# Network Proximity and Business Practices in African Manufacturing

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Patterns of correlation in innovation and contractual practices among manufacturing firms in Ethiopia and Sudan are documented. Network data that indicate whether any two firms in the utilized 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. Indeed, for certain practices, adoption decisions appear to be local strategic substitutes: if one firm in a given location uses a certain practice, nearby firms 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 codes: O1, D2, D4.

Although technological upgrading and institutional innovation are critical for growth, these factors are particularly critical in Africa, where productivity has remained low. This fact 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 the new technology is subsequently adopted by individual firms. In this model, obstacles to the circulation of information, such as

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social or economic segmentation, delay technology adoption. Delays may also arise because of funding constraints or adoption costs, such as learning by doing, experimentation, and adjustment costs. As a result, pockets of backward technology may remain.

This general view pervades much of the economic discourse on growth and development. A form of diffusion externality is either built into or hidden in all of the endogenous growth models in which technological innovation fuels growth (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 (North 1973; Mokyr 1990). Similarly, the literature on agglomeration effects ascribes a key role to the diffusion of innovative technology and business practices to nearby firms (Jacobs 1969; Fujita, Krugman and Venables 1999; Muendler, Rauch, and Tocoiand 2012). Analogous 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 considered one important channel of diffusion among firms (Jacobs 1969; Rauch and Casella 2003). Another channel is competition between firms in the same market, especially foreign firms (Kraay, Soloaga and Tybout 2002).

Another strand of the economics literature has examined the diffusion of innovations within countries and regions. A shared assumption that underlies much of this literature is that by interacting, firms learn from each other about technological and institutional innovations that raise productivity. Although there is a rigorous body of 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 descriptive and relies principally on case studies (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 a market sense. We find some evidence for a correlation in business practices, but the evidence is less convincing than one would expect if the diffusion effects were strong. Furthermore, we find evidence that along some dimensions (principally geographical distance), firms are more similar to distant firms than to nearby firms. This observation suggests that some adoption decisions are local strategic substitutes: if some firms adopt a certain practice, the incentive for other firms to adopt it appears to be reduced. This phenomenon is partly confirmed by noting that the practices for which we

1. The Sudanese data used in this paper were collected in 2007. We began work on this paper in 2009, before South Sudan seceded from Sudan in July 2011. Thus, our sample includes firms in what is now South Sudan. Throughout the text, "Sudan" means Sudan prior to the secession.

find evidence of strategic substitution, namely, R&D and vocational training to workers, are the very practices that are the 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 (Collier 2007; Page 2012).

This 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 the 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 the practice if $j$ has adopted it. This statement is equivalent to the assertion 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 $G \equiv [g_{ij}]$, where $g_{ii} = 0$. Suppose that there are $N$ agents. We follow Liu et al. (2012) and Bramoullé and Kranton (2011) in writing the payoff of agent $i$ as follows:

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

where $y_i$ denotes the action of agent $i$, $y \equiv [y_1, \ldots, y_N]$ is a vector of the actions of all of the agents, $g_i = [g_{i1}, \ldots g_{iN}]$ is a vector of the neighbors of $i$, the Greek letters are parameters, and the final term represents the cost of taking action $y_i$, which is assumed to be quadratic for the sake of simplicity. Each agent chooses $y_i \geq 0$ to maximize the payoff $\pi_i$. The first-order condition for an interior solution is

$$y_i = \alpha_i + \rho g_i y. \tag{1}$$

The parameters $\alpha_i$, $\gamma$, and $\rho$ are now straightforward to interpret: $\alpha_i$ is a profitability parameter; $\rho$ indicates whether the actions are strategic complements ($\rho > 0$), strategic substitutes ($\rho < 0$), or neither complements nor substitutes ($\rho = 0$); and $\gamma$ 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 the externalities to be negative ($\gamma < 0$) even if the actions are strategic complements ($\rho > 0$) and vice versa.

2. A network consists of links between the nodes in a finite collection of nodes (for example, firms). See Jackson (2009).

The equilibria are action vectors $y$ that solve the system of Kuhn-Tucker conditions, which combine the first-order conditions (1) with $y_i \geq 0 \; \forall \; i \in N$. The interior solutions $y$ satisfy

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

where $A \equiv [\alpha_1, \ldots \alpha_N]$. When the actions are strategic complements ($\rho > 0$) and $\alpha_i \geq 0$ for all $i$, a sufficient condition for an interior equilibrium is that ρ is smaller than the largest eigenvalue of $G$.[3] If $\alpha_i \leq 0$ for all $i \in N$, then 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 ($\rho < 0$) and show that the equilibrium configuration ultimately depends on the lowest (that is, most negative) eigenvalue of $G$. With strategic substitutes, most equilibria have some agents choosing $y_i = 0$, and (some of) their neighbors choose a strictly positive $y_i$ (that is, the actions of neighbors tend to be dissimilar). In contrast, when actions are strategic complements, the actions of neighbors reinforce each other; thus, they tend to be similar (see also Jackson 2009).

