Network Proximity and Business Practices in African Manufacturing*

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Abstract

We document empirical patterns of correlation in innovation and contractual practices among manufacturing firms in Ethiopia and Sudan. The analysis is based on network data indicating whether any two firms in our sample do business with each other, whether they buy inputs from a common supplier, and whether they sell output to a common client. We find only limited support for the commonly held idea that firms that are more proximate in a network sense are more likely to adopt similar practices. For certain practices, adoption decisions appear instead to be local strategic substitutes: if one firm in a given location uses a certain practice, other firms nearby are less likely to do so. These results suggest that the diffusion of technology and new business practices may play a more limited role in spurring growth in Africa's manufacturing sector than is often assumed in the present policy discussion.

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1. Introduction

Technological upgrading and institutional innovation are critical for growth. This is particularly true in Africa where productivity has remained low. This begs the question of why productivity-enhancing innovations have not diffused equally to different countries or regions (Parente and Prescott 1994).

This question has attracted a lot of attention in economics. Since Griliches (1958), the dominant model of technology adoption in economics is one in which information about a more productive technology diffuses through the economy and is followed by adoption of the new technology by individual firms. In this model, obstacles to the circulation of information, e.g. due to social or economic segmentation, delay technology adoption. As a result, pockets of backward technology can subsist. Delays may also arise because of funding constraints or adoption costs – e.g., learning-by-doing, experimentation, and adjustment costs.

This general view pervades much of the economic discourse of growth and development. Some form of diffusion externality is built – or hidden – in all endogenous growth models in which technological innovation fuels growth (e.g., Parente and Prescott 1994, Romer 1990, Grossman and Helpman 1991, Aghion and Howitt 1992). The literature on the industrial revolution and the rise of the Western World describes how innovations in technology and business practices diffuse to neighboring enterprises, towns, and countries (e.g., North 1973, Mokyr 1990). The literature on agglomeration effects similarly ascribes a key role to the diffusion of innovative technology and business practices to nearby firms (e.g., Jacobs 1969; Fujita, Krugman and Venables 1999; Muendler and Rauch 2011). Similar ideas underlie much of the literature on the productivity benefits from FDI and international trade (Casella and Rauch 2002; Tybout 2000). Supplier-client relationships are seen as one important channel of diffusion among firms (e.g., Jacobs 1969; Rauch and Casella 2003). Another is competition between firms in the same market, notably with foreign firms (Kray, Soloaga and Tybout 2002).

Another strand of the literature has examined the diffusion of innovations within countries and regions. A shared underlying assumption of much of this literature is that, by interacting, firms learn from each other about technological and institutional innovations that raise productivity. While there is a body of rigorous research on technology diffusion among farmers (Griliches and Lichtenberger, 1984, Young and Burke 2001), much of the existing literature on manufacturing firms in developing countries remains fairly descriptive, relying principally on case studies (Sutton and Kellow 2010, Sutton and Kpentey 2012, Sonobe and Otsuka 2011). While much can be learned from such studies, the danger is that too much weight is given to rare or unusual events.[1] While there is a shortage of rigorous statistical evidence on the diffusion of innovations across firms in least developed economies, more evidence is available for developed and middle income countries (e.g., Helmers 2010 for the UK, Rauch and Muendler 2011 for Brazil).

If information about new technologies and practices diffuses to firms that are proximate in a geographical or economic sense, we expect firms that are near each other to employ similar technology and to adopt similar practices. This observation is the starting point of this paper. We ask a simple question: are closer firms more similar in terms of how they conduct business? The novelty of our approach is that proximity is not defined simply in terms of geography but also in terms of network.

We offer statistical evidence on the possible diffusion of innovations among firms in Ethiopia and Sudan. Our approach is to examine whether innovative business practices are correlated more strongly between firms if they are close in a network or market sense. Suppose diffusion is faster within than between networks. If there are strategic complementarities in the adoption of new practices, then business practices should be more similar across firms that are close. In contrast, if strategic substitution is important, business practices should be more different across firms that are close. Hence, correlation patterns shed light on diffusion and whether practices are characterized by complementarities or substitution. Of course, finding evidence of correlation does not prove diffusion: business practices could be correlated across firms because of contextual effects, such as the influence of a common, and possibly unobserved factor. But finding no evidence of correlation would suggest that business practices do not diffuse as much or as easily as is often believed.

We find some evidence of correlation in business practices. But the evidence is less convincing than one would expect if diffusion effects were strong. We also find evidence that, along some dimensions – principally geographical distance - firms are more similar to distant firms than to firms located nearby.

[1] For instance, it has been argued that, by diffusing innovations, the sending by Daewoo of Bangladeshi workers to Korea for training played a key role in the emergence of a successful garment industry in Dacca (Doshi 2011). The problem with this kind of evidence is that it leaves out many situations in which workers were sent abroad for training but did not trigger the emergence of a new industry in their home country.

This suggests that some adoption decisions are local strategic substitutes: if some firms adopt a certain practice, this may reduce the incentive for others to do likewise. This is partly confirmed by noting that the practices for which we find evidence of strategic substitutes – R&D, vocational training to workers – are those most vulnerable to free riding by other firms.

The paper is organized as follows. Section 2 discusses the conceptual framework and some key methodological issues. A number of important caveats are introduced on the interpretation one may or may not derive from the evidence. Section 3 describes the econometric testing strategy. Section 4 provides information about the data. Econometric results are presented in Section 5 while Section 6 concludes.

2. Conceptual Framework

In this section we use the language of network analysis to explain the logic behind our testing strategy.

2.1. Diffusion in networks

To discuss diffusion in networks, a good starting point is the concept of strategic complement and its converse, strategic substitute. Consider two economic agents i and j in a network.[2] The diffusion of a practice along the network means that i is more likely to adopt if j has adopted. This is equivalent to saying that the adoption decisions of i and j are strategic complements.

To formalize this observation, let $g_{ij} = \{0, 1\}$ denote a network link between two agents i and j and let the network matrix be $G \equiv [g_{ij}]$. By convention, $g_{ii} = 0$. There are N agents. We develop the theroretical model for the general case in which choice variables are continuous. A similar reasoning applies to discrete choices. We follow Liu et al. (2010) and Bramoulle and Kranton (2011) and write the payoff of agent i as:

$$\pi_i = \alpha_i y_i + \gamma g_i y + \rho y_i g_i y - \frac{1}{2} y_i^2 \tag{2.1}$$

where y_i denotes the action of agent i, $y \equiv [y_1, ..., y_N]$ is the vector of the actions of all agents, $g_i = [g_{i1}, ...g_{iN}]$ is the vector of neighbors of i, Greek letters are parameters, and the last term represents the

[2] By network we mean a finite collection of nodes (e.g., firms) and links between nodes (e.g., Jackson 2009).

marginal cost of taking action y_i, which for simplicity of exposition is assumed to be quadratic.[3] Each agent chooses $y_i \geq 0$ so as to maximize payoff π_i. The first order condition for an interior solution is:

$$y_i = \alpha_i + \rho g_i y \tag{2.2}$$

Actions are strategic complements if $\rho > 0$ and strategic substitutes if $\rho < 0$.

By comparing equations (2.2) and (2.1), it is immediately clear that the actions of others may affect i's payoff positively ($\gamma > 0$) or negatively ($\gamma < 0$) without affecting i's action. In this case we shall speak of a positive or negative externality. In the literature on technology transfer it is common to regard positive externalities and strategic complements as synonymous. But, as equations (2.2) and (2.1) show, it is possible for externalities to be negative ($\gamma < 0$) while actions are strategic complements ($\rho > 0$), and vice versa.[4]

Equilibria are action vectors y that solve the system of Kuhn-Tucker conditions combining first order conditions (2.2) with $y_i \geq 0$ $\forall i \in N$. Interior solutions satisfy:

$$y = (I - \rho G)^{-1} A \tag{2.3}$$

where $A \equiv [\alpha_1, ... \alpha_N]$. When actions are strategic complements, i.e., $\rho > 0$, and $\alpha_i \geq 0$ for all i, a sufficient condition for an interior equilibrium is that ρ be smaller than the largest eigenvalue of G.[5] If $\alpha_i \leq 0$ for all $i \in N$, there exists an equilibrium with $y = 0$ but there may be other equilibria as well.[6]

Bramoulle and Kranton (2011) characterize the equilibria that arise in network games with strategic substitutes. They show that the equilibrium configuration ultimately depends on the lowest (i.e., most

[3] It is also possible to assume that agent i is affected by the average of the action of its neighbors – the so-called linear-in-means model. This can be accommodated in our notation by replacing ρ with ρ/n_i where n_i is the number of neighbors of i. As shown by Bramoulle and Kranton (2011), it is possible to write (2.1) in a more general way and still get a linear decision function. Since this is not essential to our demonstration, we ignore it here.

[4] To illustrate the latter, consider two friends A and B in a car and let y_i be the action of driving the car. Clearly, if A drives, B need not drive – the actions are strategic substitutes. Yet B benefits from A's driving – there is a positive externality, i.e., B is free-riding – literally! To illustrate the opposite situation, consider two tables k and m in a restaurant and let y_i denote talking loudly. Imagine that everyone prefers a quiet environment. Yet if people at table k speak loudly, people at table m must raise their voice to continue conversing: actions are strategic complements but they generate a negative externality, as in a prisoner's dilemma game.

[5] For this to be true it is sufficient that ρ be smaller than 1 over the maximum degree of any agent (Jackson 2009)

[6] To illustrate, let $N = 2$, $\alpha = -1$ and $\rho = 2$. If $y_2 = 0$, then the $y_1 \geq 0$ constraint is binding and $y_1 = 0$. If $y_2 = 1$ then $y_2 = -1 + 2 \times 1 = 1$. We thus have two equilibria: $(y_1, y_2) = (0, 0)$ and $(1, 1)$.

negative) eigenvalue of G. With strategic substitutes, i.e., $\rho < 0$, most equilibria have some agents setting their $y_i = 0$ while (some of) their neighbors choose a strictly positive y_i. In other words, when actions are strategic substitutes, actions of neighbors tend to be dissimilar. In contrast, when actions are strategic complements, the actions of neighbors reinforce each other and thus tend to be similar (see also Jackson 2009).

These observations form the basis of our testing strategy as follows. Let $\widetilde{y} \equiv y - E[y] = (I - \rho G)^{-1}\widetilde{A}$ with $\widetilde{A} \equiv A - E[A]$ since G is not a stochastic matrix. The covariance matrix of $\widetilde{y}$ is:

$$Cov(\widetilde{y}) = E[(I - \rho G)^{-1}\widetilde{A}\widetilde{A}'(I - \rho G')^{-1}] \tag{2.4}$$

where the α_i's that enter matrix A are unobserved to the researcher. If the α_i's are i.i.d., $E[\widetilde{A}\widetilde{A}'] = \sigma^2 I$ and the above expression boils down to:

$$Cov(\widetilde{y}) = \sigma^2 E[(I - \rho G)^{-1}(I - \rho G')^{-1}]$$

When matrix G is sparse, i.e., with few $g_{ij} = 1$, the ij elements of matrix $E[(I - \rho G)^{-1}(I - \rho G')^{-1}]$ that correspond to existing links ($g_{ij} = 1$) are approximately proportional to ρ^2. Other elements are functions of higher powers of ρ and are much smaller than for linked ij pairs. It is therefore possible to test $\rho \neq 0$ by comparing whether values of y are more similar for linked than unlinked pairs. In contrast, when matrix G is block-diagonal, for instance because all firms in a location are linked, then matrix $E[(I - \rho G)^{-1}(I - \rho G')^{-1}]$ is also block diagonal with equal ij covariance terms within each block (Bramoulle, Djebari, Fortin 2009).

