Network Proximity and Business Practices in African Manufacturing

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Abstract: Patterns of correlation in innovation and contractual practices among manufacturing firms in Ethiopia and Sudan are documented. Network data indicating whether any two firms in the sample do business with each other, buy inputs from a common supplier, or sell output to a common client are used for the analysis. Only limited support is found 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.

JEL classification codes: O1, D2, D4.

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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). Since Griliches (1958), the dominant model of technology adoption 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. Delays may also arise because of funding constraints or adoption costs -- e.g., learning-by-doing, experimentation, and adjustment costs. As a result, pockets of backward technology can subsist.

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, Rauch, and Tocoiand 2012). 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 (Kraay, 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 (e.g., Griliches and Lichtenberger 1984; Young and Burke 2001), much of the existing literature on manufacturing firms in developing countries remains descriptive and relies principally on case studies (e.g., Sutton and Kellow 2010; Sutton and Kpentey 2012; Sonobe and Otsuka 2011).

In this paper we offer statistical evidence on the diffusion of innovations among manufacturing firms in Ethiopia and Sudan.[1] Our approach is to examine whether innovative business practices are correlated more strongly between firms that are relatively close in a network or market sense. 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. This suggests that some adoption decisions are local strategic substitutes: if some firms adopt a certain practice, this seems to 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 -- Research and Development (R&D), vocational training to workers -- are those most vulnerable to free riding by other firms. Overall, the evidence for diffusion and complementarities is 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 in Africa (e.g. Collier, 2007; Page, 2012).

The paper is organized as follows: Section 2 discusses the conceptual framework and some key

methodological issues; Section 3 describes the econometric testing strategy; Section 4 provides information about the data; Section 5 presents econometric results; and Section 6 concludes.

I. Conceptual Framework: Diffusion in Networks

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 define the network matrix as $G \equiv [g_{ij}]$, $g_{ii} = 0$. There are N agents. We follow Liu et al. (2012) and Bramoullé and Kranton (2011) and write the payoff of agent i as:

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

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

$$y_i = \alpha_i + \rho g_i y. \qquad (1)$$

The parameters α_i, γ and ρ are now straightforward to interpret: α_i is a profitability parameter; ρ indicates whether actions are strategic complements ($\rho > 0$) strategic substitutes ($\rho < 0$) or neither complements nor substitutes ($\rho = 0$); and γ indicates whether there are positive externalities ($\gamma > 0$), negative externalities ($\gamma < 0$) or neither positive nor negative externalities ($\gamma = 0$). Note that it is possible for externalities to be negative ($\gamma < 0$) while actions are strategic complements ($\rho > 0$), and vice versa.

Equilibria are action vectors y that solve the system of Kuhn-Tucker conditions combining first order conditions (1) with $y_i \geq 0 \quad \forall i \in N$. Interior solutions satisfy:

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

where $A \equiv [\alpha_1, ... \alpha_N]$. When actions are strategic complements ($\rho > 0$) 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.[3] 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.[4]

Bramoullé and Kranton (2011) characterize the equilibria that arise in network games with strategic substitutes ($\rho < 0$). They show that the equilibrium configuration ultimately depends on the lowest (i.e., most negative) eigenvalue of G. With strategic substitutes, most equilibria have some agents setting their $y_i = 0$ while (some of) their neighbors choose a strictly positive y_i, i.e. the 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 $\tilde{y} \equiv y - E(y)$

$= \left(I - \rho G\right)^{-1} \tilde{A}$ with $\tilde{A} = A - E(A)$. The covariance matrix of $\tilde{y}$ is:

$$(2) \qquad Cov(\tilde{y}) = E\left(\left(I - \rho G\right)^{-1} \tilde{A}\tilde{A}'\left(I - \rho G\right)^{-1}\right),$$

where the α_i's that enter matrix A are unobserved to the researcher. If the α_i's are independent and identically distributed (i.i.d.), $E\left(\tilde{A}\tilde{A}'\right) = \sigma^2 I$ and the above expression boils down to:

$$Cov(\tilde{y}) = \sigma^2 E\left((I - \rho G)^{-1}(I - \rho G)^{-1}\right),$$

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. In contrast, if $\rho = 0$ and the α_i's are i.i.d., then $Cov(\tilde{y})$ is a diagonal matrix and $Cov(\tilde{y}_i, \tilde{y}_j) = 0$ for $i \neq j$. It is therefore possible to test $\rho \neq 0$ by comparing whether values of y are more, or less, similar for linked than unlinked pairs. However, if $E\left(\tilde{A}\tilde{A}'\right)$ is not a diagonal matrix (i.e. the α_i's are correlated), it is possible for $Cov(\tilde{y}_i, \tilde{y}_j) \neq 0$ even when $\rho = 0$. This is an important caveat to keep in mind when interpreting our results: similar practices could be due either to strategic complementarity ρ or to correlation in α_i's, i.e., a correlation in the profitability of taking action y between linked firms -- what Manski (1993) calls contextual effects. By a similar reasoning, dissimilar practices can be due to strategic substitution or negative correlation in α_i's.