These observations form the basis of our testing strategy: let $\tilde{y} \equiv y - E(y) = (I - \rho G)^{-1} \tilde{A}$ where $\tilde{A} = A - \mathrm{E}(A)$. The covariance matrix of $\tilde{y}$; is

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

where the $\alpha_i$s that enter matrix $A$ are unobserved by the researcher. If the $\alpha_i$s are independent and identically distributed, $E\left(\tilde{A}\tilde{A}'\right) = \sigma^2 I$ and the above expression can be simplified as follows:

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

When the matrix $G$ is sparse (that is, when few $g_{ij} = 1$), the $ij$ elements of the matrix $E[(I - \rho G)^{-1} (I - \rho G')^{-1}]$ that correspond to the existing links ($g_{ij} = 1$) are approximately proportional to $\rho^2$. Other elements are functions of higher powers of ρ and are much smaller than the elements that correspond to the linked pairs $ij$. In contrast, if $\rho = 0$ and the $\alpha_i$s are independent and identically distributed, then $Cov(\tilde{y})$ is a diagonal matrix, and $Cov(\tilde{y}_i, \tilde{y}_j) = 0$ for $i \neq j$. Therefore, it is possible to test whether $\rho \neq 0$ by determining whether the values of $y$ are more or less similar for linked pairs than for unlinked pairs. However, if

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

4. To illustrate the point, 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 $y_2 = -1 + 2 \times 1 = 1$. Thus, we have two equilibria: $(y_1, y_2) = (0, 0)$ and (1,1).

$E(\tilde{A}\tilde{A}')$ is not a diagonal matrix (that is, if the $\alpha_i$s are correlated), it is possible that $Cov(\tilde{y}_i, \tilde{y}_j) \neq 0$ even when $\rho = 0$. This possibility is an important caveat to keep in mind when interpreting our results; similar practices could be due either to strategic complementarity ρ or to a correlation between the $\alpha_i$s (that is, a correlation in the profitability of taking action $y$ between linked firms). Manski (1993) calls such correlations contextual effects. By similar reasoning, dissimilar practices may be due to strategic substitution or a negative correlation in the $\alpha_i$s.

Strategic complementarity may arise for a variety of reasons. For example, the desire to imitate others or to conform to a social norm may be reinforced by peer pressure (Young and Burke 2001) and 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 the same innovation to remain competitive. In contrast, strategic substitution would arise if agent $j$ takes action $y_j$ and 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 (see Foster and Rosenzweig [1995] for an application to farming). The 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. In addition, a desire to avoid competition may be a driving force of strategic substitution. For example, if firm $j$ decides to design its products for a high-end market, it could be optimal for firm $i$ to tailor its products to a low-end market.

### *Diffusion Dynamics*

If information diffuses between linked agents, then, in the long run, we expect all of the connected agents to have the same information. The connection may be direct, whereby the agents are linked to each other, or it may be indirect, which implies that the agents 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 exclusively on the distribution of the benefits from adoption, namely, the $\alpha_i$s, and on the local strategic complements and substitutes ρ. If agents have dissimilar $\alpha_i$s or if $\rho < 0$, we expect sporadic adoption of business technology and practices, in which some agents adopt these things but others do not, although they all have the same information. In contrast, if agents have sufficiently similar $\alpha_i$s and $\rho \geq 0$, we expect all of the agents in the same giant component to adopt similar technology and practices irrespective of whether they are directly linked. However, the latter expectation is not true in the short run. If information circulates slowly, adoption decisions are more likely to be similar among agents who are directly linked.

### *Business Practices*

Thus far, we have discussed strategic complements and substitutes in general terms. Here, we briefly discuss specific business practices for which we have data, and we speculate about 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. Because regional firms in the same sector compete with each other, they must keep up with each other in terms of productivity. However, some firms may strategically choose to focus on niche products and markets that are poorly served by other firms to avoid competition (Fafchamps 1994). Such behavior may lead to differences rather than similarities in the technology decisions of firms in the same location.

2) *Internal organization*: Innovations in the internal organization of a firm should follow similar logic. If other firms gain a competitive edge by adopting a better organizational structure, competitors should follow suit. However, this maxim may not apply to firms that eschew competitive pressure by focusing on niche markets and products (see the previous item).

3) *R&D:* If firms compete through innovation, high R&D by some firms will induce others to invest in R&D as well. Therefore, we expect R&D to be a strategic complement unless firms can act as free riders by imitating the innovations of other firms or by choosing R&D strategically 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. However, firms may free ride and hire workers who have been trained by other firms instead of providing their own training. Thus, vocational training may be a strategic complement or a substitute.

5) *Contractual practices:* Because contractual practices involve other firms by definition, strategic complementarities in this area are likely to be stronger. For instance, if one firm imports from abroad or subcontracts part of its production, other firms may find it easier to import or subcontract in the same way. However, we cannot a priori rule out strategic substitution, such as if firms purchase inputs from the importing firm rather than importing these inputs themselves.

6) *Reputational sanctions:* Because reputation sanctions contain a strong public-good component, they are very likely to exhibit strategic complementarity. Indeed, the threat of exclusion from future trade has the strongest deterrent effect if all of the 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 suggests that different types of proximity may have different effects. In principle, the strategic complementarities that arise from

information exchange apply to all of the practices listed above. If information pertaining to technological, organizational, and contracting innovations circulates through supplier-client relationships, we expect such proximity to matter. The 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 because other channels of adoption diffusion are expected to be less important in these areas. If upstream and downstream firms face different competitors, which is probable, the strategic complementarities that are driven by competition are expected to be smaller between firms that are located at different levels of the value chain. It follows that if we use geographical proximity as a proxy for competition, supplier-client proximity, which identifies different points on the value chain, may be associated with less similar practices.

