor-intensive crops (such as wheat and corn) were more common.

[3] This is mostly indebted land of sugar-cane factories that went bankrupt during the sugar crisis of the early 1990s.

Following the land occupation process, this village went through an agrarian transformation that shifted labor from former enslavement in the sugar cane plantations to household-level commercial farming. The above transformation involved the adoption of a set of new crops, including, for the first time, perennial crops, such as pineapple (*abacaxi*) and passion fruit (*maracuja*). These are perishable commercial fruits with high commercial value, whose cultivation was forbidden before the agrarian reform. Unlike subsistence farming, tropical plants rely on labor-intensive provision, efficient handling, water control and post-harvest conservation techniques.[4]

Our analysis combines unique dyadic data on social ties among farmers in a resettled community in the northeast of Brazil with detailed geo-localized data on land squatting and longitudinal farm production information. By employing unique network data on the entire village population, we can identify the role of social learning effects on households' farming choices. We first provide evidence that the geographical location of settlers during the encampment period was as good as random for our scope, and we then leverage the geographical distance between farmers, induced by the land-squatting process as an exogenous source of variation in the formation of social networks. Our empirical strategy relies on a model of social diffusion along social network lines (Bramoullé, et al. 2009), which we extend to a longitudinal setting to exploit time variation in farmer technology adoption.[5] The instrumentation procedure we propose addresses the endogeneity of social links that stems from simultaneity and assortativity. We find a large positive peer effect on the adoption of new cash crops. Having one additional peer cultivating a given cash crop increases the probability of crop-specific adoption by 9% to 14% according to the most conservative estimate. Interestingly, the effect appears to be heterogeneous across farmers along plot and crop characteristics, i.e. conditional on the characteristics shared by farmers, the social learning process of water-needing crops appears to be mostly driven by peers whose plots have similar water access conditions.

Our paper relates to the large body of literature studying the role of social networks

[4]Northeastern Brazil is a drought-ridden region where rainfall, good soil and adequate infrastructure is much less well-distributed than in the sourthern region. Overall, after being the largest world producer of sugar cane, Brazil is increasigly populated by both subsistence farmers (cultivating traditional crops such cassava, peanuts, sweet potatoes, maize) and producers of forest products, cocoa and tropical fruits.

[5]Most previous studies on peer effects have used data where individuals are partitioned into mutually exclusive and fully overlapping reference groups (e.g., all children belonging to the same class). In doing so, they assume that individuals are equally affected by all other individuals belonging to their group and by nobody outside their group. In our model the reference group has individual-level variation: if i and j are connected and j and k are connected, it does not necessarily imply that i and k are also connected.

in shaping innovation and development.[6] By using a network approach Conley and Udry (2010) document the role of social learning through social ties in the diffusion of a new cash crop with high profit margins in Ghana. They use detailed information on communication patterns among farmers to show that new growers learn how to cultivate pineapple by observing the experimentation of their peers. A number of related contributions study social learning in technology adoption in different developing settings where markets are thin and information is incomplete (Munshi 2008; Foster and Rosenzweig 2010; Maertens 2017). By learning from others (typically neighbors), a new grower updates her priors about the unfamiliar technology and adds actual information on expected net returns in her optimal (profit-maximizing) problem of adoption choice (Foster and Rosenzweig, 1995; Conley and Udry 2001). In this respect, the prospect of social learning declines with geographical distance (Fafchamps 2010) as well as with socio-economic differences within networks and groups (Fafchamps and Soderbom 2011; Agrawal et al 2010). We add to this literature by exploiting the combination of a natural experiment and detailed network data, which allows us to identify the dynamics of diffusion along network lines.

Our findings also contribute to the vital debate on the role of grassroots innovation in the inclusive and sustainable development of rural communities (Mosse, 2001; Platteau, 2004; Rigon, 2014, Kothari 2014). Criticism of the 'participatory' agrarian reform refers to it as a social program mimicking a landlord's benevolent behavior towards the most marginalized groups in the population. The main reason lies in the significant focus on housing creation rather than technical assistance, agricultural training, facilities and credit. We document, instead, the extent to which agrarian reform settlements can be centers for technological change and socio-economic development, as long as new village economies are based on intentional local organization and grassroots decision–making. Indeed, our results point to the innovative element of Brazilian agrarian reform, which involves not only access to land but especially the mobilization of people with different backgrounds from different parts of the country and the links among them.

The rest of the paper is organized as follows. Section 2 describes the setting and the Brazilian context. Data are presented in Section 3 while Section 4 describes the empirical strategy. Results are reported in Section 5. Section 6 concludes.

[6]Different studies have produced empirical evidence of peer effects in many areas, from school performances to female entrepreneurship, and from financial to insurance decisions (Katz and Case, 1991; Hoxby, 2000; Feigenberg et al. 2010; ; Banerjee et al.2013; Cai et al. 2015).

2 Brazilian land reform and agrarian settlements

Land reform is a key policy tool for reducing poverty and inequality in Brazil, where the latter take the form of lack of access to land and socio–economic exclusion (Pereira, 2003). Agrarian reform has been included in the political agenda since the 1960s and social movements, including the MST, have played a major role in its implementation. This is because the mass mobilization of people to occupy unproductive *latifúndios* has been crucial to the government's push for land expropriation.[7] Table 1 shows that social movement interventions peaked in the mid-1990s when the number of settled families increased significantly (almost 50 thousand households resettled).

Table 1: Number of families settled over time

Year	Government	Settlers per year
1964–1984	Military regime	3689
1985–1989	José Sarney	16737
1990–1992	Fernando Collor de Mello	14172
1993–1994	Itamar Franco	7183
1995–2002	Fernando Henrique Cardoso	48923
2003–2009	Luis Inacio Lula da Silva	7564

Source. L. S. de Medeiros (2013, 6)

The most innovative element of agrarian reform in Brazil is not access to land *per se* but rather the creation of a heterogeneous socio-economic space of professions and a novel autonomy in the use of working time (Inguaggiato, 2014). This is even more so in the northeastern region of Brazil, the poorest region with a tradition of large-estate cane-plantation agriculture combined with subsistence farming. Yet, in the early 1990s economic and political conditions, and especially the sugar-cane crisis, allowed social movements to mobilize people on a massive scale in order to occupy unproductive properties, hence pushing the government to expropriate land in those areas as well (Sigaud 2004). Consequently, in this setting the creation of new rural village economies and their structure are not shaped by kinship or training. They are driven, instead, by vacant land and land-scarcity conditions as well as the social movement and encampment processes. Eligibility criteria for beneficiary households of the agrarian reform include being landless, a smallholder, a wage worker or a land tenant.[8]

[7] Encampment was the main tool pushing governments to implement agrarian reform and MST has been able to make the 'landless' a new political force (Rosa 2012; De Medeiros 2013).

[8] Art. 5 Norma de Execucao No 45, de 25 de Agosto de 2005, DOU 166, de 29-8-2005, secao 1, p. 122

Importantly for our study, for a long time family farming was not considered a relevant economic activity in Brazil. This is due to the structure of land distribution on the one hand, and to the strict dependence of rural areas upon urban areas on the other hand. Before the reform in Brazil, almost 80 percent of rural properties were organized in *latifúndios* and household residences and land property have typically been separated to a large extent.[9] Hence, the creation of new agrarian reform settlements introduced a novelty by generating household farming as a major activity where residence and property dimensions are combined.[10]

Household farming represents 38% of the total value of agricultural production and employs 74% of the rural labor force in Brazil (IBGE 2018). The introduction of family farming entailed a change in crop production as well, in particular by allowing – for the first time – the cultivation of perennial crops with high profit margins. New crops (e.g. commercial fruits and cash crops) have been introduced in place of large plantations, requiring new farming techniques, a workforce over the production cycle and market access within the village.

2.1 The creation of the village settlement

The village studied in this paper was created during the Cardoso administration in the mid-1990s and is located in the north of Alagoas, in Maragogi municipality, an area that was historically – and is still today – dominated by sugar cane plantations. Alagoas is the poorest Brazilian state, with the highest land concentration rate (IBGE, 2018).

The process of settlement creation described here follows several steps, that are typical across all agrarian settlements in Brazil. The first phase entails the identification of unproductive land by a social movement. Starting from mid 1990's, in the municipality under study 18 *assentamentos* were created, which were sugarcane industry *fazendas* or *engenhos*

B.S. 35, de 29-8-2005.

[9] Historically, people used to reside in rural areas but everything they needed for their social and economic life, such as medical services, markets and banks, was located in town. Rural areas in Brazil were, therefore, not conceived as autonomous socio-economic spaces but rather as a periphery or appendix to an urban area (IBGE 2009; Wanderley 2000).