Strategic complementarity could arise for a variety of reasons. For example, the desire to imitate others or to conform to a social norm, possibly reinforced by peer pressure (e.g., Young and Burke 2001), may result in complementarity. Another possibility is that the adoption of an innovation by others lowers the output price, which forces agent i to adopt in order to remain competitive. Strategic substitution, in contrast, would arise if, when agent j takes action y_j, the incentive for individual i to take the same action weakens. For example, the possibility of free-riding has long been recognized in experimentation: agents may wait for their friends and neighbors to experiment with a new technology before deciding whether to adopt it themselves (e.g., Foster and Rosenzweig 1995 for an application to farming). Training of workers is

another possible area where strategic substitution may be important: if firm j decides to train its workers, firm i may decide to try to poach them instead of training its own workers. A desire to avoid competition could be another driving force of strategic substitution: if firm j decides to target its products to the high-end market, for example, it could be optimal for firm i to target its products to the low-end market.

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 $\rho \geq 0$, 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.

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 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 strategically choose to focus on niche products and markets that are poorly served by other firms in order to avoid competition (e.g., Fafchamps 1994). Such behavior may lead to differences, rather than similarities, in the technology decisions of firms in the same location, for example.
2) *Internal organization*: Innovations in the internal organization of the firm should follow a similar logic: if other firms gain a competitive edge by adopting a better organizational structure, 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 or choose R&D strategically as to avoid competition.
4) *Vocational training of workers*: If better trained workers raise productivity, competition between firms will lead them to train workers if new recruits are insufficiently qualified. Firms 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. However, we cannot a priori rule out strategic substitution, e.g. if firms

purchase inputs from the importing firm rather than importing themselves.

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 a reputational sanction 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. 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 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.

So far we have discussed adoption of practices. It is also possible to investigate payoffs directly, e.g., firm performance and growth. In Section 1 in the Online Appendix we derive an expression for the covariance in profits across firms.[5] We show that if $\gamma \neq 0$, i.e., if externalities are present, positive externalities manifest themselves as proximate firms having

similar performance while negative externalities imply dissimilar performance. We also show 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.

Diffusion across heterogeneous firms

Firms are heterogeneous and diffusion patterns across firms are likely to depend on enterprise characteristics.[6] For example, the scope for the diffusion of innovations between sectors may be limited if they use technologies that are very 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 across firms in the profitability parameter α_i. If adoption is dichotomous, the likelihood of adopting can be written $\lambda(\alpha_i + \rho g_i y)$ 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. In this example, correlation in adoption between firms within the same sector is not affected by network proximity, while correlation in adoption between firms in different sectors is stronger between linked firms. It is also possible 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. Heterogeneity is also important from a methodological point of view. If we fail to take into account heterogeneity, we will underestimate the importance of networks 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.

II. 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 if they are close in a network and geographical sense, i.e., if some or all elements of $\mathbf{g}_{ij}$ are equal to one or if d_{ij} is small. For this purpose we estimate models of the form:

$$\left|y_i - y_j\right| = \mathbf{g}_{ij}\boldsymbol{\theta} + \omega d_{ij} + |\mathbf{x_i} - \mathbf{x_j}|\boldsymbol{\beta} + u_{ij} \quad (3)$$

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 distance and outcome similarities, $|\mathbf{x_i} - \mathbf{x_j}|$ is a vector of absolute differences in control variables $\mathbf{x}$ included to reduce omitted variable bias, $\boldsymbol{\beta}$ is a vector of parameters, and u_{ij} is an error term.[7] A negative θ_m in (3) 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 would mean that linked or nearby firms are more dissimilar. If y is 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. A positive β means that firms that share a similar *x* tend to have more similar *y*.