Thus far, we have discussed the adoption of practices. It is also possible to investigate payoffs directly, such as by analyzing 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 $\gamma \neq 0$ (that is, if externalities are present), then positive externalities manifest as proximate firms that have similar performance. In contrast, negative externalities imply dissimilar performance. Furthermore, we show that even in the absence of externalities, firms' performance may be similar because of a correlation in firm-specific conditions $\alpha_i$ and $\alpha_j$; these correlations are the so-called contextual effects. The potential presence of these contextual effects 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 upon enterprise characteristics.[6] For example, the scope for the diffusion of innovations between sectors may be limited if these sectors use technologies that are very different. Similarly, organizational practices that are suitable for large corporations may not be useful for microenterprises.

In the model, this discrepancy is captured by differences between firms in the profitability parameter $\alpha_i$. If the adoption of new technologies and innovations is dichotomous, the likelihood of adopting can be expressed as $\lambda(\alpha_i + \rho g_i\, y)$, where $\lambda(.)$ is a logit or probit function. Whereas firms with a low $\alpha_i$ are unlikely to adopt irrespective of what neighboring firms do (that is, irrespective of $\rho g_i\, y$), firms with a high $\alpha_i$ are likely to adopt regardless of what others do. Thus, strategic complements and substitutes are very relevant for firms with intermediate values of $\alpha_i$; for these firms, adoption may only be beneficial if neighboring firms

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 increasingly been recognized in the recent literature; see, for example, Melitz (2003) and Melitz and Ottaviano (2008).

adopt (if adoption decisions are strategic complements) or do not adopt (if these decisions are strategic substitutes).

It is reasonable to assume that once they have been informed of an innovation, firms with a high $\alpha_i$ would adopt it first and other firms would adopt it later owing to $\rho g_i y$ effects. Therefore, we expect to observe the network-driven diffusion of innovation only among firms that are somewhat different, but the firms cannot be too different.

Hence, the extent to which practices and technologies diffuse may vary, depending on the heterogeneity across firms. For instance, if all of the firms in sector $A$ share a high $\alpha_A$ for a particular innovation and the firms in sector $B$ have a lower $\alpha_B$ but a large $\rho$, we expect all of the firms in sector $A$ to adopt new innovations and technologies irrespective of whether they are linked. In contrast, we expect the firms in sector $B$ to be more likely to adopt the same practices if they are linked to the sector $A$ firms. In this example, although the correlation in adoption between firms within the same sector is not affected by network proximity, the correlation in adoption between firms in different sectors is stronger if these firms are linked. It is also possible that firms are heterogeneous within sector $A$, whereas some firms may have a high $\alpha_i$ and adopt new innovations and technologies, others may have a lower $\alpha_i$ and adopt if and only if they have an adopting neighbor. Similarly, the firms in sector $B$ may all have a low $\alpha_i$ and may not adopt regardless of whether they are linked. As these two contrasting 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 $\rho$ is small in dissimilar firms, the diffusion of innovations will be more difficult in economies that are populated by very heterogeneous firms (much of sub-Saharan Africa has this characteristic). In such a context, not much should be expected from social networks and their ability to speed the diffusion of new ideas. Heterogeneity is also important from a methodological point of view because if we fail to take heterogeneity into account, we will underestimate the importance of networks for the subset of firms in which diffusion is occurring. As a result, we could erroneously accept the null hypothesis that networks play no role, and we must remember this point when we interpret our regression results.

## II. Testing Strategy

In this section, we outline the testing strategy that follows from the above reasoning. Each enterprise is a node, and we observe whether an enterprise $i$ has adopted a practice $y_i$. The vector $\mathbf{g}_{ij} = (g_{1ij}, g_{2ij}, \ldots, g_{Mij})$ represents the supplier-client links between two enterprises $i$ and $j$, and $d_{ij}$ 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—that is, whether some or all of the elements of $\mathbf{g}_{ij}$ are equal to one or if $d_{ij}$ is small.

For this purpose, we estimate models of the following form:

$$|y_i - y_j| = \mathbf{g}_{ij}\boldsymbol{\theta} + \omega d_{ij} + |\mathbf{x_i} - \mathbf{x_j}|\boldsymbol{\beta} + u_{ij} \tag{3}$$

where $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_M)$ is a vector of coefficients that are associated with network links, ω is a coefficient that reflects the relationship between the geographical distance and the outcome similarities, $|\mathbf{x_i} - \mathbf{x_j}|$ is a vector of absolute differences in the control variables **x** that is included to reduce omitted variable bias, **β** is a vector of parameters, and $u_{ij}$ is an error term.[7] A negative $\theta_{\mathrm{m}}$ in (3) means that $y$ is more similar when firms $i$ and $j$ have a link $g_{mij} = 1$. For the geographical distance $d_{ij}$, the interpretation of the sign of ω is exactly the opposite of the interpretation of the sign of $\theta_m$. Conversely, a positive $\theta_m$ or a negative ω would mean that linked or nearby firms are more dissimilar. If $y$ is more similar in proximate firms, then this occurrence is consistent with a situation in which adoptions by different firms are strategic complements; in contrast, if $y$ is dissimilar in proximate firms, then adoption by different firms may be a strategic substitute. A positive β means that firms that share a similar $x$ tend to have a more similar $y$.