[10] The concept of family farming activities describes an estate that is directly and personally exploited by the farmer and his/her family, providing the family with subsistence and an economic and social livelihood. The extension area of family farming is ruled by regional law according to the type of production (TINOCO 2008). The first definition of Familiar Property is included in the Land Statute (Estatuto da Terra, Law n. 4.504 30 November 1964, art. 4). The last Brazilian census (2010) also included settlers without title under the category 'family farmer', as opposed to the previous census in 1995. This was in addition to 'occupier', which was the only category of family involved in agrarian reform considered previously.

before the agrarian reform. The sugarcane company, which had four productive units in Alagoas, was heavily indebted to the Bank of Brazil and had to give up several productive units to the bank in order to have access to new loans (Sigaud 2004). Hence, households were recruited in towns and rural villages neighboring the city of Penedo. In the first week of January 1998, approximately eight buses with over 100 new households arrived in the village. At that time, only 15 households were living in the settlement (old settlers): the family of the only local shop tenant (*barraqueiro*) plus forteen former workers of the just-bankrupted sugar-cane factory. The new settlers entered the abandoned *fazenda* area by building their encampment (i.e. tents made of black plastic) and occupying the land. Land occupation was fast and random at that stage, while the whole period of encampment, which involved living in harsh conditions with no electricity, water or sanitation, lasted one year before the land was finally dispossessed. During the early months of occupation, many of the first settlers left the encampment and were replaced by a second round of new settlers, also recruited from neighboring area. This process increased the degree of heterogeneity across settled households even further. During the encampment, people lived off what they were able to grow and off food supply rations (*cesta basica*) provided by the municipality (Inguaggiato, 2014).

The next step included the checking of land eligibility for expropriation by INCRA and the division of land into parcels. Hence, INCRA measured the land and assigned a piece of land (*lote*) to each household, later referred to as a plot. This was done on the basis of land occupation during the encampment, and on geo-morphological characteristics of the plots (e.g. slope/roughness, wood density, water access). This is the dimension we exploit, as encampment decisions were made perennials later on.[11]

Even though households are legally entitled to use their plots, the land is still today the property of the state, which means that no land market can officially occur. Technical assistance to promote agricultural production was very weak in agrarian reform settlements in Maragogi (Leite et al. 2004). In this municipality, settlers are excluded from family farming state programs or any other governmental credit plan. Finally, as will occur in the entire state of Alagoas, the village will be officially turned into an entity autonomous from the state, which will entail that households become owners of their own land.

[11] Since the objective was to assign land in fair proportions, small adjustments in the size of parcels were done according to the geographical position and morphological characteristics of each plot.

3 Data description

Our study is based on a unique survey covering an entire village in the north of Alagoas State in northeastern Brazil, which was conducted in two waves (2012 and 2018).[12] Our data include 100 settler households, based on the complete list of village inhabitants (roster) provided by local official representatives.[13] The data collection followed an ethnographic study that gathered detailed information on the local community.[14]

As described above, the village's formation was the result of the stratification of different migration waves characterized by two main groups: originary settlers and newcomers. Figure 1 below depicts the division of plots within the village, along with protected (non-farmed) forest areas, roads and water sources (a detailed geo-morphological map of the study village along with village blueprint and geo-localized settlers are reported in Figure A1 and A2 in Appendix).

The originary settlers comprise 15 households already living in the village prior to the agrarian reform mobilization. Their houses are spread over the two main roads, where housing units were allocated by the *latifúndio* administration at the time of the plantation (see black circles in Figure 2). 'Newcomers' refers to households mobilized by the agrarian reform and engaged in a social movement or in associations fighting for land rights. Their houses are spread along the plots, depending on their first spot of occupation in 1998. Among the newcomers, some households still have the same household composition as in 1998 ('occupiers', N=64) while other newcomer households experienced some rearrangement in their internal structure.[15] We call these latter newcomers 'substitutes' (N=21). The large majority of households are still personally cultivating the plot they live on.[16]

[12] A first wave of data collection took place between July and October 2012, gathering socio-demographic data, information about farming practices, and a census of links among settlers. A second visit took place in 2018, to collect retrospective farming information for the period 2012-2018.

[13] Local officers are the most reliable source of information as they are responsible for weekly support to households in health matters (*agentes de saude*). Local health service officers are hired by the municipality to provide basic health assistance on a weekly basis to all village households. The official roster record is provided by INCRA, which registers households who were assigned a plot.

[14] Three months of fieldowork participatory observation and data collection preceded the actual survey (Inguaggiato 2014). Face-to-face interviews were conducted in Portuguese, the only language used in the study context.

[15] Land cannot be sold, but over the years some original occupiers deceased or too old to work have been replaced as household heads by a family member, often a child raised in the village. In addition, some marriages have taken place among village residents, and some children have formed their own families while still cohabiting with their parents on the family plot.

[16] Some other households are primarily occupied in non-farming activities, leaving the plot uncultivated or giving it to others in exchange for compensation in cash or kind.

Figure 1: Map of the study village in Brazil

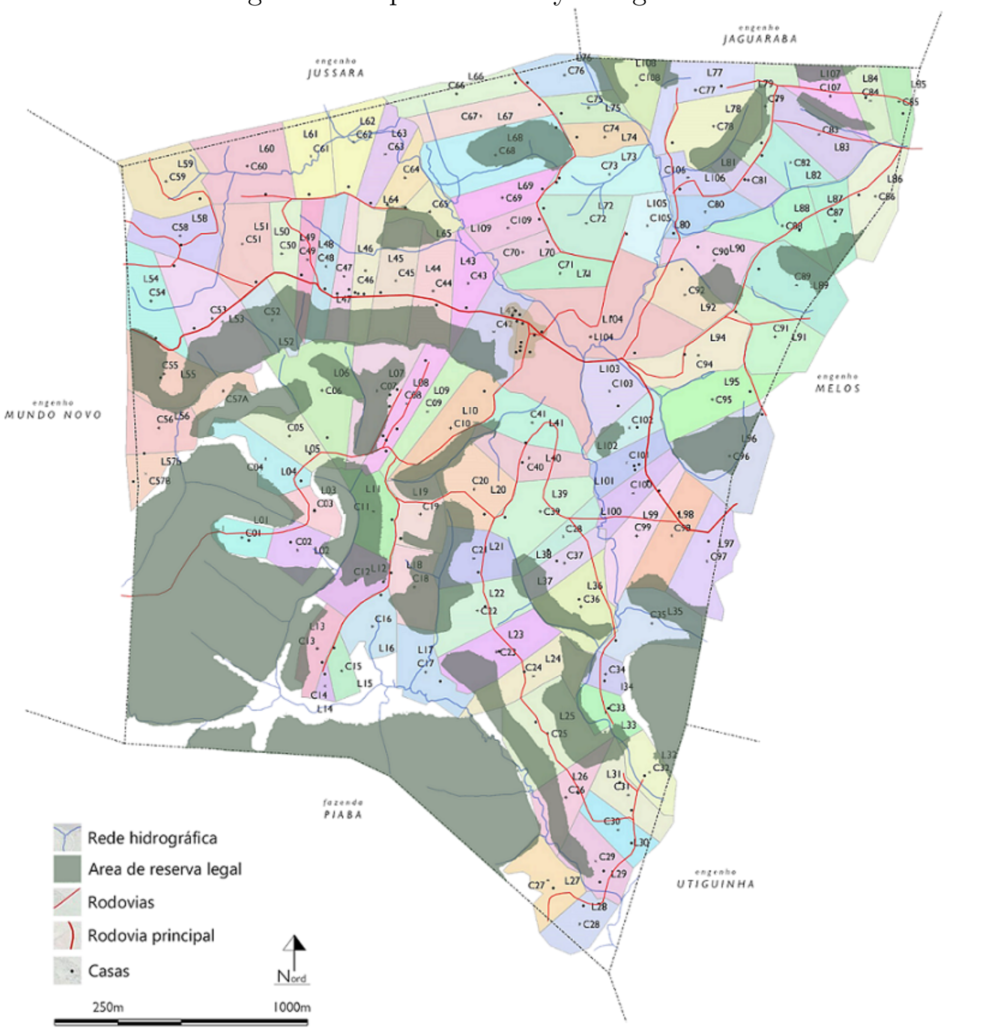
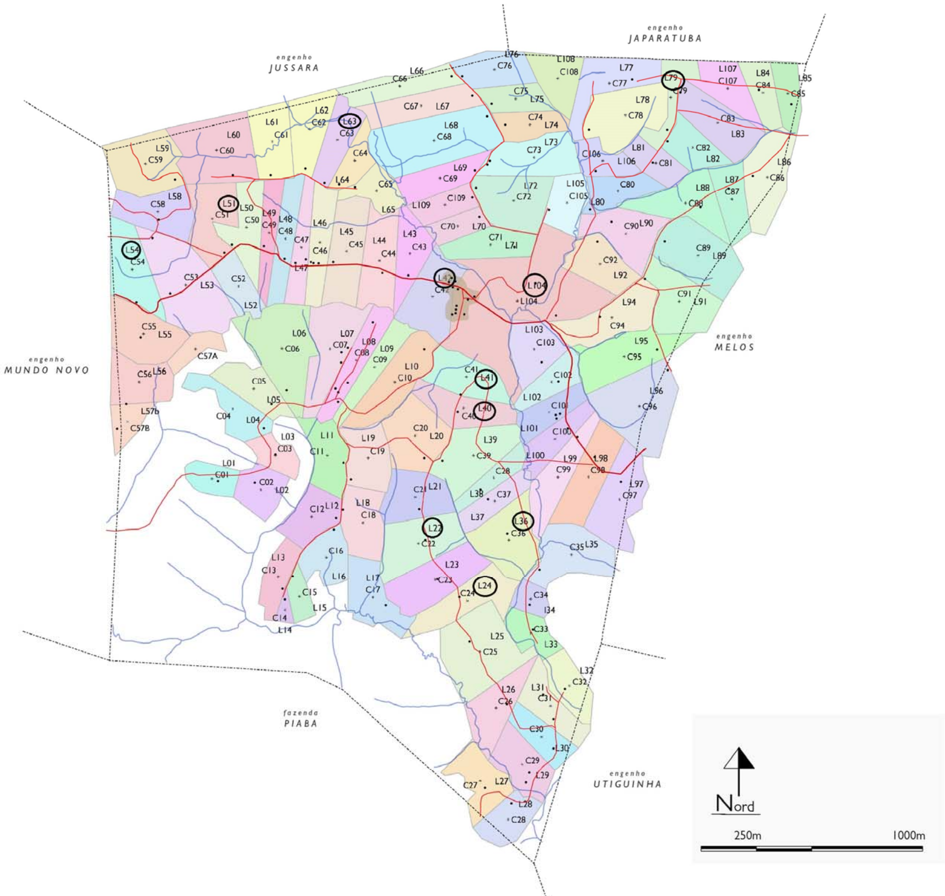


Figure 2 reports the agrarian settlement land allocation map, as well as roads, rivers and the village center. It is worth noting the relatively equal distribution of land size (conditional on morphological characteristics) and, most importantly, the equally distributed locations of originary settlers along the main village road. Figure 3 reports the geographical map of roads, river/water points and geo-coded settlers. In the next section we provide more compelling evidence that newcomers, who settled quickly during the encampment, may not have chosen their locations based on the other settlers at the site.