If $\rho = 0$ and the α_i's are i.i.d., then $Cov(\widetilde{y})$ is a diagonal matrix and $Cov(\widetilde{y}_i, \widetilde{y}_j) = 0$ for $i \neq j$. It is, however, possible for $Cov(\widetilde{y}_i, \widetilde{y}_j) \neq 0$ even when $\rho = 0$ provided that $E[\widetilde{A}\widetilde{A}']$ is not a diagonal matrix. This is an important caveat to keep in mind when interpreting our results: similar practices y could be due either to strategic complementarity ρ or to correlation in α_i's, that is, a correlation in the profitability of taking action y between linked firms – what Manski (1993) calls contextual effects. By a same reasoning, dissimilar practices can be due to strategic substitution or negative correlation in α_i's.

2.2. Adoption and diffusion of ideas

Because ideas are, in the words of Romer (1990), non-rival, the diffusion of ideas is characterized by strategic complementarity: if i has new information and communicates it to neighbor j, then j possesses that information as well. The logic is that communicating the information reduces the cost of acquiring it. Hence, if information is communicated along network links, we expect network neighbors to have similar information.

The circulation of information can, by itself, generate similarity in adoption decisions between network neighbors even if adoption is neither a strategic complement or substitute, i.e., even if $\rho = 0$ for adoption. This happens whenever information reveals the innovation to be profitable. Having the same information need not translate into similar adoption decisions, however. One possibility is that the benefits of adoption differ, e.g., $\alpha_i > 0$ but $\alpha_j < 0$. Another possibility is that adoption decisions are strategic substitutes even though being informed is a strategic complement.[7] The possibility of free-riding has long been recognized in experimentation: farmers may wait for their friends and neighbors to experiment with a new technology before deciding whether to adopt it (e.g., Foster and Rosenzweig 1995). But this possibility has seldom been recognized for adoption itself, except in some cases, such as the training of workers who are subsequently poached by competitors.

In contrast, if adoption decisions are strategic complements, similarity in adoption is more likely between network neighbors. Strategic complementarity in adoption could arise for various reasons, notably the desire to imitate others or to conform to a social norm, possibly reinforced by peer pressure (e.g., Young and Burke 2001). Another possibility is that adoption of an innovation by others lowers the output price, and this forces adoption in order to remain competitive. Adoption by others may also raise the profitability of adopting if there are externalities.

[7] To illustrate, imagine that i hears of a new DVD release from j. Both i and j want to see the movie but if i purchases it, j can borrow it and thus need not purchase it himself – he can free-ride. Strategic substitution can also arise with negative externality, as when adoption allows i to capture a market and exclude j from it.

2.3. Diffusion dynamics

If information diffuses between linked agents, in the long run we expect all connected agents to have the same information, whether the connection is direct – they are linked to each other – or indirect – they are linked through others. This insight was initially formalized in the context of epidemiologic models on networks – see Jackson (2009) and Vega-Redondo (2006) for excellent summaries of this literature.

It follows that, when information has had time to percolate through the network, adoption patterns within a giant component depend only on the distribution of benefits from adoption – the α_i's – and on local strategic complements and substitutes ρ. If agents have dissimilar α_i's or if $\rho < 0$, we expect spotty adoption of business technology and practices: some agents adopt while others do not even though they all have the same information. In contrast, if agents have sufficiently similar α_i's and if $\rho \geq 0$, we expect all agents in the same giant component to adopt similar technology and practices, irrespective of whether they are directly linked or not. The latter is not true in the short run, however: if information circulates slowly, adoption decisions are more likely to be similar among agents who are directly linked.

2.4. Business practices

So far we have discussed strategic complements and substitutes in general terms. We now briefly discuss specific business practices on which we have data and briefly speculate as to whether they are more likely to be strategic complements or substitutes for manufacturing firms in a developing country.

1. *Technology*: The adoption of more advanced equipment and machinery is likely to be a strategic complement within a given sector and region: firms compete with each other, and must keep up in terms of productivity. However, some firms may escape the need to innovate by focusing on niche products and markets that are poorly served by other firms (e.g., Fafchamps 1994).

2. *Internal organization*: Innovations in the internal organization of the firm should follow the same logic: if other firms gain a competitive edge by adopting a better internal organization, competitors should follow suit. This may however not apply to firms that eschew competitive pressure by focusing on niche markets and products – see above.

3. *R&D:* If firms compete through innovation, high R&D by some firms will induce others to invest in R&D as well. We therefore expect R&D to be a strategic complement – unless firms can free ride by imitating the innovations of other firms. Again, this does not apply to firms that escape the pressure to compete through innovation.

4. *Vocational training of workers*: If better trained workers raise productivity (in quantity or quality), competition between firms will lead them to train workers if new recruits are insufficiently qualified. They could, however, free ride and hire workers who have been trained by other firms instead of providing their own training. Vocational training can thus be a strategic complement or substitute.

5. *Contractual practices:* Because contractual practices by definition involve other firms, strategic complementarities are likely to be stronger. For instance, if one firm imports from abroad or sub-contracts part of its production, other firms may find it easier to import or sub-contract, possibly from the same foreign firms or to the same sub-contractors. Similarly, if one client convinces suppliers to offer trade credit, other clients may follow suit. However, we cannot a priori rule out the possibility of strategic substitution, for instance if firms purchase inputs from the importing firm rather than importing themselves, or if some firms crowd out the market for sub-contractors.

6. *Reputational sanctions:* Because reputation sanctions contain a strong public good component, they are most likely to exhibit strategic complementarity: the threat of exclusion from future trade has the strongest deterrent effect if all firms in the industry participate. Hence the incentive to adopt reputational sanctions is highest when most other firms have already adopted it.

The above discussion, albeit brief, suggests that different types of proximity may matter differently. Strategic complementarities that arise from information exchange apply in principle to all practices listed above. If information on technological, organizational, and contracting innovations circulates through supplier-client relationships, we expect such proximity to matter. How strong the effect is depends on whether information is a relevant bottleneck. If information about relevant innovations has had enough time to circulate and is widely available, any strategic complementarity due to information about innovations is likely to be negligible. Information sharing remains relevant for reputational sanctions, however. Hence we expect supplier-client networks to matter more for those.

Strategic complementarities that arise from competition should generate the strongest similarity among firms that share the same market, such as firms in a given sector and location. This observation applies to all practices listed above, but is most relevant for technology, internal organization, and R&D for which other channels of adoption diffusion are expected to be less important. If, as is likely, upstream and downstream firms face different competitors, strategic complementarities driven by competition are expected to be smaller between firms located at different levels of the value chain. It follows that, if we use geographical proximity as proxy for competition, supplier-client proximity – which identifies different points on the value chain – may be associated with less similar practices.

For vocational training, the proximity that matters most in addition to competition is reliance on the same labor market, which again is probably strongest for firms in the same location and sector. There may be spillovers across sectors, however. Because training may be a strategic complement or substitute, the spillover effects may materialize themselves as either similarity or dissimilarity across firms in the same location, depending on which effect is strongest.

Regarding contractual practices, spillovers due to competition are again present but there also are strategic complementarities due to network externalities: if some firms import their inputs directly, channels of communication are established and local expertise arises (e.g., about customs, transport, warehousing) that can benefit other firms. Network externalities are likely to be particularly strong for reputational sanctions, which suffer from possible coordination failure: if others do not punish, deterrence is weakened (e.g., Greif 1993, Fafchamps 2004).

2.5. Firm performance

So far we have discussed adoption of practices. It is also possible to investigate payoffs directly, e.g., firm performance and growth. To illustrate, let us replace y_i in (2.1) by its optimal value from (2.2) and let us use (2.3) to solve for y. We obtain:[8]

$$\pi_i = \frac{1}{2}\alpha_i^2 + (\rho\alpha_i + \gamma)g_i(I - \rho G)^{-1}A + \frac{1}{2}\rho^2\left(g_i(I - \rho G)^{-1}A\right)^2$$

If $\rho = 0$ this simplifies to:

$$\pi_i = \frac{1}{2}\alpha_i^2 + \gamma g_i A$$

Let $\widetilde{\pi} \equiv \pi - E[\pi] = \frac{1}{2}\widetilde{\alpha_i^2} + \gamma g_i \widetilde{A}$ where $\widetilde{\alpha_i^2} \equiv \alpha_i^2 - Var(\alpha) - E(\alpha)^2$. The covariance matrix of π is:

$$\begin{aligned} Cov(\widetilde{\pi}_i, \widetilde{\pi}_j|\rho = 0) &= E[(\frac{1}{2}\widetilde{\alpha_i^2} + \gamma g_i\widetilde{A})(\frac{1}{2}\widetilde{\alpha_j^2} + \gamma g_j\widetilde{A})'] \\ &= E\left[\frac{1}{4}\widetilde{\alpha_i^2}\widetilde{\alpha_j^2} + \frac{\gamma}{2}\widetilde{\alpha_i^2}g_j\widetilde{A} + \frac{\gamma}{2}\widetilde{\alpha_j^2}g_i\widetilde{A} + \gamma^2 g_i\widetilde{A}\widetilde{A}'g_j\right] \end{aligned} \tag{2.5}$$

which shows that if $\gamma \neq 0$, that is, if externalities are present, firm performance is correlated across connected firms.[9] If $\gamma < 0$, the correlation can be negative.[10] Positive externalities thus manifest themselves as proximate firms having similar performance while dissimilar performance is associated with negative externalities.

Equation (2.5) also shows that, even in the absence of externalities, firm performance may be similar because of correlation in firm-specific conditions α_i and α_j − the so-called contextual effects. It is the potential presence of these contextual effects that precludes the interpretation of correlated firm performance as evidence of externalities. When strategic complements or substitutes are present, equation (2.5) becomes more complicated but the intuition remains similar: profits may be correlated, positively or negatively, across proximate firms.

[8]

$$\begin{aligned} \pi_i &= \alpha_i(\alpha_i + \rho g_i y) + \gamma g_i y + \rho(\alpha_i + \rho g_i y)g_i y - \frac{1}{2}(\alpha_i + \rho g_i y)^2 \\ &= \frac{1}{2}\alpha_i^2 + (\rho\alpha_i + \gamma)g_i y + \frac{1}{2}\rho^2(g_i y)^2 \end{aligned}$$

[9] Even if $E[\widetilde{\alpha}_i\widetilde{\alpha}_j] = 0$, the $E[\widetilde{\alpha_i^2}g_j\widetilde{A}]$ terms do not vanish whenever α_i appears in g_jA, that is, whenever i is a neighbor of j.

[10] For instance, if α_i and α_j are independent and $g_i\widetilde{A} = \widetilde{\alpha}_j$ and $g_j\widetilde{A} = \widetilde{\alpha}_i$ (i and j are mutual neighbors) then $Cov(\widetilde{\pi}_i, \widetilde{\pi}_j|\rho = 0) = \gamma E[\widetilde{\alpha^2}\widetilde{\alpha}]$, which is negative iff $\gamma < 0$.

2.6. Diffusion across heterogeneous firms

Firms are heterogeneous and diffusion patterns across firms are likely to depend on enterprise characteristics. For example, the scope for the diffusion of innovations between sectors may be limited if they use technologies that are too different. Similarly, organizational practices that are suitable for large corporations may not be useful for micro-enterprises.