A negative $\theta_m$ does not by itself imply network diffusion because firms $i$ and $j$ may have correlated technology and contractual practices for reasons other than network or geographical proximity, such as because they are subject to similar contextual effects $(corr(\alpha_i, \alpha_j) > 0)$ that are not adequately controlled for by the quantities $|\mathbf{x_i} - \mathbf{x_j}|$. If these unobserved contextual effects were more strongly correlated in linked firms, they would bias $\theta_m$ below 0. Hence, if we find a significantly negative estimate of $\theta_m$, the reason may be either diffusion or unobserved contextual effects. However, if $\theta_m$ is positive or not significantly different from zero, the net effect of the diffusion and the contextual effects is likely to be positive or zero.

There are two possible exceptions to the above scenarios. The first exception is when diffusion is rapid and all firms belong to a single connected network. In this case, our identification strategy will fail because the similarity of firms will depend exclusively on their $\alpha_i$s and not on the distance between them. Hence, we will observe a zero $\theta$ even though diffusion across network links is taking place. The second exception is when the strategic complementarities and substitutes precisely offset each other. Although it is possible, this situation seems unlikely. If unobserved contextual effects can only generate positive correlations in technology and business practices, which is likely, then a nonsignificant $\theta$ indicates that the network diffusion is zero, and a positive $\theta$ suggests that the presence of

7. There are two reasons to estimate (3) in terms of its absolute deviation and not in a covariance form as in (2). First, most of the outcome variables we investigate are binary; as a result, the only information they contain is whether $y_i = y_j$. In this case, (3) boils down to a linear probability model because $|y_i - y_j| = 1$ if $y_i \neq y_j$ and 0 otherwise. Second, 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 with respect to outliers compared to using $(y_i - \bar{y})(y_j - \bar{y})$ as the dependent variable.

strategic substitution affects adoption decisions. However, we cannot completely rule out the possibility that a negative correlation between practices could be the result of a negative correlation in the profitability of adoption $\alpha_i$. For instance, if an innovation such as subcontracting is profitable for upstream firms but not for downstream firms, then firms that are linked as suppliers and clients will have negatively correlated practices because 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 that there are $n \times (n - 1)$ observations that underlie the regression ($n$ denotes the number of firms). Dyadic observations are not independent because the residual $u_{ij}$ is correlated with $u_{ik}$. To compute standard errors that are robust with respect to the correlation in the error term across firms, we use the bootstrapping procedure that is described in section 1 in our online appendix.

## III. Data

To implement our testing strategy, we use detailed firm-level data that were 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, which was implemented by the Ethiopian Development Research Institute in mid-2006.[8] The survey covered 14 major cities located in seven regions of Ethiopia, and 42 percent of the observations came from Addis Ababa. The survey included firms with at least five permanent employees in four sectors: furniture, wood, and metal; food and beverages; leather and leather products; and textiles and garments. In all, 360 manufacturing firms were surveyed. The data from the Sudanese firms were collected as part of the Investment Climate Survey, which was launched in November 2007 and conducted by H&H Consultancy. This company is a Sudanese management consulting firm with expertise in conducting complex surveys.[9] Thus, the data were collected before South Sudan seceded from Sudan in July 2011; therefore, our sample includes firms in what is now South Sudan (see note 1). The survey covered 432 manufacturing firms in eight states, and most of these firms were private. The capital city of Khartoum accounted for 52 percent of the sample observations. No sector represented more than 20 percent of the sample; hence, the survey was diverse in terms of sector. The largest sectors were food and beverages (18 percent) and fabricated metal products (16 percent). Microenterprises were not covered. After deleting the observations that had too many missing values,

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

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

we obtained a sample of 304 firms for Ethiopia and 401 firms for Sudan.[10] This subset of the observations formed our baseline sample.[11]

Summary statistics are shown in table 1, and the variables that constitute our control vector are presented first. More mature firms and firms with higher-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 (de Mel, McKenzie and Woodruff 2009; Fafchamps 2003). We also include firm size, which is represented by the (log of the) total firm employment. The average log employment is 3.37 in Ethiopia (which corresponds to 29 employees) and 2.91 in Sudan (which corresponds to 18 employees).

Next, we report information on firm practices. Initially, we focus on the variables for which strategic complementarities across firms are a priori thought to be less strong, such as innovation. We end by considering the variables for which strategic complementarities are likely to be the strongest, such as reputation mechanisms. Within each category, adoption by a given firm may be correlated across individual practices, and this correlation may be positive or negative (if some practices are partial substitutes for each other). In this case, examining each practice separately yields inefficient inferences. 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. Thus, we 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 that we consider is a dummy variable that indicates whether a firm introduced a new product in the year preceding the survey. Between one-third and one-half of the surveyed firms responded positively to this question. Approximately one-half of the firms invested in plants and equipment in the previous year in both countries. A nonnegligible proportion of the surveyed firms had spent money on R&D: 13 percent for Ethiopia and 23 percent for Sudan. In addition, we note some usage of information technology (IT), 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 nonproduction workers to total employment in Sudan than in Ethiopia, which suggests that Sudanese firms are less able to manage their workforce with a small number of clerks and managers.[12]

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. Therefore, some of our regressions will be estimated on a smaller sample than the baseline sample.

12. Fafchamps and Söderbom (2006) argue that the ratio of nonproduction workers to total employment indicates the ease with which firms manage their labor force. They show that many African firms have a high ratio of nonproduction workers to total employment despite the relative simplicity of their production processes.