The network information was collected at one point in time only (2012), and it maps

Figure 2: Agrarian settlement plot allocation map

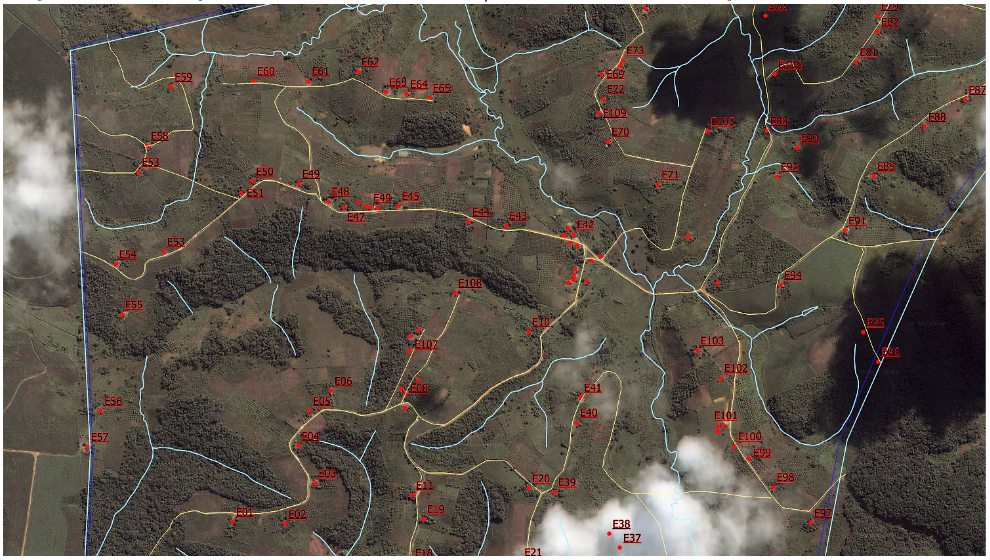


all interpersonal links among all pairs of households (dyads) – this gives $(100 * 99)/2 = 4950$ undirected dyads (9900 directed dyads). Two types of network information were collected: social network, and labor exchange network. In order to elicit the social network, respondents were invited to nominate fellow inhabitants they meet on a regular basis by going to visit them.[17] We argue that this declared relationship can represent an opportunity for social learning among households. In what follows, this information is used to define whether a link exists between farmers and to build the social network.

In addition, the survey collected detailed information on individual and household

[17]The generator questions inserted in the interview were the following: *Are there some people that you frequently meet at home to talk? Who are they? Can I know their names?*. Respondents were asked to nominate other people belonging to households residing in the village and there was no limit to the number of households that they could nominate.

Figure 3: Village map of roads, rivers/water points and geo-localized settlers



characteristics (e.g., demographics, age, education, religion), and occupational status. Importantly, a second wave of data collection took place in 2018 to gather information on adoption (and exit out of) cash fruit farming for all households since 2012. To do so, we re-interviewed all farmers and combined this piece of information with detailed administrative records about quantities and price of transactions (by farmer and by year). Hence, we have detailed farm production data (crop cultivated) for all settlers over a period of 15 years (2003 to 2017).[18] We combine this longitudinal data with detailed geo-localized and plot-level characteristics that allow us to map households' geographical positions with respect to the village center, water sources and roads throughout the area.

While focusing on our village household population, in Table 2 we report descriptive statistics for original settlers vs. newcomers (the latter, in turn, split between occupiers and substitutes). The last two columns report t-tests of the differences between groups. Unsurprisingly, original settlers appear to be different from newcomers along various dimensions (older male household head, less educated, more likely to be female-headed, more likely to already be in sugarcane business in 1996). However, there is no significant difference in the dimension of interest, namely geographical position with respect to the village center, water and roads, and the total area farmed. When we test the difference between

[18]The information about crops cultivated was collected from the registry of the local traders (e.g. the local farming cooperative, operational since 2003) where settlers sell their products. Information information was complemented by self-declared information by settlers, and interviews with the local extension officers.

first occupiers and substitutes, we see that the only significant difference is that substitute households are less likely to be female-headed, and when the head is a male, he is significantly younger. This is in line with anecdotal evidence suggesting that the replacement of deceased first occupiers by younger family members was as good as random, and unrelated to the geographical characteristics of the plot. From now on, we pool together first occupiers and substitutes and consider all newcomers together (other than for robustness checks in Section 4).

The structure of the settlers' social network is depicted in Figures 4 and 5. Figure 6 reports the undirected social networks among settlers based on the question about house visits (N=4950), with 168 links among 100 nodes (about 3 links per household on average).[19] Figure 7 plots the directed network of labor exchange (N=9900), with 118 links among 100 nodes. Both graphs reflect well-known stylized facts about social networks, known as 'small-world properties', which were initially pointed to by sociologists and physicists (Watts and Strogats 1998), namely: virtually all households are indirectly connected through a so-called 'giant component', the average number of contacts is limited, the average distance between two households (computed as the number of steps in the shortest path along the graph) is short, and two households are more likely to be linked if they share a common friend.[20]

4 Location choice and social ties

Assortativity is the pervasive tendency to match with agents with similar characteristics, which plays a confounding role in the study of social diffusion. Imagine we observe social links among potential adopters of a new technology and notice that individuals tend to buy into the technology if their peers do so. This comes as no surprise and suggests a strong correlation between social networks and behavior. But we cannot straightforwardly conclude that these observed effects are causal, because peers who share the same observable

[19]As all households were interviewed separately, we have two reports on the link between A and B (by A and B, respectively) that, in principle, may not coincide. When this is the case, we take the maximum report out of the two sides involved. This corresponds to an implicit assumption of under-reporting by one of the sides, because of omission and mistakes. This is the default choice in the literature dealing with discordant network data (De Weerdt and Fafchamps 2011, Liu et al. 2014, Banerjee et al. 2013, Comola and Fafchamps, 2014 and 2017).

[20]The undirected contact graph of Figure 6 has one giant component with 98 nodes out of 100, density of 0.03, and average clustering coefficient of 0.18. The directed labor exchange graph of Figure 7 has one giant component with 81 nodes, density of 0.01, and an average clustering coefficient of 0.02.

Table 2: Household descriptive statistics

	all (N=100)		originary (N=15)		newcomers (N=85)		occupiers (N=64)		substitutes (N=21)		t-test originary/	t-test occupiers/
	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	mean	s.d.	newcomers	substitutes
age hh head	49.2	14.9	55.1	16.0	48.2	14.5	48.0	15.3	48.7	12.3	1.68*	0.17
female	0.1	0.3	0.3	0.5	0.1	0.3	0.0	0.2	0.2	0.4	3.11***	2.54**
income	814.8	525.9	661.7	376.3	841.8	545.3	839.2	501.3	849.8	676.4	-1.2	0.08
agr. income	466.3	422.9	314.8	325.4	493.1	433.9	472.2	435.7	556.8	432.7	-1.51	0.77
n. of years in village (male)	14.5	9.0	30.6	12.5	11.7	3.9	13.5	1.9	6.3	3.4	11.38***	-12.21***
years of schooling	4.3	3.4	2.5	2.3	4.6	3.5	4.6	3.7	4.4	2.5	-2.2**	-0.22
hh farming	0.8	0.4	0.7	0.5	0.8	0.4	0.8	0.4	0.8	0.4	-1.03	-0.34
in sugar cane since '96	0.3	0.5	0.5	0.5	0.3	0.5	0.3	0.5	0.3	0.5	1.94*	0.04
distance house center	972.9	501.3	805.3	498.0	1002.4	498.9	1003.1	480.2	1000.5	564.9	-1.41	-0.02
distance house water	336.7	249.8	258.3	158.2	350.5	260.9	362.5	255.0	314.0	281.5	-1.32	-0.74
distance house road	190.1	180.5	150.4	143.4	197.1	186.1	202.1	187.8	182.0	184.4	-0.92	-0.43
distance center	99.5	48.2	84.3	49.8	102.2	47.7	102.6	45.6	101.0	54.7	-1.33	-0.13
sum plots cultiv.	4.8	4.1	3.6	3.7	5.0	4.2	5.0	4.3	4.8	3.9	-1.2	-0.23