Importantly, a 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 $(corr(\alpha_i, \alpha_j) > 0)$ not adequately controlled for by $|\mathbf{x_i} - \mathbf{x_j}|$. If unobserved contextual effects

are more strongly correlated across linked firms, they would bias θ_m below 0. Hence if we find a significantly negative estimate of θ_m, it may be due either to diffusion or to unobserved contextual effects. However, if 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 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 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.

Equation (3) 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 not independent since the residual u_{ij} is correlated with u_{ik}. To compute standard errors that are robust to correlation in the error term across firms, we use a bootstrapping procedure which is described

in Section 1 in our Online Appendix.

III. 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. The data on the Ethiopian firms were collected as part of the Ethiopia Investment Climate Survey, implemented by the Ethiopian Development Research Institute (EDRI) in mid-2006.[8] The survey covered 14 major cities located in seven regions of Ethiopia; 42% of the observations come from Addis Ababa. 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. 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.[9] The data were thus collected before South Sudan seceded from Sudan in July 2011, and our sample therefore includes firms in what is now South Sudan (see footnote 1). 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 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%). Microenterprises are not covered. After deleting observations with too many missing values, we obtain a sample of 304 firms for Ethiopia and 401 firms for Sudan.[10] This forms our baseline sample.[11]

Summary statistics are shown in Table 1. Variables constituting our control vector are presented first. 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 female-headed businesses have been shown to be less growth oriented (e.g. de Mel, McKenzie and Woodruff, 2009; 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, and 2.91 for Sudan (18 employees).

Next we report information on firm practices. We focus first on 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. We thus construct an additional dyadic dependent variable from the first principal components. The factor loadings for each category are reported in Table 1.

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. 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.

Information on labor management and investment in human capital is presented next. We find a higher ratio of non-production workers to total employment 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.[12] In both countries a substantial minority of firms had provided in-house or external training to their workers, but the majority had not.

The next panel of Table 1 covers contractual practices. Firms were asked whether they import inputs directly from abroad. 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. 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.

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. Similar results have been reported by Bigsten et al. (2000) and Fafchamps (2004) for African manufacturing.

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.[13] Using the information from this module, we construct simple measures of network proximity between firms within the two samples. Summary statistics for 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*) pair, 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 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 last proximity dummy is distance d_{ij}, defined as the log of the distance between i and j plus one.

IV. Empirical Analysis

Our objective is to test whether outcomes and practices related to technology, human capital, contracting, and reputation are more similar among firms that are close to each other, either in a network sense or geographically. To this end we estimate the parameters of the model (3). Our estimation technique is linear regression (OLS), and standard errors are bootstrapped to be robust to heteroskedasticity and correlation in error terms across firms. We refer to presented results as baseline results. Additional results are available in the Online Appendix.

Innovation and R&D

We begin by investigating the association between geographical and network proximity and innovation and R&D. 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 they do any R&D. A fourth outcome variable is constructed based on a firm-level measure of the extent of IT usage: 0 if IT is not used at all; 1 if the firm uses e-mail; and 2 if the enterprise has a business website.[14] 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 results using the first principal component of all four categories to construct the dyadic dependent variable.

The estimated network proximity coefficients differ across the two countries. For Ethiopia, the dummies for whether i and j trade with each other, have a common supplier, and a common client are 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 principal component (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 that trade with each other report the same answer (yes or no) to the question on whether any money was spent on R&D 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.

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 least at the 10% level in four of these. Hence geographical proximity tends to be associated with greater differences in innovation practices. 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 principal component (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 explanatory power. The estimated coefficients on the same sector dummy are negative in all specifications except [6], and are 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, suggesting that firms of similar size tend to adopt similar practices. There is also 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.

Human capital and labor management

Table 4 shows results for our regressions on labor management and investment in human capital. We find no evidence that network proximity is associated with greater similarity in training decisions or labor management across firms. In fact, 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; Glaeser 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. 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. Another possibility is that firms located in the same place decide to differentiate their output, which may lead to differences in technology and human capital demand. 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.

Contractual practices

Next we investigate how three measures of contractual practices correlate across firms: whether the firm imports inputs directly; whether it sells on credit; and whether it sub-contracts part of its production. Results are shown in Table 5.

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 first principal component. Sudanese firms that trade with each other thus 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 regressions modeling the difference in the first principal component. 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.

Reputation mechanisms

We now examine whether there is any evidence 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.[15] 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 may 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.

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. Dyadic differences in the principal component based on the five individual variables are 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.