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 plants & equipment last year?[(b)] | 304 | 0.52 | | 0.67 | 400 | 0.46 | | 0.70 |
| Does the firm conduct any R&D?[(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 nonproduction 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 subcontract production?[(b)] | 302 | 0.12 | | 0.33 | 382 | 0.09 | | 0.22 |
| **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 |

[(a)] 1 = less than secondary, 2 = secondary, 3 = vocational, 4 = university.

[(b)] 0 = no, 1 = yes.

[(c)] Nonproduction workers include professionals, managers, administrators, and sales personnel.

[(d)] 0 = no, 1 = maybe, 2 = yes.

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

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 imported inputs directly from abroad. Although buying directly from abroad requires trust, it is likely to improve the quality of the raw materials that are used in a firm's production process. We find a difference between the two countries: landlocked Ethiopia lagged behind Sudan. Firms were also asked whether they sold 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 does not. The data also show that subcontracting part of a firm's production to other firms is rare.

Next, we examine the extent to which the surveyed firms rely on reputation to enforce contracts with suppliers and clients. The respondents were asked five closely related questions: (i) If you have a dispute with a customer, will other customers find out? (ii) If another firm has a dispute with a customer, will you refuse to deal with that customer? (iii) If you have a dispute with a customer, will other firms refuse to deal with that 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 that supplier? For each of these questions, we code $y = 2$ for "yes," $y = 1$ for "maybe/do not 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 travels to customers and suppliers. These statistics also suggest that the reputational sanction imposed on the customers and suppliers that are 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 locations. The 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 the firms in 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, because there are 304 firms in the Ethiopian sample, there exist $304 \times 303/2 = 46,056$ unique enterprise pairs $(i, j)$ in that sample. For each pair $(i, j)$, we construct dummy variables that capture the different concepts of network proximity. When two firms are close in that network, we consider them to be linked. The most direct network proximity measure that we use is whether $i$ and $j$ buy or sell

13. Because the majority of firms (approximately 70 percent) list three names, there is truncation in the observed network because some existing links are not recorded. This problem may cause a downward bias in the estimated network effects.

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.

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. The fact that there are so few upstream and downstream links among the sample firms is partly driven by the focus of the surveys on light manufacturing because clients are seldom manufacturers. We also construct dummy variables that indicate whether *i* and *j* have a common supplier or a common client. These types of links are more common: there are 481 supplier-based links and 273 client-based links in the Ethiopian data and 171 supplier-based links and 678 client-based links in the Sudanese data. These network proximity variables constitute the core of our vector $\mathbf{g}_{ij}$. The last proximity dummy is the distance $d_{ij}$, which is defined as the log of the distance between *i* and *j* plus one.

## IV. EMPIRICAL ANALYSIS

Our objective is to test whether the outcomes and practices that are 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 that end, we estimate the parameters of model (3). Our estimation technique is linear regression (ordinary least squares), and standard errors are bootstrapped to make them robust with respect to heteroskedasticity and correlation in error terms across firms. We refer to the 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 that measure whether firms introduced a new product in the previous year, invested in plants and equipment in the previous year, or conducted any R&D. A fourth outcome variable is constructed based on a firm-level measure of the extent of IT usage; the value of this variable is zero if IT is not

used at all, one if the firm uses email, and two if the enterprise has a business website.[14] The 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 in which we use the first principal component of all four categories to construct the dyadic dependent variable.

The estimated network proximity coefficients differ in the two countries. For Ethiopia, the dummies that track whether *i* and *j* trade with each other, have a common supplier, and have a common client are statistically nonsignificant. For Sudan, we obtain a negative and statistically significant coefficient of trade in the R&D regression (column [8]), and we obtain negative and significant coefficients (at least at the 10 percent level) of having a common supplier in the regressions for investment (column [7]), R&D (column [8]), IT usage (column [9]), and the first principal component (column [10]). Hence, network proximity seems to be associated with a more similar approach to innovation and R&D throughout the firms in Sudan, but not in Ethiopia. Some of these estimated effects are large; for example, the likelihood that firms report the same answer (yes or no) to the question about whether money was spent on R&D is 34 percentage points higher for firms that trade with each other than for firms that do not trade with each other. However, because of the small number of direct links in the Sudanese data (see table 2), the estimated coefficients of direct trade should be interpreted with caution. Furthermore, we find that Sudanese firms with a common client tend to differ *more* than other firms with respect to R&D and IT usage. This finding 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 of the specifications shown in table 3, and this coefficient is statistically significant at least at the 10 percent level in four of these specifications. 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 (column [8]), IT usage (column [9]), and the first principal component (column [10]). These results suggest that for technology, strategic substitution effects dominate strategic complementarities for firms that are located near each other.

The control variables in these regressions have explanatory power. The estimated coefficients of the same-sector dummy are negative in all of the specifications except [6], and these coefficients are often statistically significant. This result indicates that, as expected, firms in the same sector tend to have similar innovation practices. Differences in firm size, which are measured as the absolute difference in the log of employment, are positively associated with differences in

14. Here, the three levels of usage are combined. The results for the alternative specifications that model email and website use are shown separately in tables S1.E and S1.S, columns [1]–[2], in the online appendix. The results are similar to those shown in table 3.