Figure 4: Undirected social network

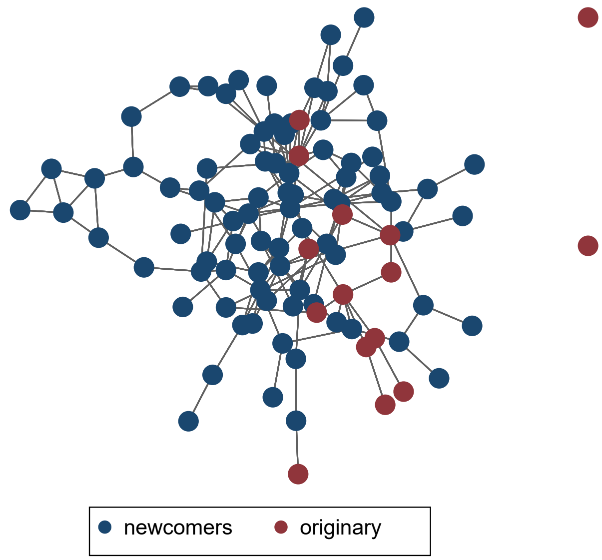
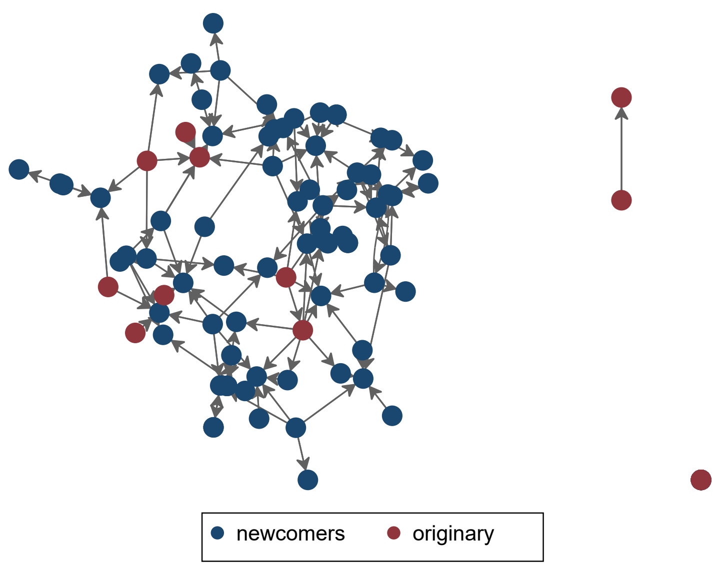


Figure 5: Directed labour-exchange network



characteristics may also share the same unobserved characteristics (e.g. attitude) which could simultaneously drive link formation and adoption. When networks are formed spontaneously as a result of individual characteristics and tastes only, researchers may try to circumvent assortativity by using group-level fixed effects (Bramoullé et al. 2009) or by explicitly modeling the process of link formation (Goldsmith-Pinkham and Imbens, 2013). More convincing identification, however, can be achieved when the formation of interpersonal links depends on exogenous shocks or random allocations of individuals to locations or groups (e.g. forced migration following natural disasters, students allocated randomly to dorms, refugees placed in housing units in displacement camps, or newly recruited soldiers randomly attributed to military units).[21] In our context, the resettlement process provides exogenous variation in the location choice of households. In fact, the encampment phase, which was made perennial and legal later on, was mainly the result of chance rather than assortativity along some unobserved dimension. In this section, we first argue that for the scope of our study, settler location choices are as good as random. Secondly, we show how location is a strong predictor of social network formation. Taken together, these results confirm that distance between households is a valid instrument for link formation, a strategy that we pursue in Section 5.

The process of land occupation by stranger households, as described in Section 2 above, in principle did not accommodate for endogenous location of settlers based on attitudes and tastes. However, one may still think that, to some extent, occupiers at the time of their arrival chose their location strategically in order to settle next to people with similar profiles. In order to reassure the reader that this is not the case, we restrict the analysis to the dyads made by two original occupiers (N=(64*63)/2=2016) and run the undirected dyadic regression[22]

$$distance_{ij} = \alpha + \beta X_{ij} + \varepsilon_{ij}$$

where $distance_{ij}$ is the distance between two households (in km), and X_{ij} is a vector of undirected dyadic regressors that represents observable characteristics proxying social vicinity, which could explain location choices. Standard errors ε_{ij} are corrected for dyadic dependence (Fachamps and Gubert 2007). Dyadic regressors included in X_{ij} are a set of dummies equal to one if: the two households share the same hometown, were recruited by

[21] Sacerdote (2001), Beaman (2012), Laschever (2013).

[22] Location assortativity concerns do not apply to dyads composed by two originary households as their housing units were allocated centrally by the administrative office of the *latifundo* well before the 1998 occupation. It also does not concern dyads made by originary and newcomer households, as there were no links between occupiers and plantation workers before the occupation.

Table 3: Location Choice (dyadic distance)

	(1)	(2)	(3)
both_agr		-0.1598	-0.1569
		[0.1190]	[0.1231]
both_cane		0.0927	0.0958
		[0.1147]	[0.1143]
both_autonomous		0.0435	0.0575
		[0.1524]	[0.1554]
both_unemployed		-0.1649	-0.1892
		[0.1584]	[0.1533]
same_hometown	-0.0483		-0.0321
	[0.0661]		[0.0683]
same_mobilizer	0.1018		0.1035
	[0.0730]		[0.0714]
const	1.3385***	1.3895***	1.3440***
	[0.0748]	[0.0746]	[0.0772]
Observations	2,016	2,016	2,016

Note: Dyadic s.e. are reported in brackets

*** p<0.01, ** p<0.05, * p<0.1

the same mobilizer,[23] or had the same professional status before arrival in 1996 (agricultural sector, sugarcane, autonomous worker, unemployed) respectively. Results are reported in Table 3, and show that distance does not appear significantly correlated with any of these factors.

We then document the fact that location is a driving force in link formation. In table 4 we report the results from the dyadic regression

$$link_{ij} = \alpha + \beta\, distance_{ij} + \gamma Z_{ij} + \varepsilon_{ij}$$

where $link_{ij}$ is the undirected measure of a social link between two households and Z_{ij} is a vector of undirected dyadic controls[24] representing socio-economic factors that have been shown to affect link formation, including a dummy equal to one if the two households

[23] We have information on the identity of the person who recruited the settler candidates just prior to 1998.

[24] Since the dyadic relationship is undirected, the regressors must enter in a symmetric fashion (i.e. dummy variables, sum and/or absolute difference of continuous attributes).

Table 4: Link Formation

	main sample			no substitutes		
	(1)	(2)	(3)	(4)	(5)	(6)
distance_housesk	-0.0394***	-0.0410***	-0.0384***	-0.0481***	-0.0485***	-0.0448***
	[0.0053]	[0.0052]	[0.0047]	[0.0075]	[0.0071]	[0.0069]
same_hometown		0.0375***	0.0391***		0.0276**	0.0288**
		[0.0118]	[0.0119]		[0.0118]	[0.0117]
abs_diff_arrival		-0.0010***	-0.0008***		-0.0012***	-0.0009***
		[0.0003]	[0.0002]		[0.0003]	[0.0002]
abs_diff_hhage		-0.0002	-0.0001		-0.0002	0.0000
		[0.0002]	[0.0002]		[0.0003]	[0.0002]
abs_diff_hhsize			-0.0003			-0.0009
			[0.0010]			[0.0013]
abs_diff_school			-0.0003			-0.0009
			[0.0010]			[0.0011]
both_farming			0.0071			0.0081
			[0.0059]			[0.0089]
same_relig			0.0228***			0.0296***
			[0.0085]			[0.0107]
constant	0.0856***	0.0906***	0.0724***	0.1017***	0.1036***	0.0838***
	[0.0091]	[0.0097]	[0.0106]	[0.0117]	[0.0133]	[0.0144]
Observations	4845	4845	4845	2976	2976	2976

Note: Dyadic standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

come from the same hometown, the absolute difference in the time of arrival,[25] absolute difference in age of household head, household size, years of schooling of the household head, and dummies if both households rely uniquely on farming for living and if they have the same religion, respectively. Standard errors ε_{ij} are corrected for dyadic dependence, as above.

The main sample (cols. 1–3) includes all dyads except the ones formed by two original settlers.[26] In columns 4 to 6, we restrict the sample further by dropping dyads including substitutes. Results show that distance is a strong predictor of link formation. In addition, households are more likely to be linked if they come from the same locality, arrived at the same time, or share the same religion.

[25] Original settlers and replacement households did not arrive in 1998.

[26] N=(100*99)/2-(15-14)/2=4845

5 Social learning and adoption

In this section, we present the main results of our analysis, which relate to the crop adoption behavior. We use longitudinal information on the adoption of two cash crops (pineapple and passion fruit), that were rarely farmed at the beginning of the period in the area, and have spread widely in the village community along the years of our study (especially pineapple). They are both commercial tropical fruits with relatively high labor demand but high profit margins (as fresh whole fruit or for juice processing). Pineapple is a perennial plant that bears a single fruit growing in about 18 months, while passion fruit is a vine whose production cycle is faster and that can last up to seven years. For these reasons, tropical fruit adoption involves a longer-term investment and higher sunk costs than does the seasonal cultivation of grains, roots and tubers. Both fruits thrive in many different soil types but while tropical areas are most suitable for pineapple plantation also with low water availability, passion fruit is more sensitive to water stress and deficits, especially during leaf production and flowering (Carr 2013).

