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Networks and Manufacturing Firms in Africa: Results from a Randomized Field Experiment

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Abstract

We run a novel field experiment to link managers of African manufacturing firms. The experiment features exogenous link formation, exogenous seeding of information and exogenous assignment to treatment and placebo. We study the impact of the experiment on firm business practices outside of the lab. We find that the experiment successfully created new variation in social networks. We find some limited evidence of diffusion of management practices, particularly in terms of firm formalisation and innovation. Such diffusion appears to be a combination of diffusion of innovation and simple imitation.

JEL codes: **D22, L26, O33**.

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1 Introduction: A novel field experiment

A growing body of applied research finds that management practices differ substantially across firms — even firms of similar size in the same sector and country: Bloom and Van Reenen (2007, 2010). This is particularly true in developing economies, where the distribution of management quality appears — relative to the United States — to have a 'far larger left tail' (Bloom, Sadun, and Van Reenen, 2012; Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013). Such heterogeneity is one important correlate to 'persistent performance differences among seemingly similar enterprises' (Gibbons and Henderson, 2012; Syverson, 2011; Hsieh and Klenow, 2009).

This kind of heterogeneity — in both management practices and firm performance — presents a mystery. It may be true that competition increases pressure on firms to change management practices, and that such competition may be less intense in developing economies (Bloom, Sadun, and Van Reenen, 2012). However, this still begs a fundamental question: *why don't best management practices diffuse from firm to firm along entrepreneurs' social networks?* Many economists view networking as a valuable business strategy — for sharing information about customers or suppliers (McMillan and Woodruff, 1999; Greif, 1993), for meeting potential business partners (Casella and Rauch, 2002), for improving a firm's access to production technologies (Parente and Prescott, 1994; Conley and Udry, 2001, 2010), for guiding a firm's policies on executive pay (Shue, 2012) and for learning about promising investment opportunities (Patnam, 2013). This may be particularly true in developing economies, where business networks can often form an attractive substitute to the relatively high transaction costs required to use the market (Rauch and Casella, 2003).

Indeed, more generally, research on social interactions often finds evidence of large diffusion effects among peers. These conclusions have been driven by a large number of studies on peer effects on adolescent health behaviours (Bifulco, Fletcher, and Ross, 2011; Fletcher, 2010;

Oster and Thornton, 2012), and on academic performance (Duflo, Dupas, and Kremer, 2011; Sacerdote, 2001; Carrell, Sacerdote, and West, 2012). That is, much of the evidence on peer effects derives from studies of young respondents, at a highly impressionable stage of their personal development — where the pressure to conform is high. But firm managers are not adolescents — and there are many good reasons to believe that firm managers face very different incentives than the kinds of samples generally used for understanding peer effects. If, for example, competitive pressures favor firms with better management techniques (Bloom, Sadun, and Van Reenen, 2012), we should expect firm managers to be reluctant to share business wisdom with their peers.

For these reasons, business networks form a pressing area for empirical research: such networks are fundamental to understanding heterogeneity in firm performance, and cannot be understood through analogies to peer effects in other contexts. However, apart from the exploratory work of Fafchamps and Söderbom (2012), remarkably little is known about diffusion of management practices along entrepreneurial networks. *Do management practices diffuse along such networks?* If so, *what kinds of management practices are affected by the behaviour of an entrepreneur's peers? Can researchers and policymakers change a firm's network in order to encourage the diffusion of best management practices?*

In this paper, we report results from a novel randomized field experiment designed to measure peer effects among manufacturing firms in Africa. We run a 'business ideas competition' in Ethiopia, Tanzania and Zambia, in which aspiring young entrepreneurs present proposals for new enterprizes to managers of established manufacturing firms.[1] By randomly assigning firm managers to different judging committees, we generate exogenous variation in firms' peer networks. This allows causal estimates of the diffusion of management practices through peer effects. To our knowledge, this is the first experiment to vary exogenously firms' networks

[1] The competition is loosely modeled on several popular reality television shows — for example, the program *Shark Tank* in the United States, and the program *Dragon's Den* in the United Kingdom and Canada.

of business peers. The experiment has exogenous link formation, exogenous seeding of information and exogenous assignment to treatment and placebo, and we study the impact of the experiment on real firm behavior outside of the lab.