TABLE 3. Correlates of Dyadic Differences: Technology Acquisition

| | Ethiopia | | | | | Sudan | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | [1] Did the firm introduce a new product last year? $\lvert y_i - y_j \rvert$ | [2] Did the firm invest in plants & equipment last year? $\lvert y_i - y_j \rvert$ | [3] Does the firm conduct any R&D? $\lvert y_i - y_j \rvert$ | [4] IT usage (0 = nothing, 1 = email, 2 = website) $\lvert y_i - y_j \rvert$ | [5] First principal component $\lvert y_i - y_j \rvert$ | [6] Did the firm introduce a new product last year? $\lvert y_i - y_j \rvert$ | [7] Did the firm invest in plants & equipment last year? $\lvert y_i - y_j \rvert$ | [8] Does the firm conduct any R&D? $\lvert y_i - y_j \rvert$ | [9] IT usage (0 = nothing, 1 = email, 2 = website) $\lvert y_i - y_j \rvert$ | [10] First principal component $\lvert y_i - y_j \rvert$ |
| *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) |

*Notes*: The table shows ordinary least squares results. A constant is included in all specifications. The numbers in parentheses are bootstrapped standard errors that are robust with respect to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10 percent, 5 percent, and 1 percent levels is indicated by *,**, and ***, respectively.

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

innovation practices in all of the 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 of differences in managers' experience or firms' ages are mostly nonsignificant.

### *Human Capital and Labor Management*

Table 4 shows the 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 in firms. In fact, we obtain a positive and statistically significant coefficient of common clients in specifications [3], [4], and [6], which indicates that firms with a common client tend to have more distinct training policies than firms that do not share a common client.

The estimated coefficients related to the distance between firms are negative in all of the specifications except [5], and these coefficients are statistically significant in four of the specifications (columns [2], [3], [4], and [6]). As with the results for innovation, this result implies that firms that are located close to each other tend to differ *more* with respect to their human capital decisions compared with firms that are far apart. This finding is consistent with strategic substitution. One possibility that is often emphasized in the literature on agglomeration effects (Henderson 1988; Glaeser et al. 1992) is that firms hire workers who have been trained by other firms. Thus, if there are more nearby firms that provide the necessary training, a given firm needs to train its workers to a lesser extent. 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 themselves in different places, both firms would face less competition and presumably higher profits. Another possibility is that firms that are 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 of greater differences between firms that are located close to each other than between firms in distant locations.

Furthermore, we find that, as expected, firms of similar size and firms in the same sector tend to be more similar with respect to their training decisions than firms of different sizes or in different sectors. The coefficients related to the other control variables, that is, differences in firms' ages and in managers' education, experience, and gender, are mostly nonsignificant. When they are significant, their coefficients are usually negative, which suggests that greater differences in these firm-level characteristics are associated with closer similarities in outcomes.

### *Contractual Practices*

Next, we investigate how the following three measures of contractual practices correlate across firms: whether a firm imports inputs directly, whether it sells on

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

| | Ethiopia | | | | Sudan | | | |
|---|---|---|---|---|---|---|---|---|
| | [1] Ratio of nonproduction workers to total employment $\lvert y_i - y_j \rvert$ | [2] Any in-house training of staff last year? $\lvert y_i - y_j \rvert$ | [3] Staff sent to formal training course last year? $\lvert y_i - y_j \rvert$ | [4] First principal component $\lvert y_i - y_j \rvert$ | [5] Ratio of nonproduction workers to total employment $\lvert y_i - y_j \rvert$ | [6] Any in-house training of staff last year? $\lvert y_i - y_j \rvert$ | [7] Staff sent to formal training course last year? $\lvert y_i - y_j \rvert$ | [8] First principal component $\lvert y_i - y_j \rvert$ |
| *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) |

*(Continued)*

TABLE 4. Continued

| | Ethiopia | | | | Sudan | | | |
|---|---|---|---|---|---|---|---|---|
| | [1] Ratio of nonproduction workers to total employment $\lvert y_i - y_j \rvert$ | [2] Any in-house training of staff last year? $\lvert y_i - y_j \rvert$ | [3] Staff sent to formal training course last year? $\lvert y_i - y_j \rvert$ | [4] First principal component $\lvert y_i - y_j \rvert$ | [5] Ratio of nonproduction workers to total employment $\lvert y_i - y_j \rvert$ | [6] Any in-house training of staff last year? $\lvert y_i - y_j \rvert$ | [7] Staff sent to formal training course last year? $\lvert y_i - y_j \rvert$ | [8] First principal component $\lvert y_i - y_j \rvert$ |
| 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) |

*Notes*: The table shows ordinary least squares results. A constant is included in all specifications. The numbers in parentheses are bootstrapped standard errors that are robust with respect to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10 percent, 5 percent, and 1 percent levels is indicated by *,**, and ***, respectively.

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

credit, and whether it subcontracts part of its production. The results are shown in table 5.

For Sudan, we find a negative and highly significant coefficient on the dummy variable that indicates whether firms *i* and *j* trade directly with each other in the models for direct imports, selling on credit, and the first principal component. Thus, Sudanese firms that trade with each other tend to have more similar contractual practices. In addition, having a common supplier is associated with a greater similarity in direct imports, although this effect is only statistically significant at the 10 percent level. In contrast, for Ethiopia, the correlation between network proximity and the similarity in contractual practices is weak and nonsignificant in all of the specifications except for subcontracting, for which we obtain a positive coefficient related to having a common supplier (column [3]).