Our dataset follows the villagers during a period of 15 years (2003 to 2017), and contains a binary indicator of whether the household has cultivated each of these two crop for each year of the panel. The aggregate adoption patterns for the crops are displayed in Figure 6. While the adoption of pineapple steadily rises over time, passion fruit is increasingly farmed up to 2010 dropping afterwards to its initial rate at the beginning of the period. Variation over time of farming choices is what we exploit in our panel estimation model below.

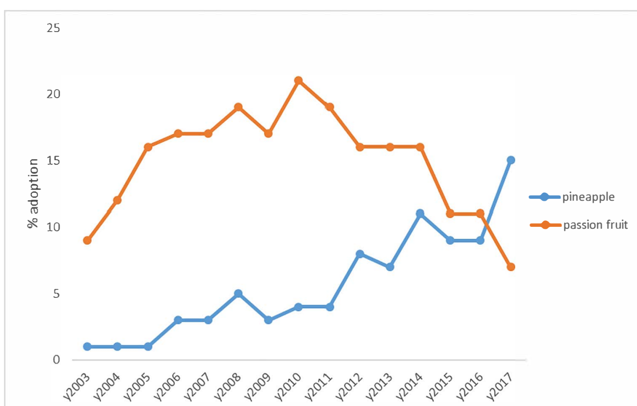


Figure 6: Adoption patterns

5.1 The model

Our aim is to document how adoption behavior spills over from peers, that is how the farming choices of peers have a positive impact on one's own choice. We frame our problem in the context of peer effects working through the network structure of social interactions. We also leverage the random location choice at the time of settlement to address network assortativity, as geographic distance during the encampment phase provides us a valid instrument for link formation.

In what follows, vectors are denoted with bold lower-case letters and matrices with bold capital letters. Let us consider a panel data with N individual (households, in our context) observed over multiple periods $t = 0, ..., 15$. Define $\mathbf{y}_c^t$ as the $n \times 1$ vector of binary outcomes representing the adoption outcome of crop c at time t, e.g. $y_{c,k}^t = 1$ if individual k is cultivating crop c at time t. Similarly, $\mathbf{x}^t$ contains time-varying individual characteristics. Let the $n \times n$ interaction matrix $\mathbf{G}$ represent the social interaction within the sample. For the scope of our study, we assume that $\mathbf{G}$ is binary and undirected ($g_{ij} = g_{ji} = 1$ if households i and j are socially connected), and time-invariant across periods (i.e. $\mathbf{G}^t = \mathbf{G}$ for all t).[27] Our model of reference is represented by the linear equation

$$\mathbf{y}_c^t = \beta \mathbf{G} \mathbf{y}_c^t + \gamma \mathbf{x}_c^t + \delta \mathbf{G} \mathbf{x}_c^t + \boldsymbol{\lambda}_t + \boldsymbol{\mu} + \boldsymbol{\epsilon}_c^t \tag{1}$$

where the dependent variable $\mathbf{y}_c^t$ is binary,[28] and the 'first lag' of the dependent variable $\mathbf{G}\mathbf{y}_c^t$ is called 'endogenous' peer effect and represents the number of peers cultivating crop c at time t. Similarly, $\mathbf{x}_c^t$ represent individual's exogenous attributes that could affect his own adoption choice, and $\mathbf{G}\mathbf{x}_c^t$ represents the so-called 'contextual' peer effect, namely the (sum of) exogenous attributes of peers.[29] $\boldsymbol{\lambda}_t$ represents a set of year-level dummies, and we denote by $\boldsymbol{\mu} = (\mu_1, ..., \mu_N)'$ the vector of individual-level effects, which we treat as fixed effects as they may be correlated with the regressors. Including both individual and year

[27] Choosing to use a binary interaction matrix implies that we estimate a linear-in-sums model, that is, a social interaction model in which the individual outcome is affected by the total number of peers who adopt (rather than the share). This is justified by a large literature on adoption along with some game-theoretical reasoning (Calvo-Armengol et al. 2009; Liu et al., 2014). However, our estimation strategy could be applied to a peer effect model where the rows sum up to unity (linear-in-means), obtaining results that are qualitatively similar.

[28] A linear probability model was also used by Fortin and Yazbeck (2015) in the context of binary-outcome network data.

[29] In the terminology of Manski (1993), $\mathbf{G}\mathbf{y}_c^t$ would be called endogenous social effects and $\mathbf{G}\mathbf{x}_c^t$ exogenous social effects. We include contextual effects for all exogenous attributes to avoid unjustified exclusion restrictions in the instrumentation strategy.

fixed effects allow us to control for all confounding unobservables that are time-invariant within the duration of our study (including risk attitude and innovation propensity – all attributes that could lead to network assortativity if unaccounted for), as well as all unobservable time-varying shocks that are common to all farmers (e.g. climate, income or market-access shocks). The vector of disturbances $\boldsymbol{\epsilon}_c^t$ is auto-correlated across periods.

5.2 Instrumentation strategy

All interaction models exploiting network data raise endogeneity concerns which relate to simultaneity, i.e. to the fact that the outcomes of an individual and his partners may be jointly determined. Note that this concern is unrelated to network assortativity, and it would also arise if social links were distributed entirely at random. Simultaneity invalidates OLS inference to the extent to which the term $\mathbf{G}\mathbf{y}^t$ in Equation (1) is correlated with the disturbance vector. We describe here two instrumentation strategy that we implement in what follows.

The standard solution to address endogeneity stemming from simultaneity is to use 'lagged' partners' characteristics (that is, the exogenous attributes of the partners of one's partners) as instruments (e.g., Kelejian and Prucha 1998; Bramoullé et al. 2009; Calvo-Armengol, Patacchini, and Zenou 2009; Drukker, Egger, and Prucha 2013; Patacchini and Zenou 2012, Comola and Prina 2020). In fact, as long as there are individuals who are excluded from one's own reference group but are included in the reference group of one's partners, their exogenous characteristics can affect one's outcome only through the partners and thus are a natural set of instruments to address the reflection problem (Manski 1993). In our context, this boils down to estimating Equation (1) via an instrumental variable techniques (2SLS) where peer behavior $\mathbf{G}\mathbf{y}_c^t$ is taken as endogenous, and the exogenous attributes of peers of peers $\mathbf{G}_c^2\mathbf{x}^t$ (second-order lagged characteristics) and of their peers $\mathbf{G}_c^3\mathbf{x}^t$ (third-order lagged characteristics) are used as excluded instruments.[30] In the context of a fixed effects model as in Equation (1) this estimation strategy, that we call 'IV-A', addresses endogeneity concerns stemming from network assortativity as long as unobserved correlates are time-invariant.[31]

[30] Instruments of higher order can be added at the cost of some additional identification requirements. See Bramoullé et al. (2009) for the identification condition and moment restrictions that also apply to our context.

[31] If we had cross-sectional data we could only condition exogeneity of the interaction matrix on network-level fixed effects (as in Bramoullé et al. 2009), which is a valid identification strategy only to the extent that the correlated unobservables are common to the entire network. Thanks to the longitudinal nature

However, given that the social interaction matrix is measured at one point in time only, one can still be concerned about endogeneity from time-varying unobserved shocks.[32] In order to address this potential concern, we augment our instrumentation strategy to take into account the potential endogeneity of the network at the time it was measured. In fact, our natural-experiment setting suggests that physical distance between households is a valid instrument for link formation (see Section 4). Thus, we use distance between households to *also* instrument the interaction matrix G. Operationally, we proceed as follows: we use the attributes of *predicted* lagged partners as an instrument for the *observed* behavior of partners. This estimation strategy, that we call 'IV-B', has been formally proved to be valid (i.e. consistent and asymptotically normal) for endogenous interaction matrices.[33] In practice, this requires computing the lagged partner characteristics as in strategy IV-A but replacing the observed network with its fitted version predicted on the basis of physical distance.[34]

5.3 Main results

Table 5 reports our main results.[35] In our chosen specifications, the vector of time-varying attributes $\mathbf{x}_c^t$ includes three variables: the first variable is $\boldsymbol{distance\ road} \times \boldsymbol{price}_c^t$, where $distance\ road_i$ is the distance from the road of the plot of residence of farmer i,[36] and $price_c^t$ is the market price of crop c (pineapple and passion fruit respectively) for year t.[37] Similarly, we include $\boldsymbol{distance\ water} \times \boldsymbol{price}_c^t$, where $distance\ water_i$ is the distance from the plot of residence of farmer i to water. These two variables are meant to represent time-varying incentive factors shaping farming adoption decisions. While we expect farmers

of our data, we can actually condition exogeneity of the interaction matrix on the individual-level effects and the time dummies (see Comola and Prina, 2020). Formally, this implies that we can assume $E[\boldsymbol{\epsilon}_c^{t_A}|\mathbf{G}, \mathbf{x}_c^{t_B}, \boldsymbol{\lambda}_t, \boldsymbol{\mu}] = 0 \quad \text{for all } t_A \neq t_B$. That is, even the (least demanding) empirical strategy 'IV-A' does not confound the effect of social links with individual fixed characteristics, or time trends.

[32] This refers to a situation in which individual-level unobserved shocks simultaneously drive link formation and individual outcomes.

[33] Kelejian and Piras (2014), Hsie and Lee (2016).