We find only limited evidence of diffusion in management practices. Our experiment succeeded in creating new business links — in the sense that participants remembered the peers to whom they had randomly been introduced, and spoke to them after the experiment — but the experiment did not change managers' reports of their business friendship networks, nor did it generate any substantial diffusion of management practices. We find reasonably strong evidence of diffusion of VAT registration and on having a bank current account, and suggestive evidence of diffusion in advertising and paying purchases before delivery. However, on the whole, we do not find widespread evidence of diffusion.

Our study therefore makes two primary contributions. First, and most importantly, we provide empirical evidence to reconcile the existing tension between recent results on productivity differences and recent results on network diffusion. Specifically, we show that diffusion results from other contexts are unlikely to assist in understanding diffusion of management practices among competing firms. Second, the paper provides a methodological contribution on the use of experimental variation to study network behaviour. Several studies have introduced exogenous variation in information to study the relevance of social links for diffusion (see, for example, Möbius, Phan, and Szeidl (2010) and Aral and Walker (2011)). But very few studies have experimentally varied network connections to measure the effect of peer relationships themselves. Centola (2010, 2011) shows how online networks may be created artificially to study behavioral diffusion in an experimental context (namely, registration for an internet health forum and participation in an internet-based diet diary). Similarly, several studies have considered the consequences of random student assignment to peer groups (Sacerdote, 2001; Zimmerman, 2003; Lyle, 2007, 2009; Shue, 2012), including one experimental study in a developing country (Duflo, Dupas, and Kremer, 2011). To our knowledge, our experiment is the first to take a similar approach with firm managers, using a novel experimental protocol that had large and significant effects on the creation of entrepreneurial linkages. In this way, our work shows that field experiments can be used not merely to study effects *within* firms or *between* firms (Bandiera, Barankay, and Rasul, 2011), but also effects through firm *peer relationships*.

The paper proceeds as follows. Section 2 outlines our experimental design, including our identification strategy. Section 3 describes our implementation of the design, in Ethiopia, Tanzania and Zambia. Section 4 summarises our results, and Section 5 concludes.

2 The experiment

2.1 Experiment protocol

The competition: To measure the effect of peer relationships on firm performance, we design an experiment in which managers of manufacturing firms are randomly matched to work together on a task. The task is related to the challenges of firm management and entrepreneurship — in order to create an environment that encourages participants to share experiences and opinions on management strategies. The task relates to real and large payoffs to encourage participants to take the task seriously, and it requires managers to interact on multiple separate occasions to give several opportunities for personal relationships to develop.

To devise a task that satisfies all these requirements, we organise a business ideas competition in which aspiring young entrepreneurs pitch new business ideas to experienced firm managers, who act as judges and are our experimental subjects. Competitions such as ours are now being run in several African countries.[2] In our competition, applicants are aspiring entrepreneurs aged between 18 and 25 (inclusive) and recruited through advertising by posters, radio and Facebook.[3] As part of the application process, aspiring entrepreneurs are required to complete a detailed questionnaire about their business proposal, and to submit a three-page written business plan. Competition judges assess these questionnaires and business plans, along with oral presentations. Judges were drawn exclusively among managers of African manufacturing firms.

Committee judges: Candidates are judged in two ways: by judging committees, and by 'non-committee judges'. Most judging committees comprise five or six judges, who work together to assess candidates. Each judging committee assesses 12 applicants.[4] This involves holding three meetings, each assessing four applicants. These meetings follow a clear protocol. Applicants enter the room one at a time. Each applicant speaks for about 10 minutes, then answers questions from committee judges for an additional 10 minutes. Judges then complete separate mark sheets, assessing different aspects of the applicant's performance and business idea. Committee members then discuss the applicant for a few minutes, before calling the next applicant. At the end of each meeting, the committee is required to reach a joint ranking of all of the candidates whom the committee has judged up to that point.[5] Each committee is responsible for awarding one prize of US$1,000, given to the committee's highest-ranked candidate.[6]

We wish to ensure that committee members interact in as natural a manner as possible, with suggestions and interjections flowing in a natural group conversation. For this reason, we pre-

[2] For example, *Project Inspire Africa* is a reality television competition designed to test and reward young African entrepreneurs in a variety of business-related challenges; the program ran for the first time in 2012, with young entrepreneurs from Kenya, Rwanda, Tanzania and Uganda. *Ruka Juu* was a reality program that ran for 11 weeks in Tanzania in 2011, focusing on six young entrepreneurs. Other competitions encourage a wider range of applicants, beyond the proverbial glare of the television lights — for example, the *Darecha Business Ideas Competition* in Tanzania and the *StartUp Cup* in Zambia.