The estimated distance coefficients vary considerably across regressions. In two regressions, they are positive and significantly different from zero (direct imports and selling on credit in Sudan; columns [5] and [6]), which suggests that firms that are close to each other have more similar contractual practices than other firms. However, in two other regressions, the coefficients are significantly negative (direct imports in Ethiopia and subcontracting in Sudan; columns [1] and [7]). For both countries, distance is statistically nonsignificant in the regressions that model the difference in the first principal component. Thus, it is difficult to see a pattern here, which may be because the relative importance of strategic substitution and diffusion varies from one contractual practice to another. Regarding the control variables, the pattern is similar to what we observed above; whereas firms of similar size and in the same sector tend to have similar contractual practices, for other controls, the results are mixed.

### *Reputation Mechanisms*

Here, we examine whether there is evidence that network links facilitate the diffusion of information on contractual disputes between suppliers and clients. The theoretical literature has emphasized the role of the diffusion of information on contractual disputes along social networks in the development of modern market institutions (North 1990; Greif 1993). Consequently, we expect to find a strong correlation in answers from firms in the same networks.

Using the five questions on the perceived consequences of disputes that are discussed in section 3, we code $y_i = 2$ for "yes," $y_i = 1$ for "maybe/do not know" and $y_i = 0$ for "no." Then, we compute $|y_i - y_j|$ for every pair of firms in the data.[15] The regression results are shown in table 6a and do not conform to theoretical expectations. Except for isolated cases in which a network regressor is significant (columns [6] and [10], but with opposite signs), the social network variables are not significant. One possible explanation is insufficient power: the

15. Columns [3]–[8] in tables S.1E and S1.S in the online appendix show the results for alternative specifications in which the reputation variables are defined as binary variables in the following way: yes = 1 and maybe or no = 0. The results are similar to those in table 5.

TABLE 5. Correlates of Dyadic Differences: Contractual Practices

| | Ethiopia | | | | Sudan | | | |
|---|---|---|---|---|---|---|---|---|
| | [1] Any direct imports of inputs? $\lvert y_i - y_j \rvert$ | [2] Do you sell on credit? $\lvert y_i - y_j \rvert$ | [3] Does firm subcontract production? $\lvert y_i - y_j \rvert$ | [4] First principal component $\lvert y_i - y_j \rvert$ | [5] Any direct imports of inputs? $\lvert y_i - y_j \rvert$ | [6] Do you sell on credit? $\lvert y_i - y_j \rvert$ | [7] Does firm subcontract production? $\lvert y_i - y_j \rvert$ | [8] First principal component $\lvert y_i - y_j \rvert$ |
| *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) |

*Notes*: The table shows ordinary least squares results. A constant is included in all specifications. The numbers in parentheses are bootstrapped standard errors that are robust with respect to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 10 percent, 5 percent, and 1 percent levels 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 another 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 that 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 that 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 another firm has a customer dispute, will you refuse to deal with that customer? $\lvert y_i - y_j \rvert$ | If you have a customer dispute, will other firms refuse to deal with that 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 that 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 | −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) |

*(Continued)*

TABLE 6a. Continued

| | Ethiopia | | | | | Sudan | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | [1] If you have a customer dispute, will other customers find out? $\lvert y_i - y_j \rvert$ | [2] If another firm has a customer dispute, will you refuse to deal with customer? $\lvert y_i - y_j \rvert$ | [3] If you have a customer dispute, will other firms refuse to deal with that customer? $\lvert y_i - y_j \rvert$ | [4] If you have a supplier dispute, will other suppliers find out? $\lvert y_i - y_j \rvert$ | [5] If you have supplier dispute, will other firms refuse to deal with that supplier? $\lvert y_i - y_j \rvert$ | [6] If you have a customer dispute, will other customers find out? $\lvert y_i - y_j \rvert$ | [7] If another firm has a customer dispute, will you refuse to deal with that customer? $\lvert y_i - y_j \rvert$ | [8] If you have a customer dispute, will other firms refuse to deal with that customer? $\lvert y_i - y_j \rvert$ | [9] If you have a supplier dispute, will other suppliers find out? $\lvert y_i - y_j \rvert$ | [10] If you have supplier dispute, will other firms refuse to deal with that supplier? $\lvert y_i - y_j \rvert$ |
| 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) |

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

| | [1] Ethiopia $\lvert y_i - y_j \rvert$ | [2] Sudan $\lvert y_i - y_j \rvert$ |
|---|---|---|
| *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) |

*Notes*: The table shows ordinary least squares results. A constant is included in all specifications. The numbers in parentheses are bootstrapped standard errors that are robust with respect to heteroskedasticity and cross-observation correlation in the error terms involving the same firms. Statistical significance at the 5 percent level is indicated by**.

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

five categorical reputation variables may contain insufficient information to identify the social network coefficients. Additionally, no network variable is significant in the principal component regressions shown in table 6b; hence, combining the information contained in all five of them does not lead to better results. Furthermore, the coefficients related to the control variables are nonsignificant in the vast majority of cases.

There are two possible interpretations of these findings: either the information about contractual disputes does not diffuse along the type of social networks that we have been able to measure, or this 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 of the distance variable. Even though information may diffuse rapidly along social networks within certain areas, the diffusion of information need not happen everywhere because strategic complementarities in diffusion create the possibility of multiple equilibria. If there are multiple equilibria, we expect to find that firms that are distant from each other perceive the consequences of contractual disputes differently.