Firm performance and growth

So far we have focused on business practices that may diffuse within networks. We have also

investigated whether the results above are mirrored in labor productivity and growth rates, our measures of firm performance. Results for specifications in which the dependent variable is defined as the absolute difference across firms in these performance indicators are shown in Section 4 in the Online Appendix. For Ethiopia we find little evidence that firms that are closer in the social network sense have more similar performance. For Sudan, we find evidence that firms that share the same supplier have more similar performance than firms that do not. The other results related to network links and geographical distance are weak, however. The overall conclusion from our analysis is that network links and geographical proximity are not strongly associated with convergence in performance across firms.

Heterogeneous diffusion and networks

We now return to the points raised in Section I related to diffusion patterns across heterogeneous firms. Could the reason we find only limited evidence of diffusion be that the firms are too heterogeneous? 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 S2.E and S2.S in the Online Appendix. For Ethiopia, the sector-network interaction term is statistically non-significant in every specification, while the sector-distance interaction term is significant in only one specification (formal training; Table S2.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 S2.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.

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.[16] Results are shown in Tables S3.E and S3.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 three specifications (Table S3.S, col. 6, 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.

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 S4.E and S4.S in the Online Appendix. For Sudan, the coefficients on $sametown_{ij}$ are always negative whenever they are significant, suggesting that strategic substitution effects do not primarily operate within towns. For Ethiopia, the picture is more mixed: we obtain positive and significant coefficients in five of the regressions shown in Table S4.E col. 1-24, and negative and significant coefficients in three. Overall, the support for the idea that strategic substitution effects operate primarily within towns is thus quite limited.

V. 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, buy inputs from a common supplier, or 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; and (ix) except for supplier-based links in Sudan, differences in firm performance are only weakly related to geographical and network proximity. Overall, the strongest results are for innovation.

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. 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. But 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 have 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 sources of improved firm performance.

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TABLE 1. Summary Statistics

	Ethiopia				Sudan			
	Obs	Mean	Std.dev.	Loadings	Obs	Mean	Std.dev.	Loadings
1. Firm characteristics								
Firm age (years)	304	17.93	16.1		401	15.21	14.1	
Education of top manager[(a)]	303	2.71	1.20		399	2.92	1.25	
Experience of top manager (years)	304	14.5	9.77		395	17.2	12.9	
Any female owner?[(b)]	304	0.23			382	0.15		
Log(firm employment)	304	3.37	1.66		399	2.61	1.14	
2. Innovation and R&D								
Did the firm introduce a new product last year?[(b)]	304	0.35		0.70	391	0.48		0.58
Did the firm invest in plant & equipment last year?[(b)]	304	0.52		0.67	400	0.46		0.70
Does the firm do any research and development?[(b)]	304	0.13		0.72	388	0.23		0.74
IT usage: 0 = nothing, 1=email, 2=website	304	0.59	0.76	0.48	401	0.45	0.78	0.74
3. Human capital and labor management								
Ratio of non-production workers to total employment[(c)]	304	0.27	0.17	0.24	398	0.42	0.30	0.22
Any in-house training of staff last year?[(b)]	304	0.28		0.83	397	0.27		0.80
Staff sent to formal training course last year?[(b)]	304	0.28		0.84	398	0.12		0.80
4. Contractual practices								
Any direct imports of inputs?[(b)]	304	0.31		0.67	401	0.51		0.74
Do you sell on credit?[(b)]	304	0.53		0.65	401	0.64		0.73
Does firm sub-contract production?[(b)]	302	0.12		0.33	382	0.09		0.22

The table continues on the next page.

TABLE 1 continued

	Ethiopia				Sudan			
	Obs	Mean	Std.dev.	Loadings	Obs	Mean	Std.dev.	Loadings
5. Reputation mechanism								
If you have a dispute with a customer, will other customers find out?[(d)]	304	1.049	0.948	0.47	400	0.808	0.934	0.48
If another firm has a dispute with a customer, will you refuse to deal with that customer?[(d)]	304	0.457	0.815	0.67	401	0.783	0.954	0.65
If you have a dispute with a customer, will other firms refuse to deal with that customer?[(d)]	304	0.474	0.717	0.43	401	0.788	0.899	0.63
If you have a dispute with a supplier, will other suppliers find out?[(d)]	304	0.914	0.926	0.46	401	0.783	0.925	0.69
If you have a dispute with a supplier, will other firms refuse to deal with that supplier?[(d)]	304	0.398	0.682	0.47	401	0.656	0.861	0.64

Notes:
[(a)] 1=less than secondary, 2=secondary, 3=vocational, 4=university.
[(b)] 0 = no, 1 = yes.
[(c)] Non-production workers include professionals, managers, administrators, sales personnel.
[(d)] 0 = no, 1 = maybe, 2 = yes.
Source: Authors' computations based on data described in the text.