[3] An example of a promotional poster is included in Appendix 1.

[4] The design is slightly different in Zambia, as we discuss shortly.

[5] Thus, a committee ranks four candidates after its first meeting, eight candidates after its second meeting and 12 candidates after its final meeting.

[6] In a companion paper, we study the effects of these prizes on candidates.

scribe no specific protocol by which committee members are to discuss candidates or to reach their decision. As with a criminal jury, we require only that each committee chooses a chair and reaches a final consensus ranking at the end of each meeting (which every committee did). Each committee judge then receives about US$25 for each session.

At the conclusion of the competition, we hold a prize-giving ceremony in each country. These ceremonies are attended by the committee judges and the competition winners. Judges at these ceremonies receive free food and drinks, and are seated with their other committee members. These ceremonies are designed to thank participants and congratulate the successful aspiring entrepreneurs — and to provide an opportunity for informal social engagement between committee members so as to reinforce the treatment.

Non-committee judges: Candidates are also assessed by 'non-committee judges'. These judges assess the submitted business plans individually, assigning scores without seeing the applicants' oral presentations, and without conferring with other judges.[7] Each non-committee judge attends only once, and receives about US$25. The role of the non-committee judge is therefore designed to act as a placebo to the committee judges: non-committee judges were randomised from the same pool of firm managers as the committee judges and were exposed to the same pool of new business proposals. We will estimate only on firms that participated in the experiment; that is, firms whose representatives were either committee judges or non-committee judges.

Assignment of judges: Judges are assigned to their tasks randomly. Each judge attends the competition venue at an agreed time. To maximise participation, judges are allowed to choose their preferred competition session.[8] Having arrived at this session, judges are then randomly assigned either to act as a non-committee judge, or to join a specified judging committee. This assignment is done by having participants draw cards from a bag. The use of a 'physical

[7] Non-committee judges were seated separately, and completed their work under 'examination conditions'.
[8] Our identification strategy — described shortly — will control for any possible endogeneity arising from this choice.

randomisation device' is intended to reassure participants that assignment is random (Harrison, Humphrey, and Verschoor, 2010).

Distribution of factsheets: At the conclusion of the prize-giving ceremonies, we distribute factsheets to both committee and non-committee judges. Three of the factsheets summarise descriptive results from the baseline survey. These results are grouped into topics of 'labour', 'innovation' and 'exporting'. A fourth factsheet relates to the implementing research group (the Centre for the Study of African Economies at the University of Oxford). The distribution of factsheets is designed to introduce random variation in information between participants, to provide a further basis for testing information diffusion. The factsheet assignment — that is, random distribution of descriptive information from an earlier survey — is loosely styled on the work of Jensen (2010).

Two-thirds of the judges each receive two factsheets; the other one-third receive none. The assignment of factsheets to judges is randomised, such that each possible pairing of factsheets is equally likely. In appendix we provide further details of the randomisation and show the English-language versions of the factsheets.[9]

Dyadic data: Our follow-up survey (discussed shortly) includes a set of dyadic questions, that is, questions in which respondent i is asked directly about respondent j. For committee judges, we ask about (i) all other judges who served on the same committee, (ii) a random sample of other committee judges who participated in the competition, and (iii) a random sample of non-committee judges who participated in the competition. For non-committee judges and entrepreneurs who did not participated, we ask about a random sample of committee judges and a random sample of non-committee judges. We ask each respondent about 10 committee judges in total, and five non-committee judges. Judges are identified to respondents by name and firm – for example, "I will now ask about Mary Smith, from Alpha Manufacturing…".

[9] The factsheets were distributed in English in Zambia, in Amharic in Ethiopia, and in Swahili in Tanzania.