[34] In our setting, this requires the following steps: 1) run a cross-section dyadic regression of link formation on physical distance (plus a constant term), and construct the 'fitted' interaction matrix $\widehat{\mathbf{G}}$; 2) compute the attributes of *predicted* lagged second- and third-order partners $\widehat{\mathbf{G}}^2\mathbf{x}_c^t$ and $\widehat{\boldsymbol{G}}^3\mathbf{x}_c^t$; 3) estimate the 2SLS model in Equation (1) with $\mathbf{G}\mathbf{y}_c^t$ as endogenous and $\widehat{\mathbf{G}}^2\mathbf{x}_c^t$ and $\widehat{\boldsymbol{G}}^3\mathbf{x}_c^t$ as excluded instruments.

[35] Descriptive statistics (for regressors and excluded instruments) are reported in the Appendix Table A1.

[36] Precisely, the distance is computed from the house located on the plot. We have recalculated all distances from plot centroids, for a virtually identical result.

[37] This is the yearly average selling price for raw (i.e. non-processed) fruit.

further away from either water or roads to be less likely to adopt cash crops (the distance, being time-invariant, is absorbed by individual-level fixed effects), we expect the differential effect of distance to change as long as crop-specific (time-varying) prices increase. Finally, the dummy $coop\ member_i^t$ equals one if i's head of household is member of the village cooperative in year t.

In columns (1) and (4) of Table 5 we report for the sake of reference the OLS estimates from the specification of Equation (1) for pineapple and passion fruit – following the discussion above, these estimates are biased. Columns (2) and (5) report instrumental variable results from estimation strategy IV-A, where $\mathbf{G}\mathbf{y}_c^t$ in Equation (1) is instrumented with the lagged-partner characteristics $\mathbf{G}^2\mathbf{x}_c^t$ and $\mathbf{G}^3\mathbf{x}_c^t$. Columns (3) and (6) report instrumental variable results from the estimation strategy IV-B, where $\mathbf{G}\mathbf{y}_c^t$ in Equation (1) is instrumented with the *fitted* counterparts of the excluded lagged-partner instruments, namely $\widehat{\mathbf{G}}^2\mathbf{x}_c^t$ and $\widehat{\boldsymbol{G}}^3\mathbf{x}_c^t$.

Results from Table 5 suggest a positive and significant peer effect in the adoption process of pineapple and passion fruit: according to specification IV-A having one additional peer cultivating the crop in year t increases the probability of adoption by 9% for pineapple and 14% for passion fruit. The effect is small but sizable, since the average number of peers is 3 within the sample, and the adoption rate varies from 0 to 15% for pineapple and from 7% to 21% for passion fruit during the time span of the panel. In specification IV-B the peer effect remains positively significant, and larger in magnitude. This increase, which is especially sizable for pineapple, is in line with the empirical network literature showing that the estimated coefficient of peer effects tend to be larger when instrumented, but it could also be partly due to the fact that the instrumentation strategy IV-B is extremely exigent in the context of a panel data which has relatively few observations (with respect to the time span), weakening the instruments power. Cooperative membership has a positive effect in all specifications, while the remaining individual characteristics have an heterogeneous effect depending on the crop. All specifications suggest that the contextual effects (i.e. the effect of peers characteristics) contribute to explain the process of social diffusion, and appear to be heterogeneous across crops.

6 Alternative specifications

This section is devoted to discussing alternative specifications of our baseline model.

Table 5: Main results

	pineapple			passion fruit		
	(1) OLS	(2) IV - A	(3) IV - B	(4) OLS	(5) IV - A	(6) IV - B
$\mathbf{Gy}_c^t$	0.03**	0.09**	0.39***	0.07***	0.14***	0.25***
	(0.01)	(0.04)	(0.12)	(0.01)	(0.04)	(0.08)
$\boldsymbol{distance\ road} \times \boldsymbol{price}_c^t$	-0.18***	-0.18***	-0.17**	0.12	0.09	0.04
	(0.06)	(0.06)	(0.08)	(0.10)	(0.10)	(0.11)
$\boldsymbol{distance\ water} \times \boldsymbol{price}_c^t$	0.01	0.04	0.20**	-0.01	-0.03	-0.07
	(0.04)	(0.05)	(0.09)	(0.07)	(0.08)	(0.08)
$\boldsymbol{coop.\ member}^t$	0.22***	0.23***	0.23***	0.59***	0.59***	0.59***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbf{G}\left(\boldsymbol{distance\ road} \times \boldsymbol{price}_c^t\right)$	0.07**	0.08***	0.15***	-0.04	-0.04	-0.04
	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)	(0.05)
$\mathbf{G}\left(\boldsymbol{distance\ water} \times \boldsymbol{price}_c^t\right)$	-0.02	-0.04*	-0.13***	-0.01	0.01	0.03
	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)	(0.03)
$\mathbf{G}\left(\boldsymbol{coop.\ member}^t\right)$	-0.02	-0.03**	-0.09***	-0.04**	-0.09***	-0.15***
	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.05)
household f.e.	yes	yes	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes	yes	yes
R-squared	0.13	-	-	0.36	-	-
Weak identif. test	-	32.1	4.8	-	33	8.7
Observations	1,500	1,500	1,500	1,500	1,500	1,500
Number of id	100	100	100	100	100	100

NOTES: Autocorrelation-robust standard errors in parentheses (kernel=Bartlett; bandwidth=3). Cragg-Donald Wald F statistic for weak identification reported. Statistically significant coefficients are indicated as follows: * 10%, ** 5% and *** 1%

6.1 Lags in peer effects

Since there is no *a priori* motivation to believe that social effects are strictly contemporaneous, we have re-estimated the IV models of Equation (1) by assuming one lag in the peer effects. This corresponds to the estimating equation

$$\mathbf{y}_c^t = \beta \mathbf{G}\mathbf{y}_c^{t-1} + \gamma \mathbf{x}_c^t + \delta \mathbf{G}\mathbf{x}_c^{t-1} + \boldsymbol{\lambda}_t + \boldsymbol{\mu} + \boldsymbol{\epsilon}_c^t \tag{2}$$

As above, the instrumentation strategy IV-A relies on the characteristics at time $t-1$ of peers of peers ($\mathbf{G}^2\mathbf{x}_c^{t-1}$) and their peers ($\mathbf{G}^3\mathbf{x}_c^{t-1}$), and instrumentation strategy IV-B relies on the characteristics at time $t-1$ of expected peers of peers ($\widehat{\mathbf{G}}^2\mathbf{x}_c^{t-1}$) and their peers ($\widehat{\mathbf{G}}^3\mathbf{x}_c^{t-1}$). Results from Table 6 go in the same direction (for sign, significance and magnitude) as the main results of Table 5.

6.2 Heterogeneous social effects

Last, but importantly, we explore the heterogeneity of social effects. In fact, one may imagine that, for the scope of social learning in agriculture, not all peers are the same. Munshi (2004), for instance, highlights the effectiveness of learning from others who share similar (observed and unobserved) characteristics in the context of the Green Revolution. To explore this hypothesis, we split the sample into two groups according to the ease of water access from the plot. On the one hand, we know for certain that water access is an important determinant of crop selection and agricultural success, especially in tropical and sub-tropical climates. On the other hand, as we can already see from the figures in Section 3, there is considerable heterogeneity in plot locations with respect to water, and two households located within a reasonable distance can have important differences in terms of water access. This is also reflected in our social network data: if we split the household sample in two groups according to water access (above/below the sample median of distance from water, which is 240 meters), we notice that out of the 168 (undirected) social links among farmers, 99 of them are between households of the same type (47 links between households both above the median, 52 links between households both below the median), while 69 links are between households of different types (one above and the other below the median).

In what follows, we test the hypothesis that social learning is stronger among farmers

Table 6: Lagged social effects

	pineapple		passion fruit	
	(1)	(2)	(3)	(4)
	IV - A	IV - B	IV - A	IV - B
$\mathbf{Gy}_c^{t-1}$	0.10**	0.47***	0.13**	0.29***
	(0.04)	(0.16)	(0.05)	(0.11)
$\boldsymbol{distance\ road} \times \boldsymbol{price}_c^t$	-0.18***	-0.19**	0.11	0.05
	(0.06)	(0.09)	(0.10)	(0.12)
$\boldsymbol{distance\ water} \times \boldsymbol{price}_c^t$	0.02	0.15*	0.03	0.02
	(0.05)	(0.08)	(0.08)	(0.08)
$\boldsymbol{coop.\ member}^t$	0.24***	0.24***	0.58***	0.58***
	(0.03)	(0.04)	(0.03)	(0.03)
$\mathbf{G}\left(\boldsymbol{distance\ road} \times \boldsymbol{price}_c^{t-1}\right)$	0.09***	0.18***	-0.04	-0.05
	(0.03)	(0.06)	(0.06)	(0.06)
$\mathbf{G}\left(\boldsymbol{distance\ water} \times \boldsymbol{price}_c^{t-1}\right)$	-0.04*	-0.14***	-0.01	0.01
	(0.02)	(0.05)	(0.03)	(0.04)
$\mathbf{G}\left(\boldsymbol{coop.\ member}^{t-1}\right)$	-0.04***	-0.11***	-0.11***	-0.21***
	(0.02)	(0.03)	(0.03)	(0.07)
household f.e.	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes
Weak id. test	31.5	4	24.9	5.7
Observations	1,400	1,400	1,400	1,400
Number of id	100	100	100	100