In the model this is captured by differences in α_i, the marginal return from a new practice y. If adoption is dichotomous, the likelihood of adopting can be written:

$$y_i = \lambda(\alpha_i + \rho g_i y) \tag{2.6}$$

where $\lambda(.)$ is a logit or probit function. Firms with a low α_i are unlikely to adopt irrespective of what neighboring firms do, i.e., irrespective of $\rho g_i y$, while firms with a high α_i are likely to adopt no matter what others do. Strategic complements and substitutes are thus most relevant for firms with intermediate values of α_i: for them, adoption may only be beneficial if neighboring firms adopt (if adoption decisions are strategic complements) or do not adopt (if they are strategic substitutes).

It is reasonable to assume that, once informed of an innovation, firms with a high α_i would adopt first while other firms would adopt later thanks to $\rho g_i y$ effects. We therefore expect to observe network-driven diffusion of innovation only among firms that are different, but not too much.

This affects inference in a fundamental way. For instance, if all firms in sector A share a high α_A for a particular innovation, but firms in sector B have a lower α_B but a large ρ, we expect all A firms to adopt, irrespective of whether they are linked or not, but we expect B to be more likely to adopt if they are linked to A firms. It follows that, in this example, correlation in adoption y between firms within the same sector is not affected by network proximity, while correlation in y between firms in different sector is stronger between linked firms. It is also conceivable that firms are heterogeneous within sector A: some have a high α_i and adopt while others with a lower α_i adopt only if they have an adopting neighbor. Firms in sector B, by contrast, may all have a low α_i and not adopt, whether linked or not. As these two contrasted examples illustrate, it is not entirely clear a priori what makes firms too similar or too different for network effects to affect diffusion.

The economic importance of diffusion across heterogeneous firms is potentially high. For example, if ρ is small across dissimilar firms, the diffusion of innovations will be harder in economies populated by very heterogeneous firms (e.g., much of Sub-Saharan Africa). In such a context, not much should be expected from social networks and their ability to speed up the diffusion of new ideas. If true, this would contradict the considerable optimism over agglomeration economies as a source of growth that has been expressed in the recent literature on Africa (e.g. Collier, 2007; Page, 2012; Sonobe and Otsuka 2011).

Heterogeneity is also important from a methodological point of view. Suppose there is scope for diffusion across some, but not all, firms. Our objective is to determine whether network links are associated with similar firm practices and outcomes. If we fail to take into account heterogeneity, the estimated average network effect will underestimate the effect for the subset of firms for which diffusion is taking place. As a result, one may end up erroneously accepting the null hypothesis that networks play no role, a point that we need to keep in mind when interpreting our regression results.

3. Testing strategy

We now outline the testing strategy, which follows from the above reasoning. Each enterprise is a node. We observe whether an enterprise i has adopted a practice y_i. The vector $\mathbf{g}_{ij} = (g_{1ij}, g_{2ij}, ..., g_{Mij})$ represents supplier-client links between two enterprises i and j, while d_{ij} represents the geographical distance between them. We want to test whether two enterprises i and j are more likely to have a similar practice y_i (or performance π_i) if they are close in a network and geographical sense, that is, if some or all elements of $\mathbf{g}_{ij}$ are equal to one or if d_{ij} is small.

For this purpose we estimate a model of the form:

$$|y_i - y_j| = \mathbf{g}_{ij}\boldsymbol{\theta} + \omega d_{ij} + \mathbf{x}_{ij}\boldsymbol{\beta} + u_{ij} \tag{3.1}$$

where $\boldsymbol{\theta} = (\theta_1, \theta_2, ..., \theta_M)$ is a vector of coefficients associated with network links, ω is a coefficient reflecting the relationship between geographical distances and outcome similarities, $\mathbf{x}_{ij}$ is a set of control variables included to reduce omitted variable bias, $\boldsymbol{\beta}$ is a vector of parameters, and u_{ij} is an error term. A similar regression model is used for π_i. There are two reasons for estimating (3.1) in absolute deviation, not in covariance form as in (2.4) or (2.5). First, most outcome variables we investigate are binary and the only information they contain is whether $y_i = y_j$ or not. In this case, (3.1) boils down to a linear probability model since $|y_i - y_j| = 0$ if $y_i \neq y_j$ and is 0 if they are the same. Secondly, in the more general case when y is continuous, model (3.1) captures the main idea behind (2.4) or (2.5) but offers the advantage of being more robust to outliers compared to using $(y_i - \overline{y})(y_j - \overline{y})$ as the dependent variable.

As explained in Fafchamps and Gubert (2007), equation (3.1) works irrespective of whether y_i is a continuous or dichotomous variable. A negative θ_m in (3.1) means that y is more similar when firms i and j have a link $g_{mij} = 1$. For geographical distance d_{ij} the interpretation of the sign of ω is the opposite. Conversely a positive θ_m or negative ω means that linked or nearby firms are more dissimilar. When y_i is a business practice and it is shown to be more similar across proximate firms, this is consistent with adoption by different firms being strategic complements; if it is dissimilar, this suggests that adoption by different firms is a strategic substitute. When π_i is the dependent variable and it is shown to be similar, we take this as consistent with the hypothesis that adoption generates positive externalities across firms.

Since by construction, $|y_i - y_j| = |y_j - y_i|$, it follows that x_{ij} regressors must be formulated such that:

$$\mathbf{g}_{ij}\boldsymbol{\theta} + \mathbf{x}_{ij}\boldsymbol{\beta} + \omega d_{ij} = \mathbf{g}_{ji}\boldsymbol{\theta} + \mathbf{x}_{ji}\boldsymbol{\beta} + \omega d_{ij}$$

where $d_{ij} = d_{ji}$ by definition. We therefore need network proximity regressors $\mathbf{g}_{ij}$ to be undirected, i.e., such that $g_{mij} = g_{mji}$ for each element in $\mathbf{g}$. Similarly we need $\mathbf{x}_{ji} = \mathbf{x}_{ij}$. The purpose of including $\mathbf{x}_{ij}$ is to control for similarity in α_i between firms that may be correlated with proximity $\mathbf{g}_{ij}$, and hence to reduce omitted variable bias. Let x_i denote one such characteristic associated with α_i. To ensure that $\mathbf{x}_{ji} = \mathbf{x}_{ij}$, we follow Fafchamps and Gubert (2007) and create regressors of the form $|x_i - x_j|$. The estimated model is:

$$|y_i - y_j| = \mathbf{g}_{ij}\boldsymbol{\theta} + \omega d_{ij} + |\mathbf{x_i} - \mathbf{x_j}|\boldsymbol{\beta} + u_{ij} \tag{3.2}$$

A positive and significant β means that firms that share a similar x tend to have a more similar y.

Equation (3.2) is a dyadic regression. The dependent and independent variables are defined for every pair of firms i, j in the data, which implies there are $n \times (n-1)$ observations underlying the regression (n denoting the number of firms). Dyadic observations are typically not independent since residual u_{ij} is likely to be correlated with u_{ik}.[11] This complicates the computation of standard errors. In particular, robust standard errors must correct for cross-observation correlation in the error terms involving the same enterprises.

To obtain consistent standard errors, we use bootstrapping. Let $\widehat{\boldsymbol{\theta}}, \widehat{\omega}$ and $\widehat{\boldsymbol{\beta}}$ denote the parameter estimates obtained from estimating (3.2). Bootstrapping is implemented as follows: (i) we draw a random sample s of n firms by drawing from the firm-level dataset with replacement; (ii) for this artificial sample of n firms we construct the corresponding $n(n-1)$ dependent variables $|y_i - y_j|_s$, links $\mathbf{g}_{ij}^s$, distance d_{ij}^s and controls $\mathbf{x}_{ij}^s$; (iii) we estimate equation (3.2) for this sample and store the parameter estimates $\widehat{\boldsymbol{\theta}}_s, \widehat{\omega}_s$ and $\widehat{\boldsymbol{\beta}}_s$; (iv) after repeating the process (i)-(iii) J times, we use the standard deviations of $\widehat{\boldsymbol{\theta}}_s, \widehat{\omega}_s$ and $\widehat{\boldsymbol{\beta}}_s$ as estimates of the standard errors of $\widehat{\boldsymbol{\theta}}, \widehat{\omega}$ and $\widehat{\boldsymbol{\beta}}$.

As noted in the introduction, a significantly negative θ_m does not by itself imply network diffusion: firms i and j may have correlated technology and contractual practices for reasons other than network or geographical proximity, e.g., because they are subject to similar contextual effects α_i not adequately controlled by $\mathbf{x}_i$. If unobserved contextual effects are correlated with proximity g_{mij}, they would bias θ_m below 0. Hence if we find a significantly negative θ_m, it may be due either to diffusion or to unobserved contextual effects. However, if we find that θ_m is positive or not significantly different from zero, the net effect of diffusion and contextual effects is likely to be positive or zero.

There are two possible exceptions. The first is when diffusion is rapid and all firms belong to a single connected network. In this case our identification strategy will fail: how similar firms are will only depend on their α_i's, not on distance between them. Hence we will observe a zero θ even though diffusion across network links is taking place.

The second exception is when strategic complementarities and substitutes precisely offset each other. While possible, this seems unlikely. If unobserved contextual effects could only generate positive correlation in technology and business practices, as is likely, then a non-significant θ indicates that network

[11] In particular, $u_{ij} = u_{ji}$.

diffusion is 0 while a positive θ suggests the presence of strategic substitution effects in adoption decisions. We cannot, however, completely rule out the possibility that negative correlation between practices could be the result of negative or positive correlation in the profitability of adoption α_i. For instance, if an innovation, say sub-contracting, is profitable for upstream firms but not for downstream firms, then firms linked as supplier and client will have negatively correlated practices since suppliers, by definition, are upstream relative to their clients.

4. Data

To implement our testing strategy we use detailed firm-level data collected under the leadership of the World Bank in Ethiopia and Sudan. Virtually the same questionnaire and sampling strategies were used in the two countries. One of the authors was involved in the design of the questionnaire.

The data on the Ethiopian firms were collected as part of the Ethiopia Investment Climate Survey, fielded by the Ethiopian Development Research Institute (EDRI) in mid-2006. The survey covered 14 major cities located in seven regions of Ethiopia. Forty-two percent of the observations come from Addis Ababa. As shown on the map in Figure 1, the survey has wide geographical coverage, with long distances between some of the firms in the sample. The average distance between any two firms is 282 kilometers. The longest distance recorded in these data is 876 kilometers, which is the distance (as the crow flies) between Dilla in the South and Adrigat in the North. The national manufacturing census provided the sampling frame for the survey. The survey includes firms with at least five permanent employees in four sectors: furniture, wood and metal; food and beverages; leather and leather products; and textile and garment. Three hundred and sixty manufacturing firms were surveyed. See Mengistae and Honorati (2009) for more details on the survey methodology.