2.2 Identification strategy

Creation of network links: We begin our analysis by measuring the effect of the experiment on network formation. We do this by testing whether judges remember being on the same committees, and whether judges have had any discussions since the experiment. We use a very simple dyadic regression structure; having asked firm i about firm j, we estimate:

$$y_{ij} = \alpha_0 + \alpha_1 \cdot S_{ij} + \varepsilon_{ij}, \tag{1}$$

where y_{ij} is some outcome of interest (for example, a dummy for whether the representative of firm i said that (s)he had spoken to the representative of firm j), and S_{ij} is a dummy for whether i and j were on the same committee together.[10] We use the dyadic clustering method of Fafchamps and Gubert (2007).[11]

We begin by considering whether respondents remember having been on the same judging committee, defining y_{ij} as a dummy for whether judge i answers in the affirmative to the question, "Were you on a judging panel with this person?".[12] We expect that judges on the same committee will be much more likely to answer 'yes' (indeed, if all respondents had perfect recall, we would have $\beta_0 = 0$ and $\beta_1 = 1$). We go on to estimate whether judge i spoke to judge j, and then consider topics of discussion (namely, whether the judges discussed 'export strategies', 'labour management' and 'innovation and business advice').

Perceptions of business networks: We complement the dyadic regressions by testing whether the experiment changed committee judges' perceptions of their business networks. For this, we will take a set of outcomes recording respondents' perception of business friend-

[10] That is, C_{ij} is defined from our official records of committee membership.

[11] We thank Bruno Caprettini for providing very useful code for dyadic regressions with an incomplete adjacency matrix. Note that, because our network adjacency matrix is sparse, the dyadic method is almost identical here to the two-way clustering method of Cameron, Gelbach, and Miller (2011).

[12] That is, we are estimating equation 1 as a Linear Probability Model. Since P_{ij} is binary, we would obtain identical estimates if we were to use marginal effects from a probit or logit model.

ship networks (for example, measuring whether the respondent has any friends or relatives as bank officials). For judge i randomized from session s, we estimate:

$$y_{is1} = \beta \cdot C_i + \mu_s + \varepsilon_{is}, \tag{2}$$

where y_{is1} is a measure of business friendship networks at time $t = 1$. We cluster ε_{is} by judging committee.[13]

Diffusion of business practices: Several papers have studied natural experiments in which peers are randomly matched. Sacerdote (2001) studies the consequences of random assignment of of roommates and dormmates at Dartmouth College; he argues that matched peers exhibit significant positive correlation in academic results and joining of social groups. However, even peer groups formed by random assignment are susceptible to common shocks; for this reason, positive correlations between peers' outcome variables need not imply network diffusion. This has been emphasised by Lyle (2007, 2009) in studying academic peer effects among cadets at West Point. Lyle argues that researchers should estimate network diffusion by considering the effects of peers' *pre*-assignment characteristics (see also Zimmerman (2003)). This approach has been adopted in several subsequent papers, including by Duflo, Dupas, and Kremer (2011).

This is the approach we take. To measure diffusion, we use a 'linear-in-sum' specification, in which we explain a firm's management practices at follow-up by the number of its peers having adopted particular management practices at baseline. The management practices that we consider are each represented by dummy variables; we therefore nest the linear-in-sum specification within a probit model. (This follows directly the general approach of Banjeree, Chandrasekhar, Duflo, and Jackon (2013), who nest a linear-in-means specification within a logit model.)

[13] For clustering purposes, non-committee judges are each dealt with as belonging to a 'one-person committee'.

Specifically, for firm i in randomization session s at time $t = 1$, we estimate:

$$\begin{aligned}
&\Pr\left(y_{is1} = 1 \;\middle|\; \{y_{js0} : j \in \mathcal{C}_i\}, y_{is0}, \sum_{k \in \mathcal{S}_i} y_{ks0}, n_s \right) \\
&= \Phi\left(\beta_0 + \beta_1^p \cdot \sum_{j \in \mathcal{C}_i} y_{js0} + \beta_1^n \cdot \sum_{j \in \mathcal{C}_i} (1 - y_{js0}) + \beta_2 \cdot y_{is0} + \beta_3 \cdot \sum_{k \in \mathcal{S}_i} y_{ks0} + \beta_4 \cdot n_s \right),
\end{aligned} \tag{3}$$

where y_{is1} is a dummy for whether the firm follows a particular management practice, $\mathcal{S}_i$ is the set of firms in the same randomization session as firm i (with cardinality n_s) and $\mathcal{C}_i$ is the set of other firms on the same committee as firm i (defined as an empty set for non-committee judges). Therefore, the term $\sum_{j \in \mathcal{C}_i} y_{js0}$ is the sum of firm i's committee peers who had adopted the same management practice at the time of the baseline survey. β_1^p is our main parameter of interest; if firm i is more likely to adopt a management practice because it had more peers who had adopted by baseline, we will estimate $\beta_1^p > 0$.