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

Source: Authors' computations based on data described in the text.

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 principal component	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 principal component
	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$
i & j trade with each other	0.0492	-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. Source: Authors' computations based on data described in the text.

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	Any in-house training of staff last year?	Staff sent to formal training course last year?	First principal component	Ratio of non-production workers to total employment	Any in-house training of staff last year?	Staff sent to formal training course last year?	First principal component
	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$	$\|y_i-y_j\|$
i & j trade with each other	-0.0218	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. Source: Authors' computations based on data described in the text.

TABLE 5. Correlates of Dyadic Differences: Contractual Practices

	Ethiopia				Sudan			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Any direct imports of inputs?	Do you sell on credit?	Does firm sub-contract production?	First principal component	Any direct imports of inputs?	Do you sell on credit?	Does firm sub-contract production?	First principal component
	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$	$\lvert y_i-y_j \rvert$
i & j trade with each other	0.0245	-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. Source: Authors' computations based on data described in the text.

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? $\lvert y_i-y_j\rvert$	If other firm has a customer dispute, will you refuse to deal with customer? $\lvert y_i-y_j\rvert$	If you have a customer dispute, will other firms refuse to deal with customer? $\lvert y_i-y_j\rvert$	If you have a supplier dispute, will other suppliers find out? $\lvert y_i-y_j\rvert$	If you have supplier dispute, will other firms refuse to deal with supplier? $\lvert y_i-y_j\rvert$	If you have a customer dispute, will other customers find out? $\lvert y_i-y_j\rvert$	If other firm has a customer dispute, will you refuse to deal with customer? $\lvert y_i-y_j\rvert$	If you have a customer dispute, will other firms refuse to deal with customer? $\lvert y_i-y_j\rvert$	If you have a supplier dispute, will other suppliers find out? $\lvert y_i-y_j\rvert$	If you have supplier dispute, will other firms refuse to deal with supplier? $\lvert y_i-y_j\rvert$
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)

See Table 6b for notes.

TABLE 6b. Correlates of Dyadic Differences: Perceived Consequences of Disputes, First Principal Component

	[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 5% level is indicated by **. Source: Authors' computations based on data described in the text.

NOTES

[1]The Sudanese data used in this paper were collected in 2007 and we started to work on this paper in 2009, i.e. before South Sudan seceded from Sudan in July 2011. Our sample thus includes firms in what is now South Sudan. Throughout the text, "Sudan" is to be understood to mean Sudan prior to the secession.

[2]A network consists of links between a finite collection of nodes (e.g., firms). See Jackson (2009).

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

[4]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).

[5]The Online Appendix can be obtained at http://soderbom.net/Fafchamps_Soderbom_Online_Appendix_2013.pdf, and at http://wber.oxfordjournals.org.

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

[7]There are two reasons for estimating (3) in absolute deviation, not in covariance form as in (2). 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) boils down to a linear probability model since $\left|y_i-y_j\right|=1$ if $y_i\neq y_j$ and 0 if they are the same. Secondly, in the more general case when y is continuous, model (3) captures the main idea behind (2) but offers the advantage of being more robust to outliers compared to using $(y_i-\bar{y})(y_j-\bar{y})$ as the dependent variable.

[8]See Mengistae and Honorati (2009) for details on the survey methodology. For a thorough report on the survey, see World Bank (2009).

[9]See H&H Consultancy (2008) for details on the survey methodology.

[10]Maps of the survey locations are shown in Section 3 in the Online Appendix.

[11]For some of our outcome variables there are missing values in the baseline sample. Some of our regressions will therefore be estimated on a smaller sample than the baseline sample.

[12]Fafchamps and Söderbom (2006) argue that the ratio of non-production workers to total employment proxies for the ease with which firms manage their labor force, and show that many African firms have a high ratio of non-production workers to total employment in spite of the relative simplicity of their production processes.

[13]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.

[14]Here the three levels of usage are combined. Results for alternative specifications modeling e-mail and website use separately are shown in Tables S1.E and S1.S, columns 1-2, in the Online Appendix. The results are similar to those shown in Table 3.

[15]Columns 3-8 in Tables S.1E and S1.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.

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