The data on Sudanese firms were collected as part of the Investment Climate Survey launched in November 2007 and conducted by H&H Consultancy, a Sudanese management consulting firm with expertise in conducting complex surveys. The survey covered 432 manufacturing firms, most of them private, in 8 states. The capital city of Khartoum accounts for 52% of the sample observations. The survey concentrates on firms with permanent employees, and does not cover microenterprises. The manufacturing survey is diverse in terms of sectors – no sector represents more than 20% of the sample, with the largest sectors being food and beverages (18%) and fabricated metal products (16%). See H&H (2008) for more details on the survey methodology. After deleting observations with too many missing values, we obtain a sample of 304 firms for Ethiopia and 401 firms for Sudan. This forms our baseline sample.[12]

Summary statistics are shown in Table 1. Key firm characteristics are presented first. These are variables thought to influence – or be associated with – innovation. They constitute our control vector. More mature firms and firms with a better quality management should be more adept at recognizing the value of new technologies and business practices. Female ownership is included because, in the study of de Mel, McKenzie and Woodruff (2009), female-headed businesses have been shown to be less growth oriented (see also Fafchamps, 2003). We also include firm size, as proxied by the (log of) total firm employment. The average log employment is 3.37 in Ethiopia, which corresponds to 29 employees. The largest firm in the sample employs more than 3,000 employees. For Sudan, the average log size is 2.91 which corresponds to 18 employees.

Next we report information on firm practices. We focus on variables that show some variation across firms in the two samples we have. In the conceptual section we argued that the stronger strategic complementarities are, the harder it is for decentralized diffusion to take place in loosely connected networks. We thus begin by reporting variables for which strategic complementarities across firms are a priori thought to be less strong, such as innovation; we end with variables for which strategic complementarities are likely to be strongest, such as reputation mechanisms.

Within each category, adoption by a given firm may be correlated across individual practices, either positively or negatively (e.g., if some practices are partial substitutes for each other). In this case, examining each practice separately yields inefficient inference. To guard against this possibility, we follow the approach suggested by Kling, Liebman and Katz (2007) and summarize the available information within each category using factor analysis. The principal component of each category, reported in Table 1, is used as an additional dependent variable.

[12] For some of our outcome variables (e.g. value-added) there are missing values in the baseline sample. Some of our regressions will therefore be estimated on a smaller sample than the baseline sample.

Adoption of any of the practices listed in Table 1 is potentially subject to strategic complementarities, although these complementarities may involve economic agents other than the manufacturing firms on which we focus. With this caveat in mind, we begin by reporting variables related to innovation broadly defined. Given that the two country samples include firms in different sectors, there are many technologies that are useful for some firms but not others. The main exception is IT, which is potentially relevant to all firms. For this reason, we focus on firms' conscious effort to innovate by introducing new products or by investing in new equipment and machinery. As a practice, innovation is subject to diffusion, within sectors as well as across sectors. It is also potentially subject to strategic complementarities – e.g., let others take the risk of innovating and copy only what proves successful.[13]

The first variable we consider is a dummy variable indicating whether the firm introduced a new product in the year preceding the survey. Between a third and a half of the surveyed firms responded positively to this question. Around half of the firms invested in plant and equipment in the previous year, for both countries. We also have information on whether the firm records positive expenditures on R&D. We regard R&D as an organizational arrangement enabling the firm to have a systematic approach to innovation. A non-negligible proportion of surveyed firms spend money on R&D: 13% for Ethiopia and 23% for Sudan. We also note some usage of IT technology, mostly in the form of email. At the time of the surveys, few manufacturing firms in Sudan or Ethiopia had a website.

The development of new products and the adoption of a new production technology potentially generate strategic complementarities across firms: if other firms innovate, remaining competitive may require that the firm innovate as well in order to remain competitive. But the incentive to innovate nevertheless exists even when other firms do not innovate. Thus, although diffusion may be reinforced by strategic complementarities, if the profitability of a product or technology has been demonstrated by another firm, copying the same product or technology generates individual benefits that are not subject to coordination failure. Hence there are a priori no obstacles to widespread diffusion.

Information on labor management and investment in human capital is presented next. We first report the ratio of non-production to production workers. Non-production workers include professionals,

[13] Caria (2010), for instance, provides evidence that more risk averse Ghanaian farmers seek agricultural technology information from more risk averse farmers. See also Foster and Rosenzweig (1995).

managers, administrators, and sales personnel. Fafchamps and Söderbom (2006) argue that this ratio is related to the ease with which firms manage their labor force, and they show that many African firms are top-heavy, with a high ratio of production to non-production workers in spite of the relative simplicity of their production processes. Here we find a higher ratio in Sudan than in Ethiopia, suggesting that the Sudanese firms are less able to manage their workforce with a small number of clerks and managers. Labor management can be facilitated if workers are better trained. Surveyed firms were asked whether they had provided any in-house training to their workers, or sent any of them to a formal training course in the year preceding the survey. In both countries a substantial minority of firms had provided training to their workers, but the majority had not.

Workers trained by one firm may be hired by other firms, making worker training a strategic substitute: if other firms offer vocational training, my firm need not do it if I can hire their trained workers. This may hinder diffusion of the practice, or generate negative correlation across firms in the same sector, as some firms free-ride on others. For hierarchical management, strategic complementarities may arise through the operation of the labor market. If workers are unused to working in a hierarchical environment, the firm may need to hire more middle management and clerical workers in information processing, monitoring, and coordination tasks. Hence a firm that first institutes a multi-tiered structure may benefit others through the learning effect it has on the workforce. These effects, however, are likely to extend beyond the manufacturing sector which, in the two study countries, accounts for only a small proportion of total employment. Still, we may observe some similarities among firms that are close in a network sense.

The next panel of Table 1 covers contractual practices. Firms were asked whether they import inputs directly from abroad. The alternative is to source inputs locally or to purchase inputs from an importer. Buying directly from abroad requires trust but is likely to improve the adequacy of the raw materials to the firm's production process. We find some difference between the two countries, with landlocked Ethiopia lagging behind Sudan. Firms were also asked whether they sell on credit to any of their customers. The main alternative is payment on delivery. A majority of manufacturing firms sell on credit to at least some of their customers, but a large minority do not. The data also show that sub-contracting part of production to other firms is rare.

Importing directly from suppliers abroad – as opposed to buying from a local importer – requires a modicum of trust that ultimately relies on a good market environment, e.g. predictability of the handling and custom operations at the port of entry. Presumably, the more firms import directly, the more knowledge they collectively acquire regarding procedures and sources of supply, and the more this information can diffuse among firms. There is therefore room for diffusion of practices through the diffusion of information along business networks.

Supplier credit is closely associated with invoicing, for which there may be strategic complementarities across firms: the more likely other suppliers are to offer supplier credit to clients, the less perilous it is to offer supplier credit as well. According to this reasoning, we expect supplier credit to diffuse more easily among suppliers who have the same clients – or clients in the same geographical area.

Next we examine the extent to which surveyed firms rely on reputation to enforce contracts with suppliers and clients. Respondents were asked five closely related questions as follows: (i) If you have a dispute with a customer, will other customers find out? (ii) If some other firm has a dispute with customer, will you refuse to deal with the customer? (iii) If you have a dispute with a customer, will other firms refuse to deal with the customer? (iv) If you have a dispute with a supplier, will other suppliers find out? (v) If you have a dispute with a supplier, will other firms refuse to deal with the supplier?

For each of these questions we code $y = 2$ for yes, $y = 1$ for maybe/don't know, and $y = 0$ for no, hence high values correspond to stronger reputation effects. The summary statistics presented in Table 1 suggest that news about a dispute often travel to customers and suppliers. They also suggest that the reputational sanction imposed on customers and suppliers involved in a dispute is not severe: firms typically continue to deal with customers and suppliers that have been involved in a dispute. These findings suggest that reputation mechanisms are weak, a point already made by Bigsten et al. (2000) and by Fafchamps (2004) for African manufacturing.

Firm performance indicators are reported at the bottom of Table 1. The first variable in the list is (the log of) value added per employee, expressed in US$, as a crude indicator of productivity.[14] The country

[14]Surveyed firms were asked to estimate the replacement value of their equipment and machinery, but much of this information is either missing or unreliable. This is hardly surprising given how thin the secondary market for equipment is

averages for this variable correspond to USD 1,700 for Ethiopia and USD 5,900 for Sudan. We also report available information about growth in employment and revenue.[15] Surveyed firms often report considerable growth in employment and revenue, although there is massive variation across firms and between years, as suggested by the comparison between one-year and three-year growth rates in revenue.

A key module of the survey contains information about the names of the firms' trading partners and their approximate geographical location. Respondents were asked to name up to three clients and three suppliers.[16] Using the information from this module, we construct simple measures of network proximity between firms within the two samples. These measures are reported in Table 2.

We begin by constructing a dyadic dataset of unique firm pairs. For instance, there are 304 firms in the Ethiopian sample. This means that there exist $304 \times 303/2 = 46,056$ unique enterprise pairs (i, j) in that sample. For each i, j pairs, we construct dummy variables capturing different concepts of network proximity. When two firms are close in the sense of that network, we say they are linked. The most direct network proximity measure we use is whether i and j buy or sell from each other. We are only able to identify a small number of such links in our data – 60 in Ethiopia and 5 in Sudan. That there are so few upstream and downstream links among sample firms is partly driven by the focus of the surveys on light manufacturing sector for which clients seldom are manufacturers. We also construct dummy variables indicating whether i and j have a common supplier or a common client. These types of links are more common: there are 481 (171) supplier-based links and 273 (678) client-based links in the Ethiopian (Sudanese) data, respectively. These network proximity variables constitute the core of our $\mathbf{g}_{ij}$ vector. The next proximity dummy is whether i and j belong to the same manufacturing sector. The last one is geographical distance d_{ij}, defined as the log of the distance between i and j plus one.

in both countries. It is therefore very difficult for respondents to estimate how much it would cost to replace their – often antiquated – equipment.

[15] Reported as the $\log(X_t/X_{t-1})$ where X is employment or revenue, respectively. If the growth g rate of X is small, then $\log(X_t/X_{t-1}) \approx g$.

[16] Since the majority of firms (about 70%) list 3 names, this creates truncation in the observed network because some existing links are not recorded. This may cause a downward bias in the estimated network effects.

5. Empirical Analysis

Our objective is to test whether the outcomes and practices listed in Table 1 are more similar among firms that are close to each other, either in a network sense or geographically. To this end we estimate the model (3.2). In general, a large value of the dependent variable means that firms i and j are dissimilar in terms of y. If y is binary, the dependent dyadic variable will be equal to one if the two firms record different values of y and zero otherwise. The null hypothesis is that network status does not matter for whether y is the same or different across firms. If diffusion is more rapid within than between networks, and y is not influenced by strategic substitution, $E|y_i - y_j|$ should be lower across linked than non-linked firms. In this case, we would obtain a negative coefficient on relevant elements of the network vector $\mathbf{g}_{ij}$. For geographical distance d_{ij}, the interpretation of the sign of ω is the opposite. Given that we only have cross-section data, results are uninformative about the speed of diffusion.

The set of control variables $\mathbf{x}$ includes a dummy equal to 1 if firms i and j belong to the same sector, and absolute differences across i and j in firm age, education of the manager, experience of the manager, gender of the owner, and firm size proxied by the log of the number of employees. A positive coefficient on $|x_i - x_j|$ implies that the outcome variable y is more similar for firms that have a similar x. Our estimation technique is linear regression (OLS), and standard errors are bootstrapped to be robust to heteroskedasticity and dyadic correlation in error terms across firms.[17] We refer to results presented in the paper as baseline results. Additional results are available in an Online Appendix.[18]

5.1. Innovation and R&D

We begin by investigating the association between geographical and network proximity and the attitude and practices of firms with respect to innovation and R&D. Since our data come from a wide variety of light manufacturing enterprises, we focus on indicators that are relevant for all firms irrespective of sector. We construct dyadic dependent variables from dummy variables measuring whether firms introduced a new product in the previous year, invested in plant and equipment in the previous year, and whether

[17] The reason we use bootstrapping instead of the approach suggested by Fafchamps and Gubert (2007) is that their formula, based on that of Conley (1999), is not guaranteed to generate positive variance estimates.