NOTES: Autocorrelation-robust standard errors in parentheses (kernel=Bartlett; bandwidth=3). Cragg-Donald Wald F statistic for weak identification reported. Statistically significant coefficients are indicated as follows: * 10%, ** 5% and *** 1%

with similar plot characteristics in terms of water access. In order to do so, we generalize the linear social interaction model of Equation (1) by allowing for heterogeneous peer effects according to plot type (above/below the median distance to water). Our estimating equation becomes:

$$\mathbf{y}_c^t = \beta_S \mathbf{G}_S \mathbf{y}_c^t + \beta_D \mathbf{G}_D \mathbf{y}_c^t + \gamma \mathbf{x}_c^t + \delta_S \mathbf{G}_S \mathbf{x}_c^t + \delta_D \mathbf{G}_D \mathbf{x}_c^t + \boldsymbol{\lambda}_t + \boldsymbol{\mu} + \boldsymbol{\epsilon}^t \tag{3}$$

where we now define two distinct social interaction matrices representing links between peers of the same type ($\mathbf{G}_S$) versus peers of different types ($\mathbf{G}_D$).[38] By construction, $\mathbf{G}_S + \mathbf{G}_D = \mathbf{G}$. Thus, the so-called endogenous peer effects $\mathbf{G}_S \mathbf{y}^t$ ($\mathbf{G}_D \mathbf{y}_c^t$) represent the number of peers of the same (different) type that cultivate crop c at time t. Similarly, the contextual peer effects $\mathbf{G}_S \mathbf{x}^t$ ($\mathbf{G}_D \mathbf{x}_c^t$) represent the attributes of peers of the same (different) type at time t. As above, $\boldsymbol{\lambda}_t$ and $\boldsymbol{\mu}$ are year- and individual-level fixed effects, and ${\boldsymbol{\epsilon}_{\boldsymbol{c}}}^t$ is auto-correlated across periods. Both instrumentation strategies are expanded to take into account the split of the interaction matrices, namely, for IV-A we take $\mathbf{G}_S^2 \mathbf{x}^t, \mathbf{G}_D^2 \mathbf{x}_c^t, \mathbf{G}_S^3 \mathbf{x}^t, \mathbf{G}_D^3 \mathbf{x}_c^t$ and for IV-B we take $\widehat{\mathbf{G}}_S^2 \mathbf{x}^t, \widehat{\mathbf{G}}_D^2 \mathbf{x}_c^t, \widehat{\mathbf{G}}_S^3 \mathbf{x}^t, \widehat{\mathbf{G}}_D^3 \mathbf{x}_c^t$ as excluded instruments for the endogenous terms $\mathbf{G}_S \mathbf{y}_c^t, \mathbf{G}_D \mathbf{y}_c^t$.[39]

Results reported in Table 7[40] show an interesting pattern of heterogeneity with respect to crops: for pineapple, both types of friends contribute to the same way to the social learning process (both endogenous peer effect coefficients are significant and of same magnitude which is comparable to the main results of Table 5). However, for passion fruit we notice that the peer effect reported in Table 5 flow through the network of peers of a similar type: the estimated coefficient for $\mathbf{G}_S \mathbf{y}^t$ is significant and slightly larger than the homogeneous effect reported in Table 5, while the coefficient for $\mathbf{G}_D \mathbf{y}_c^t$ appears non-significant. This is an interesting results, which is likely to relate to the different water needs of the two cash crops, lower for pineapple than for passion fruit (Carr, 2013; DeAzevedo et al., 2007). Note that our estimation strategy includes individual-level effects which account for time-invariant unobserved characteristics, such as farmer attitude and plot attributes. Once we

[38] $g_{S_{ij}} = g_{S_{ji}}$ equals one if households i and j are socially connected and they are of the same type, and zero otherwise. Conversely, $g_{D_{ij}} = g_{D_{ji}}$ equals one if households i and j are socially connected and they are of different types, and zero otherwise.

[39] This follows from the identification conditions and instrumentation strategy formally developed by Dieye and Fortin (2016) for the general heterogeneous social network model.

[40] Descriptive statistics (for regressors and excluded instruments) are reported in Table A2 of the Appendix.

control for these time-invariant factors, we still find that farmers learn crops which require high level of water from those peers with the same water access conditions. This provides evidence of the role of plot-dependent heterogeneity in the social diffusion of agricultural practices.

Table 7: Heterogeneous social effects

	pineapple		passion fruit	
	(1)	(2)	(3)	(4)
	IV - A	IV - B	IV - A	IV - B
$\mathbf{G}_S\mathbf{y}^t$	0.17***	0.37***	0.14***	0.35***
	(0.05)	(0.13)	(0.05)	(0.11)
$\mathbf{G}_D\mathbf{y}^t$	0.18*	0.42**	-0.05	0.06
	(0.09)	(0.17)	(0.08)	(0.12)
$\boldsymbol{distance\ road} \times \boldsymbol{price}_c^t$	-0.16**	-0.14*	0.08	-0.01
	(0.06)	(0.08)	(0.10)	(0.12)
$\boldsymbol{distance\ water} \times \boldsymbol{price}_c^t$	-0.03	0.03	-0.11	-0.22*
	(0.06)	(0.08)	(0.10)	(0.12)
$\boldsymbol{coop.\ member}^t$	0.22***	0.22***	0.57***	0.56***
	(0.03)	(0.03)	(0.03)	(0.03)
$\mathbf{G}_S\,(\boldsymbol{distance\ road} \times \boldsymbol{price}_c^t)$	0.18***	0.28***	-0.08	-0.05
	(0.06)	(0.09)	(0.09)	(0.10)
$\mathbf{G}_S\,(\boldsymbol{distance\ water} \times \boldsymbol{price}_c^t)$	-0.04	-0.10**	0.02	0.06
	(0.03)	(0.04)	(0.04)	(0.05)
$\mathbf{G}_S\,(\boldsymbol{coop.\ member}^t)$	-0.04**	-0.06**	-0.07**	-0.18***
	(0.02)	(0.03)	(0.03)	(0.06)
$\mathbf{G}_D\,(\boldsymbol{distance\ road} \times \boldsymbol{price}_c^t)$	0.09**	0.13**	0.02	0.03
	(0.04)	(0.06)	(0.06)	(0.07)
$\mathbf{G}_D\,(\boldsymbol{distance\ water} \times \boldsymbol{price}_c^t)$	-0.10***	-0.20***	-0.03	-0.02
	(0.04)	(0.06)	(0.04)	(0.04)
$\mathbf{G}_D\,(\boldsymbol{coop.\ member}^t)$	-0.07*	-0.14**	-0.01	-0.08
	(0.04)	(0.06)	(0.05)	(0.07)
household f.e.	yes	yes	yes	yes
year f.e.	yes	yes	yes	yes
Weak id. test	6.9	2.6	10.6	3.5
Observations	1,500	1,500	1,500	1,500
Number of id	100	100	100	100

NOTES: Autocorrelation-robust standard errors in parentheses (kernel=Bartlett; bandwidth=3). Cragg-Donald Wald F statistic for weak identification reported. Statistically significant coefficients are indicated as follows: * 10%, ** 5% and *** 1%

7 Conclusions

Social connectedness is instrumental for economic growth and development in that it eases information, collective action, investment and trade. In particular, while both innovation and good institutions have been emphasized as indispensable for economic efficiency and factor accumulation, social capital is the ‘missing link’ between institutional quality and economic performance, amd even more so in transition and developing settings (Durlauf and Fafchamps, 2005; Guiso et al. 2010).

In this paper, we study the role of peers and social learning in the diffusion of cash crops with high profit margins in a newly created village in northeastern Brazil. The village settlement is the result of the Brazilian agrarian reform, where stranger households find themselves living next to each other during a major economic transformation, namely the shift from wage working to family farming. We causally identify the effect of social ties on farming innovation. Our quasi-experimental setting allows us to overcome the challenges stemming from the fact that that social capital and development are typically simultaneously determined.

We combine geo-localized data on farming plots with dyadic data on social ties among old and new settlers, who moved into the village in a manner typical of the agrarian reform settlements and - without any formal training - from alien landless households turned into commercial farmers. We provide evidence that their geographical location during the encampment period is as good as random for our scope. We then leverage geographical distance between farmers, induced by the land squatting process, as an exogenous source of variation in the formation of social networks.

Using longitudinal data on farming decisions over 15 years to estimate a model of social diffusion along network lines, we find consistent evidence of learning from peers in the decision to adopt new cash fruits (pineapple and passion fruit). Having one additional peer cultivating cash crops increases the probability of crop-specific adoption by 9% to 14% in the most conservative estimate. Conditional on unobserved individual characteristics, our results suggest that social diffusion is heterogeneous along observed plot and crop characteristics, i.e. the decision to grow water-sensitive crops is strongly responsive to peers with similar water–access conditions.

Our findings offer new insights into the role of social learning in the transformation of rural societies. By using a network perspective, we examine a newly created community populated by people with different backgrounds engaged in a participatory development process, and provide causal evidence of peer influence as a driver of technological change. This has implications for innovation policy in developing settings where the decentralized participation of citizens via networks can be key for economic growth and development.