We also include the sum of peers *not* adopting at baseline, $\sum_{j \in \mathcal{C}_i} (1 - y_{js0})$.[14] This allows us to test between two alternative mechanisms for diffusion. If $\beta_1^p = -\beta_1^n$, firms are merely imitating their peers: they are more likely to adopt a management practice if more of their peers have done so, and *less* likely to adopt if *fewer* of their peers have adopted. But if $\beta_1^p > 0$ and $\beta_1^n = 0$, we have an asymmetric process: a firm is more likely to adopt if it had more peers who had adopted, but the firm's decision to adopt is unaffected by the number of peers not adopting. This asymmetric process is similar to Rogers's (1962) famous notion of 'diffusion of innovations', and to 'infection' models of diffusion (Kermark and McKendrick, 1927; Banjeree, Chandrasekhar, Duflo, and Jackon, 2013).

To these terms we add several controls. First, we add the lagged dependent variable, y_{is0}; this is

[14] The inclusion of this term exploits the random assignment of non-committee judges; without non-committee judges, we would not be able to include $\sum_{j \in \mathcal{C}_i} (1 - y_{js0})$, because it would be collinear with $\sum_{j \in \mathcal{C}_i} y_{js0}$.

because, even where groups are formed randomly, y_{is0} correlates with $\mathcal{C}_i y_{js0}$, so its omission creates an endogeneity problem (see Guryan, Kroft, and Notowidigdo (2009) and Caeyers (2013)). Second, we add the sum of adopters in the randomization session, and the size of that session; this controls for possible endogeneity by self-selection into the randomization session. We continue to cluster observations by judging committee (where, as before, non-committee judges are defined, for clustering purposes, as each comprising a single-judge committee).[15]

Inference with multiple outcomes: Our experiment is designed to test for diffusion across a wide range of different business practices. We use three methods for inference in this multiple-hypothesis context; we use these methods both for estimating the perceptions of business networks and for estimating the diffusion of business practices. Our primary method of dealing with multiple outcomes is the 'sharpened q value' approach of Benjamini, Krieger, and Yekutieli (2006). This requires us to group outcomes into related families; the q value then controls for each family the False Discovery Rate ('FDR'), 'the expected proportion of rejections that are type I errors' (Anderson, 2008).

For completeness, we also report two other inference measures. First, we report standard p-values for each estimation separately. This is less conservative than the q-value; it is the appropriate measure for a reader interested in diffusion of some particular business practice, ignoring the fact that we tested multiple outcomes (for example, if a reader is interested specifically in whether VAT registration diffuses through networks). Further, we report for each outcome the Family-Wise Error Rate ('FWER'). This is defined as 'the probability of at least one type 1 error in the family' (Gibson, McKenzie, and Stillman, 2011; Shaffer, 1995). We compute the FWER using a Westfall-Young Stepdown Bootstrap (Westfall and Young, 1993; Kling, Liebman, and Katz, 2007; Gibson, McKenzie, and Stillman, 2011; Casey, Glennerster, and Miguel, 2012). Specifically, we use the algorithm summarized by Anderson (2008), where

[15] That is, we estimate using Maximum Pseudo-Likelihood.

we re-randomize within each competition session.[16] Because it controls the probability of *at least one* type 1 error — rather than merely the expected *rate* of type 1 errors — the FWER correction is very demanding (Gibson, McKenzie, and Stillman, 2011). For this reason — and given that our sample size is not particularly large — we will use the sharpened q for hypothesis testing.

3 Experiment implementation

3.1 Sample

We ran this experiment in 2011 in Ethiopia, Tanzania and Zambia. Participating manufacturing firms were initially surveyed between November 2010 and January 2011, as part of a World Bank study on 'African Competitiveness in Light, Simple Manufactured Goods'.[17] In each country, a sampling frame was constructed from firm lists obtained from the Bureau of Statistics, Chambers of Commerce and other similar organisations. These sources do not provide sufficient coverage of small and informal firms, so the sampling frame is complemented by firms selected in geographical areas with a concentration of informal firms.