[18] The Online Appendix is available at http://soderbom.net/Fafchamps_Soderbom_Online_Appendix_2012.pdf

they do any R&D. A fourth outcome variable is constructed based on firm-level measures of the extent of IT usage. Specifically, we distinguish three levels of IT usage in the data: 0 if IT is not used at all; 1 if the firm uses e-mail; and 2 if the enterprise has a business website.[19] Dyadic regression results are shown in Table 3, columns [1]-[4] for Ethiopia and columns [6]-[9] for Sudan. In columns [5] and [10] we report similar results using the principal component of all four categories to construct the dyadic dependent variable.

Estimated coefficients for the network proximity variables differ across the two countries. For Ethiopia, the coefficients on the dummies for whether i and j trade with each other, have a common supplier, and a common client are small and statistically non-significant. For Sudan we obtain a negative and statistically significant coefficient on trade in the R&D regression (col. 8), and negative and significant coefficients (at least at the 10% level) on having a common supplier in the regressions for investment (col. 7), R&D (col. 8), IT usage (col. 9), and the first common factor (col. 10). Hence network proximity seems to be associated with a more similar approach to innovation and R&D across firms in Sudan but not in Ethiopia. Some of these estimated effects are large: for example, the likelihood that firms trading with each other adopt the same R&D policy (yes or no) is 34 percentage points higher than for firms that do not trade with each other. Due to the small number of direct links in the Sudanese data (see Table 2), the estimated coefficients on direct trade should be interpreted with caution, however. We further find that Sudanese firms with a common client tend to differ *more* than other firms with respect to R&D and IT usage. This is not consistent with the notion that network proximity tends to result in similar practices regarding innovation.[20]

Next we consider the role of geographical distance between firms. For Ethiopia, the distance coefficient is negative in all five specifications shown in Table 3, and statistically significant at the 10% level or better in four of these. Hence geographical proximity tends to be associated with greater differences

[19] Here the three levels of usage are combined. Results for alternative specifications modeling e-mail and website use separately are shown in Tables A1.E and A1.S, columns 1-2, in the Online Appendix. The results are similar to those shown in Table 3.

[20] A possible reason for this finding is that buyers concentrate purchases of a certain type of product on a single supplier. For example, a client may need a sophisticated product and a simple product. If the client buys the sophisticated product from a firm that specializes in the production of such goods (which may require R&D and extensive IT usage) and the simple product from a different firm that specializes in simple goods (which does not require R&D or IT), firms that share the same client will fill different, rather than similar, client needs. This could give rise to the empirical result observed here. Whatever the reason, it suggests that competition for the same clients do not induce firms to adopt a similar R&D policy or IT usage.

in innovation policy. The results are similar for Sudan: the distance coefficient is negative and highly statistically significant in the models for R&D (col. 8), IT usage (col. 9), and for the first common factor (col. 10). These results suggest that, for technology, strategic substitution effects dominate strategic complementarities for firms located near each other.

The control variables in these regressions have some explanatory power. The estimated coefficients on the same sector dummy are negative in all specifications except [6], and often statistically significant. This indicates that, as expected, firms in the same sector tend to have similar innovation practices. Differences in firm size, measured as the absolute difference in log employment, are positively associated with differences in innovation practices in all specifications. This suggests that firms of similar size tend to adopt similar practices regarding innovation. The results also provide some evidence that managers of the same gender or with similar levels of education select similar innovation practices. The coefficients on differences in managers' experience or firm age are mostly non-significant.

5.2. Human capital and labor management

Table 4 shows results for our regressions on labor management and investment in human capital. As explained in the data section, labor management is proxied by the ratio of non-production workers to total employment, as a measure of hierarchical differentiation within the firm. We find no evidence that network proximity is associated with greater similarity in training decisions or labor management across firms. We obtain a positive and statistically significant coefficient, on common client in specifications [3], [4] and [6], indicating that firms with a common client tend to have more different training policies than firms not sharing a common client.

The estimated coefficients on distance between firms are negative in all specifications except [5], and statistically significant in four of these (col. 2, 3, 4 and 6). Similar to the results for innovation, this implies that firms located close to each other tend to differ *more* with respect their human capital decisions than firms located far apart. This is consistent with strategic substitution. One possibility, often emphasized in the literature on agglomeration effects (e.g., Henderson 1988; Glaser et al. 1992), is that firms hire workers trained by other firms: the more other firms nearby provide the necessary training, the less they need to do so themselves. If firms that sell to the same clients produce close substitutes, they probably have similar production technology and similar manpower needs and can thus free ride on the training offered by other firms. Alternatively, strategic substitution may be driven by incentives to avoid local competition. For example, if two firms with similar human capital produce similar output, they will compete with each other if they are based in the same local market. By locating in different places, both firms would face less competition and presumably higher profits. Alternatively, firms located in the same place may optimally decide to differentiate their output, which may lead to differences in technology and human capital needs. Mechanisms such as these would result in the pattern that we observe in the data, i.e., greater differences between firms located close to each other than between firms in locations far apart.

We further find that, as could be expected, firms of similar size and firms in the same sector tend to be more similar with respect to training decisions than firms of different size or in different sectors. The coefficients on the other control variables – differences in firm age and in managers' education, experience and gender – are mostly non-significant; when they are significant, their coefficient is usually negative, suggesting that greater differences in such firm-level characteristics are associated with closer similarity in outcomes.

5.3. Contractual practices

Next we investigate how contractual practices correlate across firms. We focus on three measures of contractual practices: whether the firm imports inputs directly; whether it sells on credit; and whether it sub-contracts part of its production. Dyadic regression results are shown in Table 5. Because each of these practices raises the risk of contract non-compliance, we see them as symptoms of better governance.

For Sudan we find a negative and highly significant coefficient on the dummy variable indicating whether firms i and j trade directly with each other in the models for direct import, selling on credit, and the principal component. In other words, Sudanese firms that trade with each other tend to have more similar contractual practices. Having a common supplier is also associated with a greater similarity in direct import, although this effect is only statistically significant at the 10% level. For Ethiopia, in contrast, the correlation between network proximity and similarity in contractual practices is weak and non-significant in all specifications except for sub-contracting, for which we obtain a positive coefficient on having a common supplier (col. 3).

The estimated distance coefficients vary considerably across regressions. In two regressions they are positive and significantly different from zero (direct import and selling on credit in Sudan; col. 5 and 6), suggesting that firms located close by have more similar contractual practices. But in two other regressions the coefficients are significantly negative (direct import in Ethiopia and subcontracting in Sudan; col. 1 and 7). For both countries distance is statistically non-significant in the principal component regressions. It is thus hard to see a pattern here, perhaps because the relative importance of strategic substitution and diffusion varies from one contractual practice to another. Regarding control variables, the pattern is similar to what we have observed above: firms of similar size and in the same sector tend to have similar contractual practices, while for other controls results are more mixed.

5.4. Reputation mechanisms

We now examine whether there is any evidence in our data that network links facilitate the diffusion of information on contractual disputes between suppliers and clients. The theoretical literature has emphasized the role that diffusion of information on contractual disputes along social networks plays in the development of modern market institutions (e.g., North 1990, Greif 1993). Consequently we expect to find a strong correlation in answers along social networks.

Using the five questions on the perceived consequences of disputes discussed in Section 3, we code $y_i = 2$ for yes, $y_i = 1$ for maybe / don't know, and $y_i = 0$ for no, and then compute $|y_i - y_j|$ for every pair of firms in the data.[21] Regression results, shown in Table 6a, do not conform to theoretical expectations. Except in a couple of isolated cases where a network regressor is significant (col. 6 and 10 – but with opposite signs), social network variables are not significant. One possible explanation is insufficient power: the five categorical reputation variables contain insufficient information to identify social network coefficients. Does combining the information contained in all five of them lead to better results? Not really: no network variable is significant in the principal component regressions shown in Table 6b. The coefficients on the control variables are also non-significant in the vast majority of cases.

[21] Columns 3-8 in Tables A.1E and A1.S in the Online Appendix show results for alternative specifications in which the reputation variables are defined as binary variables: yes = 1 and maybe or no = 0. The results are similar to those in Table 5.

There are two possible interpretations to these findings: either information about contractual disputes does not diffuse along the kind of social networks we have been able to measure; or information diffuses so well that social links do not matter. One way to identify which of these two interpretations is more likely is to examine the coefficient on the distance variable: even though information may diffuse rapidly along social networks within certain areas, information diffusion need not happen everywhere. This is because strategic complementarities in diffusion create the possibility of multiple equilibria. If this is the case, we expect to find that firms located far away from each other perceive the consequences of contractual disputes differently.

This is not what we find. For Ethiopia, the distance coefficient is negative and highly significant in three of the specifications shown in Table 6a, but positive and significant in the remaining two. The principal component of the five individual variables is negatively and significantly related to distance. For Sudan, the distance coefficient is negative and significant in two out of five individual regressions, and in the remaining cases it is not statistically significant. These findings are difficult to reconcile with the idea of widespread diffusion of contractual information among firms in the same location. If multiple equilibria are present, they seem to coexist within locations, so that some firms recognize there are reputational consequences to contractual disputes, while others in the same location do not.

5.5. Firm performance and growth

So far we have focused on business practices that may diffuse within networks. In this sub-section we focus on firm performance directly: ultimately we care about the adoption of technological and institutional innovations because we believe that they improve firm productivity and performance. While we have found the network effects to be rather weak, some of our empirical results are consistent with strategic substitution. We now investigate whether these results are mirrored in labor productivity and growth rates. In modeling these outcomes, the dependent variable is defined as the absolute difference across firms in the performance indicators. Results are shown in Table 7.

For Ethiopia we find little evidence that firms that are closer in the social network sense have more similar performances: the same supplier dummy is the only statistically significant network variable, but the sign of the estimated coefficient is positive rather than negative. The situation is not improved by combining the available performance information into a single principal component variable. For Sudan, we find that firms that share the same supplier have consistently more similar performances than firms that do not.[22] We also find a significantly negative coefficient on the trade dummy in the employment growth regression, and a negative and significant coefficient on the same client dummy in the one-year revenue growth regression (col. 8).

Similar to previous findings, we obtain some evidence that there is more dissimilarity among firms located near each other: distance has a significantly negative coefficient in two of the regressions. But it is significantly positive in another. The overall conclusion from Table 7 is that network links and geographical proximity are not strongly associated with convergence in performance across firms.

5.6. Heterogeneous diffusion and networks

We now return to the points raised in Section 2.6 related to diffusion patterns across heterogeneous firms. The implication of heterogeneity for diffusion is of substantive economic interest in our setting. Could the reason we find only limited evidence of diffusion be that the firms in our sample are too heterogeneous for diffusion to be relevant? If heterogeneity across firms drastically reduces the scope for diffusion, this implies that African economies are in a poor position to benefit from diffusion since their population of firms is highly heterogeneous.[23]

To investigate if the evidence for diffusion is stronger among pairs of firms in the same sector, we interact our network and distance variables with a dummy for whether firms i and j belong to the same industrial sub-sector and add these interaction terms to the baseline specification. In order to economize on the number of explanatory variables, the same industry dummy is interacted with a single network variable $anylink_{ij}$, which is a dummy variable equal to 1 if there is any link - direct trade, common client or common supplier - between firms i and j.