However, we do not find distinct perceptions of contractual disputes in distant areas. For Ethiopia, although the distance coefficient is negative and highly significant in three of the specifications shown in table 6a, it is positive and significant in the remaining two specifications. Dyadic differences in the principal component that is 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; thus, whereas some firms recognize that there are reputational consequences to contractual disputes, others in the same location do not.

### *Firm Performance and Growth*

Thus far, we have focused on those business practices that may diffuse within networks. We have also investigated whether the above results are mirrored in labor productivity and growth rates, which are our measures of firm performance. The results for the 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 other firms. However, other results related to network links and geographical distance are weak. The overall conclusion from our analysis is that network links and geographical proximity are not strongly associated with any convergence in the performance of firms.

### *Heterogeneous Diffusion and Networks*

Now, we return to the points raised in section I that are related to the diffusion patterns across heterogeneous firms. We ask whether the reason we find only limited evidence of diffusion is that the firms are too heterogeneous. To investigate whether the evidence for diffusion is stronger among pairs of firms in the same sector, we interact our network and distance variables with a dummy that tracks whether firms $i$ and $j$ belong to the same industrial subsector, and we add these new interaction terms to the baseline specification. To minimize the number of explanatory variables, the same industry dummy is interacted with a single network variable $anylink_{ij}$, which is a dummy variable that is equal to one if there is any link between firms $i$ and $j$. Such a link would amount to direct trade, a common client or a common supplier.

The results for all of the outcome variables are shown in tables S2.E and S2.S in the online appendix. For Ethiopia, the sector-network interaction term is statistically nonsignificant in every specification, and the sector-distance interaction term is significant in only one specification (formal training; see table S2.E, column [8]; the term has a positive sign). For Sudan, the sector-network

interaction term is statistically nonsignificant in every specification, and the sector-distance interaction term is significant in just one specification (direct imports; see table S2.S, column [10]; the term has a positive sign). These results suggest that sector heterogeneity is not the reason for limited diffusion. They also imply that strategic substitution is equally strong within each sector and across different sectors.

We repeat this type of analysis, which focuses on firm-size heterogeneity instead of sector heterogeneity. To that end, we interact $anylink_{ij}$ and the distance variable ($d_{ij}$) with a dummy that tracks whether firms $i$ and $j$ are of similar size, and we add these new interaction terms to the baseline model.[16] The results are shown in tables S3.E and S3.S in the online appendix. For Ethiopia, the size-network interaction term is statistically nonsignificant in all regressions. However, the size-distance term is negative in the vast majority of cases and is often statistically significant. This result suggests that strategic substitution is *stronger* across firms of similar size than across firms of differing size, which may be because geographically close firms strategically choose to differentiate themselves from each other to reduce competition. For Sudan, the network-size interaction term is statistically nonsignificant in all specifications, and the size-distance interaction term is significant in just three specifications (table S3.S, columns [6], 11 and 20). On balance, we find little evidence that size heterogeneity is a likely reason for slow diffusion, and we 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 of the geographical distance change if we add a dummy variable $sametown_{ij}$ to the baseline specification. This dummy variable is equal to one if firms $i$ and $j$ are located in the same town and zero otherwise. We want to establish whether market differentiation within towns causes the result that a 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 such that firms in different towns pose no competitive threat to each other irrespective of the distance between these towns, events in town $k$ will not affect the strategic decisions of firms in town $l \neq k$. In this case, the relevant geographical circumstance is whether firms are in the same town; thus, conditional on $sametown_{ij}$, distance does not matter. Thus, by adding $sametown_{ij}$ to the set of explanatory variables, we generalize the baseline's functional form with respect to the effect of distance.

The results that are 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, which suggests

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

that strategic substitution effects do not primarily operate within towns. For Ethiopia, the picture is more mixed: although we obtain positive and significant coefficients in five of the regressions shown in table S4.E columns [1]–[24], we obtain negative and significant coefficients in three regressions. Overall, the support for the idea that strategic substitution effects operate primarily within towns is 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 that indicate 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 firms' locations to investigate whether firms that are near each other tend to be more similar or dissimilar than firms that are geographically 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 that are 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 that are located close to each other differ more with respect to training decisions than firms that are geographically 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.

Thus, our results 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. Furthermore, we find some evidence that for certain practices, adoption decisions are local strategic substitutes. Hence, if one firm adopts, other nearby firms are less likely to do so. What should we make of these results? First, we again note that a correlation in practices does not imply diffusion because there may be unobserved contextual effects. Second, the evidence presented here does not imply that the diffusion of innovation between firms can never be important or even critical for growth. However, 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, which is consistent with the observation that firms in developing countries are often more heterogeneous than firms in developed countries (see, for example, Bloom et al. [2012] for evidence that the quality of management practices is more heterogeneous for the firms in Brazil, China, and India than in the U.S.). Third, it is possible that we searched for diffusion in the wrong place (that is, among existing firms) because it is possible that, in general, the diffusion of innovations takes place not because existing firms learn to imitate each other but rather because new firms emerge that adopt innovative practices. This interpretation is consistent with the findings reported in the exporting literature: although there is limited evidence that incumbent firms learn from exporting, there is 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). Fourth, 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 of the network links. In addition, it is likely that our network-link variables are measured with error, which may cause the network effects to be underestimated in our analysis. Despite these caveats, we note that in several ways, the evidence for diffusion and complementarities is 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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