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A Appendix

Figure A1: Geo–morphological map of the study village in Brazil

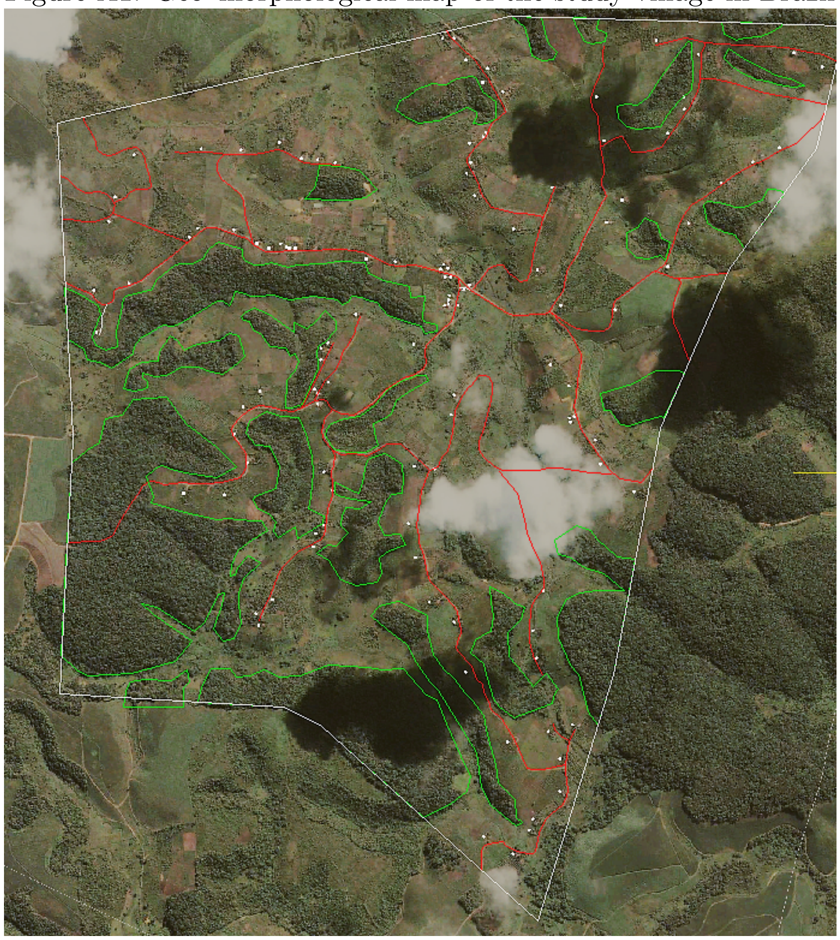

Figure A2: Village blueprint and geo-localized settlers

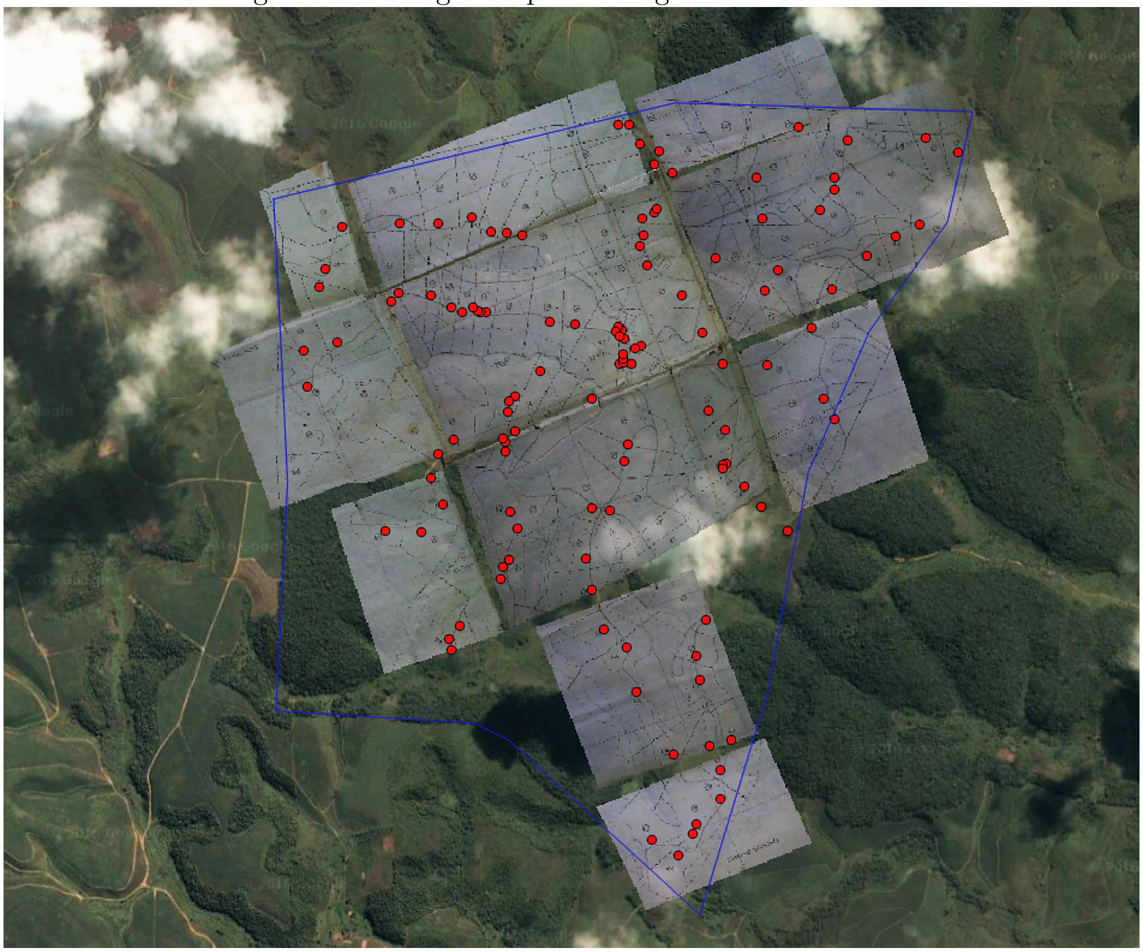

Table A1: Descriptive statistics (main results, N=1500)

		pineapple		passion fruit	
		mean	s.d.	mean	s.d.
	$\mathbf{y}^t$	0.15	0.36	0.16	0.37
	$\mathbf{G}\mathbf{y}^t$	0.71	1.00	0.75	1.08
distance road $\times$ ***price***$_c$	$\mathbf{x}^t$	0.15	0.17	0.20	0.20
	$\mathbf{G}\mathbf{x}^t$	0.45	0.46	0.60	0.52
	$\mathbf{G}^2\mathbf{x}^t$	2.02	1.72	2.68	1.85
	$\mathbf{G}^3\mathbf{x}^t$	8.78	8.73	11.64	9.75
distance water $\times$ ***price***$_c$	$\mathbf{x}^t$	0.27	0.25	0.36	0.28
	$\mathbf{G}\mathbf{x}^t$	0.92	0.92	1.23	1.03
	$\mathbf{G}^2\mathbf{x}^t$	4.37	4.17	5.80	4.62
	$\mathbf{G}^3\mathbf{x}^t$	20.39	21.94	27.04	24.88
coop member	$\mathbf{x}^t$	0.23	0.42	0.23	0.42
	$\mathbf{G}\mathbf{x}^t$	1.04	1.25	1.04	1.25
	$\mathbf{G}^2\mathbf{x}^t$	5.09	5.72	5.09	5.72
	$\mathbf{G}^3\mathbf{x}^t$	26.51	28.08	26.51	28.08

Table A2: Descriptive statistics (heterogeneous social effects)

		pineapple		passion fruit	
		mean	s.d.	mean	s.d.
	$\mathbf{y}^t$	0.15	0.36	0.16	0.37
	$\mathbf{G}_S\mathbf{y}^t$	0.44	0.77	0.51	0.88
	$\mathbf{G}_D\mathbf{y}^t$	0.27	0.57	0.24	0.55
distance road $\times$ ***price***$_c$	$\mathbf{x}^t$	0.15	0.17	0.20	0.20
	$\mathbf{G}_S\mathbf{x}^t$	0.25	0.28	0.33	0.32
	$\mathbf{G}_S^2\mathbf{x}^t$	0.72	0.82	0.96	0.94
	$\mathbf{G}_S^3\mathbf{x}^t$	2.30	3.08	3.05	3.60
	$\mathbf{G}_D\mathbf{x}^t$	0.21	0.34	0.27	0.40
	$\mathbf{G}_D^2\mathbf{x}^t$	0.56	0.76	0.75	0.88
	$\mathbf{G}_D^3\mathbf{x}^t$	1.29	2.00	1.70	2.37
distance water $\times$ ***price***$_c$	$\mathbf{x}^t$	0.27	0.25	0.36	0.28
	$\mathbf{G}_S\mathbf{x}^t$	0.57	0.75	0.75	0.88
	$\mathbf{G}_S^2\mathbf{x}^t$	1.83	2.62	2.42	3.08
	$\mathbf{G}_S^3\mathbf{x}^t$	6.19	9.79	8.20	11.60
	$\mathbf{G}_D\mathbf{x}^t$	0.36	0.58	0.47	0.69
	$\mathbf{G}_D^2\mathbf{x}^t$	1.05	1.45	1.40	1.69
	$\mathbf{G}_D^3\mathbf{x}^t$	2.35	4.20	3.11	5.01
coop member	$\mathbf{x}^t$	0.23	0.42	0.23	0.42
	$\mathbf{G}_S\mathbf{x}^t$	0.65	1.01	0.65	1.01
	$\mathbf{G}_S^2\mathbf{x}^t$	2.37	3.68	2.37	3.68
	$\mathbf{G}_S^3\mathbf{x}^t$	9.17	14.38	9.17	14.38
	$\mathbf{G}_D\mathbf{x}^t$	0.39	0.68	0.39	0.68
	$\mathbf{G}_D^2\mathbf{x}^t$	0.99	1.67	0.99	1.67
	$\mathbf{G}_D^3\mathbf{x}^t$	2.74	4.26	2.74	4.26