Results for all outcome variables are shown in Tables A2.E and A2.S in the Online Appendix. For Ethiopia, the sector-network interaction term is statistically non-significant in every specification, while

[22] Due to missing data on value-added for the few Sudanese firms between which there is a direct trading link, we cannot estimate a coefficient on the trade dummy for Sudan in specifications [6] and [10].

[23] Heterogeneity across firms has been increasingly recognized in the recent literature; see e.g. Melitz (2003) and Melitz and Ottaviano (2008).

the sector-distance interaction term is significant in only one specification (formal training; Table A2.E, col. 8; positive sign). For Sudan, the sector-network interaction term is statistically non-significant in every specification, while the sector-distance interaction term is significant in just one specification (direct imports; Table A2.S, col. 10; positive sign).

These results suggest that sector heterogeneity is not the reason behind slow diffusion. They also imply that strategic substitution is equally strong within as across sectors. That is, within local markets, firms tend to be different from each other regardless of sector. Why strategic substitution effects operate across sectors is unclear, but it could be due, for example, to the fact that few consumers in a particular area can afford to buy expensive high-quality products. If there is, say, a high-quality garment firm in an area, it may not be a good idea to set up a high-quality furniture firm next to it if consumers have limited purchasing power for high-quality products. It might be profitable in such a case to produce low-cost furniture, for example. Similar examples could be constructed for the decision to train workers or to offer credit to customers.

We repeat this type of analysis focusing on firm size heterogeneity instead of sector heterogeneity. To this end we interact $anylink_{ij}$ and the distance variable (d_{ij}) with a dummy for whether firms i and j are of similar size, and add these interaction terms to the baseline model.[24] Results are shown in Tables A3.E and A3.S in the Online Appendix. For Ethiopia, the size-network interaction term is statistically non-significant throughout. However, the size-distance term is negative in the vast majority of cases and is often statistically significant. This suggests that strategic substitution is stronger across firms of similar size than across firms of differing size, perhaps because geographically close firms strategically choose to differentiate themselves from each other in order to reduce competition. For Sudan, the network-size interaction term is statistically non-significant throughout, and the size-distance interaction term is significant in just two specifications (Table A3.S, col. 11 and 20). On balance, we find little evidence that size heterogeneity is a likely reason for slow diffusion, and note that the results for Ethiopia lend further support to the idea that strategic substitution may be important.

[24] Firms are defined as having a similar size if the absolute log difference in employment is less than 0.2.

5.7. Market Differentiation within Towns

Finally we investigate how the estimated coefficients on geographical distance change if we add to the baseline specification a dummy variable $sametown_{ij}$ which is equal to 1 if firms i and j are located in the same town and zero otherwise. We wish to establish whether market differentiation within towns drives the result that shorter geographical distance between firms is associated with greater differences in business practices. It seems plausible to suppose that strategic substitution is strongest within towns. If markets are localized so that, irrespective of distance, firms in different towns pose no competitive threat to each other, events in town k will not affect the strategic decisions of firms in town $l \neq k$. In this case, the relevant geographical distinction is whether firms are in the same town or not, so that conditional on $sametown_{ij}$, distance does not matter. By adding $sametown_{ij}$ to the set of explanatory variables, we thus generalize the baseline functional form with respect to the effect of distance.

Results based on this specification, for all outcome variables, are shown in Tables A4.E and A4.S in the Online Appendix. We find that the coefficients on $sametown_{ij}$ are often positive and significant, and the inclusion of $sametown_{ij}$ in the model makes the coefficients on the distance variable smaller and less significant. These results lend some support to the idea that strategic substitution effects operate primarily within towns.

6. Conclusions

In this paper we have documented empirical patterns of correlation in the adoption of innovation and contractual practices among manufacturing firms in Ethiopia and Sudan. Our empirical analysis is based on network data indicating whether any two firms in our sample do business with each other, whether they buy inputs from a common supplier, and whether they sell output to a common client. We also exploit data on firm location in order to investigate if firms located near each other tend to be more similar, or more different, than firms located far apart.

Our results can be summarized as follows: (i) for Sudan, but not for Ethiopia, there is some evidence that network proximity is associated with similar innovation strategies; (ii) for both countries, there is relatively strong evidence that firms located close to each other differ more with respect to innovation than firms that are far apart; (iii) there is no evidence that network proximity is associated with greater similarity in training decisions or labor management across firms; (iv) there is some evidence that firms located close to each other differ more with respect to training decisions than firms located far apart; (iv) for Sudan, but not for Ethiopia, there is some evidence that network proximity is associated with similar contractual practices; (vi) differences in contractual practices across firms are only weakly related to geographical proximity; (vii) there is no evidence that network proximity is associated with greater similarity in the perceived consequences of disputes; (viii) there is some evidence that geographical proximity is associated with greater differences in the perceived consequences of disputes; (ix) for Sudan, but not for Ethiopia, there is evidence that network proximity is associated with similar firm performance; (x) differences in firm performance are only weakly related to geographical proximity.

Our results thus provide limited support for the commonly held idea that firms that are more proximate in a network sense are more likely to adopt similar contractual and technological innovation practices. The strongest results are for innovation and, in the case of Sudan, firm performance. We also find some evidence that, for certain practices, adoption decisions are local strategic substitutes, so that if one firm adopts, other firms located nearby are less likely to do so.

What should we make of these results? First we again note that correlation in practices does not imply diffusion: there may be unobserved contextual effects. Secondly, the evidence presented here does not imply that the diffusion of innovation between firms can never be important or even critical for growth. We only say that diffusion between firms should not be taken for granted: many of the firms in our sample follow antiquated business practices even when some neighboring firms do not. This is consistent with the observation that firms in developing countries often are more heterogeneous than in developed countries (see e.g. Bloom et al. 2012 for evidence that the quality of management practices is more heterogeneous across firms in Brazil, China and India than in the U.S.).

Thirdly, it is possible that we looked for diffusion in the wrong place, i.e., among existing firms. Perhaps the diffusion of innovations takes place not so much because existing firms learn to imitate each other, but rather because new firms emerge that adopt innovative practices. This interpretation is consistent with findings reported in the exporting literature, e.g., there is limited evidence that incumbent firms learn from exporting, but ample evidence that firms that begin exporting are more productive than average, even when they are new entrants (Clerides, Lach and Tybout 1998; Fafchamps, El Hamine and Zeufack 2008). Fourthly, we acknowledge that our data suffers from certain limitations. One potentially important limitation is that the survey asked for a maximum of three clients and suppliers, which implies that we do not have complete coverage of all network links. It is also likely our network link variables are measured with error. This may cause the network effects to be underestimated in our analysis. These caveats notwithstanding, we note that, in several ways, the evidence for diffusion and complementarities is rather much weaker than one might expect, given the emphasis in much of the current policy discussion on diffusion and agglomeration economies as a source of improved firm performance.

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Table 1: Summary statistics

	Ethiopia				Sudan				
1. Firm characteristics	n.obs.	mean	std.dev.	loadings	n.obs.	mean	std.dev.	loadings	Description of variable
Firm age	304	17.93	16.14		401	15.21	14.1		Years
Education of top manager	303	2.71	1.2		399	2.92	1.25		see note (a)
Experience of top manager	304	14.5	9.77		395	17.2	12.93		Years
Any female owner?	304	23.0%			382	15.2%			0=no; 1=yes
Log(firm employment)	304	3.37	1.66		399	2.61	1.14		
2. Technology									
Did the firm introduce a new product last year?	304	34.9%		0.70	391	47.8%		0.58	0 = no, 1 = yes
Did the firm invest in plant & equipment last year?	304	52.0%		0.67	400	45.8%		0.70	
Does the firm do any research and development?	304	13.2%		0.72	388	22.9%		0.74	0 = no, 1 = yes
IT usage	304	0.586	0.762	0.48	401	0.454	0.780	0.74	0 = nothing, 1=email, 2=website
3. Human capital and labor management									
Ratio of non-production workers to total employment	304	27.2%	0.169	0.24	398	42.2%	0.296	0.22	Percentage; see note (b)
Any in-house training of staff last year?	304	28.0%		0.83	397	26.7%		0.80	0 = no, 1 = yes
Staff sent to formal training course last year?	304	28.0%		0.84	398	12.3%		0.80	0 = no, 1 = yes
4. Contractual practices									
Any direct imports of inputs?	304	30.6%		0.67	401	50.9%		0.74	0 = no, 1 = yes
Do you sell on credit?	304	53.3%		0.65	401	64.3%		0.73	0 = no, 1 = yes
Does firm sub-contract production?	302	11.6%		0.33	382	9.4%		0.22	0 = no, 1 = yes

The table continues on the next page.

Table 1 continued

	Ethiopia				Sudan				
5. Reputation mechanism									
If you have a dispute with a customer, will other customers find out?	304	1.049	0.948	0.47	400	0.808	0.934	0.48	0 = no, 1 = maybe, 2 = yes
If another firm has a dispute with a customer, will you refuse to deal with that customer?	304	0.457	0.815	0.67	401	0.783	0.954	0.65	0 = no, 1 = maybe, 2 = yes
If you have a dispute with a dispute, will other firms refuse to deal with that customer?	304	0.474	0.717	0.43	401	0.788	0.899	0.63	0 = no, 1 = maybe, 2 = yes
If you have a dispute with a supplier, will other suppliers find out?	304	0.914	0.926	0.46	401	0.783	0.925	0.69	0 = no, 1 = maybe, 2 = yes
If you have a dispute with a supplier, will other firms refuse to deal with that supplier?	304	0.398	0.682	0.47	401	0.656	0.861	0.64	0 = no, 1 = maybe, 2 = yes
6. Firm performance and growth									
Log(value-added per employee)	284	7.44	1.268	0.20	203	8.680	3.177	0.45	Log USD
Employment growth last 3 years	282	0.225	0.605	0.38	346	0.040	0.784	0.40	Dlog
Revenue growth last year	287	0.251	0.66	0.80	301	0.424	1.598	0.67	Dlog
Revenue growth last 3 years	270	0.493	1.265	0.81	259	-0.471	2.212	0.80	Dlog

Notes: (a) 1=less than secondary, 2=secondary, 3=vocational, 4=university. (b) Non-production workers include professionals, managers, administrators, sales personnel.

Table 2. Dyadic Data

	Ethiopia	Sudan
Number of unique enterprise pairs	46,056	80,200
i & j trade with each other (number of pairs)	60	5
i & j have a common supplier (number of pairs)	481	171
i & j have a common client (number of pairs)	273	678
Average distance between i & j (kilometers)	282	421
Minimum distance between i & j (kilometers)	0	0
Maximum distance between i & j (kilometers)	876	1,770
i & j are in the same sector (number of pairs)	13,033	9,490

Table 3. Correlates of Dyadic Differences: Technology Acquisition

	Ethiopia					Sudan				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	Did the firm introduce a new product last year?	Did the firm invest in plant & equipment last year?	Does the firm do any research and development ?	IT usage (0 = nothing, 1=email, 2=website)	First common factor	Did the firm introduce a new product last year?	Did the firm invest in plant & equipment last year?	Does the firm do any research and development ?	IT usage (0 = nothing, 1=email, 2=website)	First common factor
	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$
i & j trade with each other	0.0492	-0.0471	0.0957	-0.0703	0.0792	0.0147	-0.205	-0.339**	0.451	-0.302
	(0.126)	(0.117)	(0.108)	(0.188)	(0.240)	(0.350)	(0.326)	(0.140)	(0.572)	(0.237)
i & j have common supplier	-0.0175	-0.00152	0.0461	-0.0630	-0.0202	-0.0799	-0.154*	-0.183***	-0.272**	-0.310**
	(0.0400)	(0.0456)	(0.0408)	(0.0660)	(0.0684)	(0.0740)	(0.0791)	(0.0648)	(0.109)	(0.130)
i & j have common client	0.0666	-0.0259	0.0110	0.0602	-0.0645	0.0247	0.00539	0.123***	0.229***	0.178*
	(0.0586)	(0.0705)	(0.0692)	(0.0948)	(0.0973)	(0.0223)	(0.0336)	(0.0350)	(0.0607)	(0.101)
log Distance btw i & j	-0.00478**	-0.00129	-0.0104*	-0.0173**	-0.0154*	0.000372	-0.000603	-0.0122***	-0.0221***	-0.0176***
	(0.00238)	(0.00175)	(0.00543)	(0.00694)	(0.00833)	(0.00166)	(0.00223)	(0.00301)	(0.00531)	(0.00601)
i & j belong to same sector	-0.0323*	-0.0561**	-0.0218	-0.0567**	-0.101***	0.00460	-0.00129	-0.0133	-0.0955***	-0.0299
	(0.0171)	(0.0260)	(0.0141)	(0.0280)	(0.0345)	(0.0101)	(0.0134)	(0.0185)	(0.0302)	(0.0310)
Abs diff firm age	-0.000611	-0.00079***	-0.00100	-0.00187	-0.00322*	0.000121	0.000259	0.000361	-0.00318***	-0.00102
	(0.000572)	(0.000273)	(0.00105)	(0.00131)	(0.00173)	(0.000283)	(0.000369)	(0.00103)	(0.00120)	(0.00134)
Abs diff managers' education	0.00863	0.0141	-0.00995	0.0644**	0.0475**	0.00567	0.0409***	0.00756	0.0189	0.0664***
	(0.00906)	(0.00956)	(0.00833)	(0.0286)	(0.0226)	(0.00616)	(0.0144)	(0.00927)	(0.0167)	(0.0235)
Abs diff managers' experience	-0.000763	0.000110	-0.000577	-0.000880	-0.00312*	-5.03e-06	-0.000301	-0.000411	-2.72e-05	-0.000124
	(0.000897)	(0.000386)	(0.00132)	(0.00151)	(0.00169)	(0.000287)	(0.000265)	(0.00116)	(0.00218)	(0.00240)
Owners' genders differ	-0.00147	0.000586	-0.00558	0.0904**	0.00909	0.00113	0.0354*	0.0978**	0.435***	0.241***
	(0.0186)	(0.00596)	(0.0285)	(0.0454)	(0.0482)	(0.00629)	(0.0187)	(0.0396)	(0.0909)	(0.0751)
Abs diff log employment	0.00623	0.0219**	0.0304**	0.189***	0.121***	0.0232**	0.0525***	0.0394**	0.167***	0.198***
	(0.00943)	(0.00903)	(0.0137)	(0.0264)	(0.0298)	(0.00912)	(0.0143)	(0.0175)	(0.0421)	(0.0457)

Note: The table shows OLS results. A constant is included in all specifications. The numbers in ( ) are bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 4. Correlates of Dyadic Differences: Human Capital and Labor Management

	Ethiopia				Sudan			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Ratio of non-production workers to total employment $\lvert y_i-y_j \rvert$	Any in-house training of staff last year? $\lvert y_i-y_j \rvert$	Staff sent to formal training course last year? $\lvert y_i-y_j \rvert$	First common factor $\lvert y_i-y_j \rvert$	Ratio of non-production workers to total employment $\lvert y_i-y_j \rvert$	Any in-house training of staff last year? $\lvert y_i-y_j \rvert$	Staff sent to formal training course last year? $\lvert y_i-y_j \rvert$	First common factor $\lvert y_i-y_j \rvert$
i & j trade with each other	-0.0218	0.0807	-0.0451	-0.0514	-0.0859	-0.121	0.368	-0.200
	(0.0334)	(0.107)	(0.133)	(0.220)	(0.0879)	(0.263)	(0.340)	(0.336)
i & j have common supplier	0.0136	0.0439	0.0113	0.0857	-0.000342	0.0313	-0.0195	0.0743
	(0.0141)	(0.0473)	(0.0413)	(0.0799)	(0.0442)	(0.0842)	(0.0549)	(0.147)
i & j have common client	0.0161	0.0396	0.127**	0.215*	-0.0403	0.0826**	0.0210	0.174
	(0.0237)	(0.0742)	(0.0627)	(0.124)	(0.0288)	(0.0375)	(0.0713)	(0.142)
log Distance btw i & j	-0.00193	-0.0168***	-0.0153***	-0.0251***	0.00320	-0.00803**	-0.000397	-0.00612
	(0.00159)	(0.00299)	(0.00291)	(0.00824)	(0.00195)	(0.00315)	(0.00434)	(0.00847)
i & j belong to same sector	-0.00244	-0.0173	-0.0304*	-0.0480*	0.00212	-0.0341*	-0.00869	-0.0644*
	(0.00491)	(0.0123)	(0.0177)	(0.0262)	(0.00623)	(0.0189)	(0.0159)	(0.0374)
Abs diff firm age	-0.000149	-0.000207	0.00180	0.00225	-0.000522*	-0.000423	0.000882	0.000211
	(0.000336)	(0.000720)	(0.00114)	(0.00210)	(0.000299)	(0.000662)	(0.000992)	(0.00183)
Abs diff managers’ education	-0.00392*	0.0112	0.00644	0.0328	0.00381	-0.000336	-0.0145***	-0.0148
	(0.00237)	(0.0184)	(0.0160)	(0.0351)	(0.00339)	(0.00576)	(0.00474)	(0.0131)
Abs diff managers’ experience	0.000213	-0.00167**	-0.000966	-0.000834	0.000259	-0.00155***	0.000637	-0.000751
	(0.000477)	(0.000803)	(0.000838)	(0.00165)	(0.000598)	(0.000501)	(0.00108)	(0.00185)
Owners’ gender differ	0.00767	0.0181	-0.0120	-0.00539	0.0298*	0.0446	0.0847	0.204*
	(0.0111)	(0.0258)	(0.0177)	(0.0403)	(0.0176)	(0.0375)	(0.0542)	(0.114)
Abs diff log employment	0.0110**	0.0876***	0.0987***	0.230***	0.0182***	0.0567***	0.0780***	0.207***
	(0.00490)	(0.0155)	(0.0143)	(0.0309)	(0.00569)	(0.0170)	(0.0205)	(0.0499)

Note: The table shows OLS results. A constant is included in all specifications. The numbers in ( ) are bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 5. Correlates of Dyadic Differences: Contractual Practices

	Ethiopia				Sudan			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Any direct imports of inputs? $\lvert y_i-y_j \rvert$	Do you sell on credit? $\lvert y_i-y_j \rvert$	Does firm sub-contract production? $\lvert y_i-y_j \rvert$	First common factor $\lvert y_i-y_j \rvert$	Any direct imports of inputs? $\lvert y_i-y_j \rvert$	Do you sell on credit? $\lvert y_i-y_j \rvert$	Does firm sub-contract production? $\lvert y_i-y_j \rvert$	First common factor $\lvert y_i-y_j \rvert$
i & j trade with each other	0.0245	-0.0122	0.110	0.114	-0.423**	-0.436**	0.0488	-0.813**
	(0.117)	(0.105)	(0.119)	(0.252)	(0.174)	(0.177)	(0.331)	(0.380)
i & j have common supplier	-0.0186	-0.00130	0.0755**	-0.116	-0.145*	0.0150	0.0479	0.0304
	(0.0501)	(0.0404)	(0.0366)	(0.0751)	(0.0762)	(0.0789)	(0.0812)	(0.135)
i & j have common client	0.0838	-0.0139	0.0765	0.184	-0.0457	-0.00759	-0.0310	-0.0390
	(0.0572)	(0.0524)	(0.0702)	(0.124)	(0.0422)	(0.0430)	(0.0651)	(0.0998)
log Distance btw i & j	-0.0123**	-0.000254	0.00530	-0.00906	0.00814***	0.00915**	-0.00867**	0.00854
	(0.00572)	(0.00143)	(0.00671)	(0.00796)	(0.00314)	(0.00422)	(0.00417)	(0.00923)
i & j belong to same sector	-0.0397**	-0.0171	-0.00192	-0.0368	-0.0299*	-0.00602	-0.00572	-0.0459
	(0.0160)	(0.0155)	(0.00908)	(0.0286)	(0.0157)	(0.0137)	(0.0131)	(0.0279)
Abs diff firm age	-0.000424	0.000480	-0.00207***	-0.00417***	0.000105	-8.22e-05	-0.000668	0.000303
	(0.000804)	(0.000556)	(0.000636)	(0.00145)	(0.000240)	(0.000582)	(0.000563)	(0.00107)
Abs diff managers' education	0.0299	0.000668	-0.0204***	0.0373	0.0215*	0.00583	0.00164	0.0278
	(0.0199)	(0.00500)	(0.00748)	(0.0279)	(0.0112)	(0.00657)	(0.00477)	(0.0173)
Abs diff managers' experience	-0.00152*	0.000485	-0.00178	0.00456**	-9.80e-05	-0.000212	-0.000397	-0.000631
	(0.000779)	(0.000642)	(0.00120)	(0.00210)	(0.000305)	(0.000728)	(0.000633)	(0.00121)
Owners' gender differ	0.0457	0.00391	0.0235	0.0402	0.00257	-0.0164	0.0109	-0.00210
	(0.0297)	(0.00948)	(0.0306)	(0.0420)	(0.00677)	(0.0126)	(0.0382)	(0.0392)
Abs diff log employment	0.131***	0.00259	0.0150	0.138***	0.0659***	0.00494	-0.00398	0.0977***
	(0.0150)	(0.00473)	(0.0132)	(0.0312)	(0.0145)	(0.00781)	(0.0123)	(0.0264)

Note: The table shows OLS results. A constant is included in all specifications. The numbers in ( ) are bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 6a. Correlates of Dyadic Differences: Perceived Consequences of Disputes

	Ethiopia					Sudan				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	If you have a customer dispute, will other customers find out?	If other firm has a customer dispute, will you refuse to deal with customer?	If you have a customer dispute, will other firms refuse to deal with customer?	If you have a supplier dispute, will other suppliers find out?	If you have supplier dispute, will other firms refuse to deal with supplier?	If you have a customer dispute, will other customers find out?	If other firm has a customer dispute, will you refuse to deal with customer?	If you have a customer dispute, will other firms refuse to deal with customer?	If you have a supplier dispute, will other suppliers find out?	If you have supplier dispute, will other firms refuse to deal with supplier?
	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$
i & j trade with each other	-0.187	0.0330	-0.0502	0.124	0.0158	-0.704*	-0.209	0.557	0.280	0.366
	(0.206)	(0.178)	(0.166)	(0.207)	(0.161)	(0.373)	(0.622)	(0.515)	(0.614)	(0.637)
i & j have common supplier	-0.0159	0.0321	-0.0611	-0.0335	-0.0490	-0.154	-0.0828	-0.0368	-0.105	-0.113
	(0.0914)	(0.0896)	(0.0663)	(0.0914)	(0.0745)	(0.166)	(0.164)	(0.145)	(0.141)	(0.164)
i & j have common client	0.0480	0.0293	-0.0588	0.00750	0.0853	0.0580	0.0328	-0.104	-0.105	0.112**
	(0.0795)	(0.129)	(0.0990)	(0.0916)	(0.111)	(0.0557)	(0.0669)	(0.116)	(0.111)	(0.0475)
log Distance btw i & j	0.0110**	-0.0198***	-0.0171***	0.0104*	-0.0268***	-0.00683**	-0.00611**	-0.000383	-0.00298	-0.00474
	(0.00562)	(0.00578)	(0.00487)	(0.00544)	(0.00530)	(0.00306)	(0.00310)	(0.00323)	(0.00282)	(0.00475)
i & j belong to same sector	-0.00832	-0.0163	0.00167	-0.0201	-0.0113	-0.00888	-0.0213	-0.00301	-0.00127	0.0275*
	(0.0272)	(0.0258)	(0.0187)	(0.0254)	(0.0186)	(0.0213)	(0.0281)	(0.0194)	(0.0186)	(0.0164)
Abs diff firm age	-0.000181	-0.000755	-0.00166	0.000648	5.85e-05	-0.000854	0.000383	0.000530	-0.000695	0.00154
	(0.000404)	(0.00180)	(0.00109)	(0.000791)	(0.00149)	(0.000725)	(0.00106)	(0.000944)	(0.000812)	(0.00156)
Abs diff managers' education	-0.00403	-0.00790	-0.00932	-0.00511	-0.00802	0.000897	0.00325	0.00229	-0.00144	0.00723
	(0.00757)	(0.0117)	(0.0110)	(0.00884)	(0.0112)	(0.00726)	(0.00754)	(0.00795)	(0.00705)	(0.00943)
Abs diff managers' experience	0.000140	-0.00130	0.00309	0.00114	0.00286	0.000672	0.000130	-0.00113	-0.000772	-0.00118
	(0.000932)	(0.00303)	(0.00264)	(0.00151)	(0.00312)	(0.000804)	(0.000917)	(0.000703)	(0.000948)	(0.00144)
Owners' gender differ	-0.00783	-0.00611	0.0600	0.0184	0.0541	0.0298	0.00190	-0.0103	0.0157	0.0261
	(0.0131)	(0.0558)	(0.0550)	(0.0299)	(0.0597)	(0.0332)	(0.0341)	(0.0252)	(0.0387)	(0.0461)
Abs diff log employment	0.00230	-0.00417	0.00893	0.0151	0.0102	0.0219	-0.0130	-0.00426	-0.0267***	-0.0311**
	(0.00661)	(0.0180)	(0.0150)	(0.0132)	(0.0190)	(0.0157)	(0.0113)	(0.0114)	(0.00875)	(0.0133)

Note: The table shows OLS results. A constant is included in all specifications. The numbers in ( ) are bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 6b. Correlates of Dyadic Differences: Perceived Consequences of Disputes, First Common Factor

	[1] Ethiopia	[2] Sudan
	$\lvert y_i - y_j \rvert$	$\lvert y_i - y_j \rvert$
i & j trade with each other	-0.0757	0.339
	(0.146)	(0.782)
i & j have common supplier	0.00852	0.0100
	(0.0841)	(0.151)
i & j have common client	0.0573	0.0579
	(0.118)	(0.0874)
log Distance btw i & j	-0.0152**	0.00614
	(0.00734)	(0.00704)
i & j belong to same sector	-0.0130	0.0163
	(0.0258)	(0.0188)
Abs diff firm age	-0.000904	-0.00117
	(0.00168)	(0.000985)
Abs diff managers' education	-0.00478	0.00139
	(0.0133)	(0.00863)
Abs diff managers' experience	0.00290	0.000487
	(0.00340)	(0.00169)
Owners' gender differ	0.00676	0.0369
	(0.0613)	(0.0481)
Abs diff log employment	0.00317	-0.0111
	(0.0164)	(0.0136)

Note: The table shows OLS results. A constant is included in all specifications. The numbers in ( ) are bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Table 7. Correlates of Dyadic Differences: Firm Performance and Growth

	Ethiopia					Sudan				
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	Log(value-added per employee) $\lvert y_i-y_j \rvert$	Labor. growth last 3 years $\lvert y_i-y_j \rvert$	Revenue growth last year $\lvert y_i-y_j \rvert$	Revenue growth last 3 years $\lvert y_i-y_j \rvert$	First common factor $\lvert y_i-y_j \rvert$	Log(value-added per employee) $\lvert y_i-y_j \rvert$	Labor growth last 3 years $\lvert y_i-y_j \rvert$	Revenue growth last year $\lvert y_i-y_j \rvert$	Revenue growth last 3 years $\lvert y_i-y_j \rvert$	First common factor $\lvert y_i-y_j \rvert$
i & j trade with each other	-0.0758	-0.0850	-0.0437	0.338	0.165		-0.534**	-0.413	1.652	
	(0.284)	(0.130)	(0.121)	(0.657)	(0.424)		(0.221)	(0.676)	(2.483)	
i & j have common supplier	-0.106	0.0152	0.246**	0.00522	0.109	-1.651***	-0.277**	-0.904***	-0.711**	-0.480**
	(0.111)	(0.0668)	(0.113)	(0.129)	(0.142)	(0.453)	(0.122)	(0.337)	(0.350)	(0.203)
i & j have common client	-0.182	-0.0136	0.195	-0.0119	0.113	-0.986	0.0900	-0.586***	0.307	-0.00893
	(0.136)	(0.0929)	(0.151)	(0.202)	(0.195)	(0.660)	(0.139)	(0.203)	(0.443)	(0.216)
log Distance btw i & j	-0.0247**	0.0139	0.0179*	0.0193	0.0235	-0.0612	-0.0173	-0.0515**	-0.0515	-0.0103
	(0.0122)	(0.0106)	(0.0108)	(0.0168)	(0.0149)	(0.0386)	(0.0111)	(0.0240)	(0.0346)	(0.0187)
i & j belong to same sector	-0.0819*	0.00508	-0.00350	-0.0243	-0.0130	-0.135	-0.0555	-0.0465	-0.0624	-0.0756
	(0.0447)	(0.0247)	(0.0185)	(0.0515)	(0.0349)	(0.156)	(0.0394)	(0.0680)	(0.133)	(0.0869)
Abs diff firm age	-0.00314	0.00267	-0.00260***	-0.00564***	-0.00397***	-0.00493	0.00112	0.00862	0.00458	0.00602
	(0.00200)	(0.00347)	(0.000730)	(0.00161)	(0.00146)	(0.00781)	(0.00216)	(0.00651)	(0.00746)	(0.00459)
Abs diff managers’ education	-0.00722	0.00380	-0.00917	0.00885	-0.0164	0.0460	-0.00466	-0.0333	-0.0201	0.0114
	(0.0280)	(0.0117)	(0.0116)	(0.0310)	(0.0174)	(0.0472)	(0.0116)	(0.0228)	(0.0268)	(0.0251)
Abs diff managers’ experience	0.000671	7.15e-06	-0.00272	-0.00171	-0.00410	-0.00732	0.000766	0.00303	-0.00385	-0.00186
	(0.00321)	(0.00226)	(0.00204)	(0.00453)	(0.00284)	(0.00578)	(0.00132)	(0.00695)	(0.00580)	(0.00313)
Owners’ gender differ	0.121	0.103	-0.0813**	-0.220***	-0.110*	0.375	-0.00723	-0.161	0.0558	-0.138
	(0.0932)	(0.0669)	(0.0389)	(0.0686)	(0.0582)	(0.582)	(0.0614)	(0.134)	(0.275)	(0.0960)
Abs diff log employment	0.0786**	0.00792	-0.0257**	-0.0375	-0.0235	0.00718	0.0654**	0.0906	0.102	0.0611
	(0.0311)	(0.0242)	(0.0117)	(0.0360)	(0.0223)	(0.110)	(0.0258)	(0.0709)	(0.114)	(0.0600)

Note: The table shows OLS results. A constant is included in all specifications. The numbers in ( ) are bootstrapped standard errors that are robust to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10%, 5% and 1% level is indicated by *,** and ***, respectively.

Figure 1. Survey locations in Ethiopia

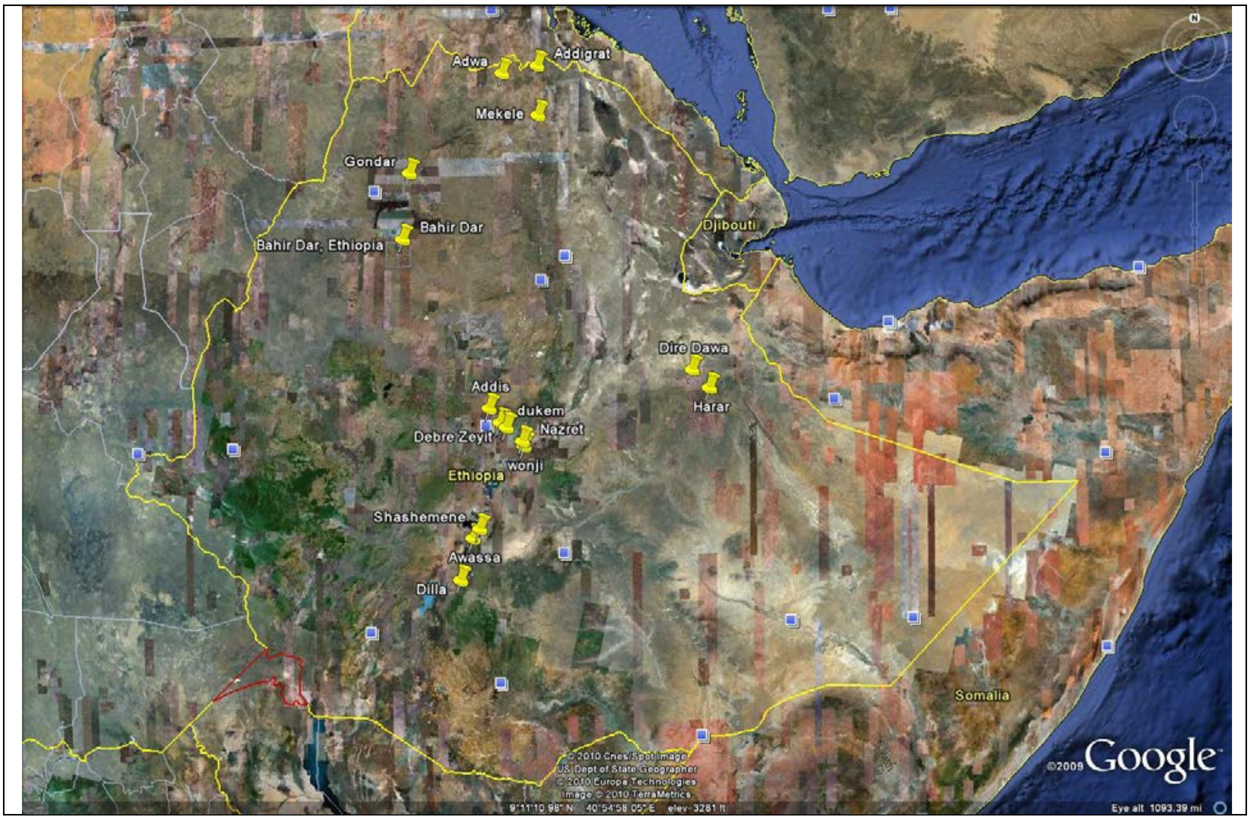

Figure 2. Survey locations in Sudan