The sample is designed to cover a combination of small firms (with 1 – 20 permanent employees) and medium firms (21 – 100 permanent employees), with approximately half of sampled firms in each category. Figure 1 shows the distributions of firm size across the three countries.[18]

< Figure 1 here. >

The sample is designed to cover a variety of manufacturing sectors. Specifically, we sought to divide the sample more or less equally between food processing, garment manufacturing,

[16] We use 1000 replications for each family.

[17] This project is summarised at `http://econ.worldbank.org/africamanufacturing`, and the main report has been published as Dinh, Palmade, Chandra, and Cossar (2012).

[18] Note that, for graphical clarity, we have truncated the firm size above at 25; a total of 21 firms had more than 25 permanent employees at baseline.

leather products, metal products and wood products. Table 1 records the distribution of manufacturing sector by country.

< Table 1 here. >

Within each firm, we interview someone in a senior management position — in most cases, the firm manager. Table 2 shows the distribution of respondents' management position by country, for the sample participating in the experiment.[19]

< Table 2 here. >

Tables 3 and 4 test balance in baseline covariates. Table 3 compares baseline covariates between committee and non-committee judges. For each variable, the table reports p-values for a t-test of equality in means and a Kolmogorov-Smirnov test for distributional equality. The table shows that the samples are generally well balanced: the only significant differences between groups are in the distribution of baseline permanent employees (though not a significant mean difference), and a significant difference in whether the firm had acquired machinery in the previous year.[20]

< Table 3 here. >

Table 4 compares the same covariates between firms that participated in the experiment (*i.e.* either as committee or non-committee judges) and those that did not (*i.e.* those firms that either refused or were not approached). The table shows that selection into the experiment itself is effectively 'as if random'. The only significant difference is that non-participant firms are slightly larger, on average, at baseline.

[19] In Tanzania and Zambia, our original sample also includes a number of respondents holding relatively junior roles in their firms; for example, respondents who described themselves as 'technicians'. In those two countries, we deliberately favoured more senior respondents for participation in the experiment. Where we needed to use more junior respondents to fill judging committees, we then exclude them from the analysis.

[20] Of course, these differences could have been eliminated had we randomised after matching on covariates; for example, using the method of Bruhn and McKenzie (2009). However, we decided that the particular challenges of running a socialisation experiment with firm managers weighed in favour of the simpler randomisation device, *i.e.* drawing cards from a bag. There were two main reasons for this. First, we wanted to reassure participants that assignment to committees was done randomly. Second, we wanted to allow the possibility that judges may not arrive at their agreed time; *i.e.* we wanted to randomise the group of judges who actually arrived, rather than those who merely indicated their willingness to do so.

< Table 4 here. >

We conducted a follow-up survey in each country between November 2011 and January 2012. This involved resurveying the firms that participated in the experiment and those that did not.

3.2 Running the experiment

The Aspire Business Ideas Competition was run simultaneously in Addis Ababa, Dar es Salaam and Lusaka in July and August 2011. 192 competitors participated in Ethiopia. In Tanzania, the number was 179. In Zambia, where we received fewer applications, we had only 90 competitors. We distributed a total of 40 prizes, each of US$1,000: 16 prizes in each of Ethiopia and Tanzania, and eight prizes in Zambia.[21]

Table 5 shows the consequent assignments to committee and non-committee judging; Table 6 shows how committee judges were assigned to different committees.[22]

< Table 5 here. >

< Table 6 here. >

4 Results

4.1 Creation of network links

We begin by considering the probability of creating network links (equation 1). Table 7 reports results. The table shows that being on the same panel had a large and highly significant effect on the probability of creating a relevant network link. Column 1 shows that there is a 2.5%

[21] In Zambia, we had 16 committees — but, because of the smaller number of applicants, awarded only eight prizes. We chose the eight prize winners from the 16 highest-ranked applicants by randomly matching committees in pairs. Within each pair, we awarded the prize to the committee winner with the better average scores from the 'non-committee judges'.

[22] Note that two committees in Zambia each comprised only two judges (shown in square brackets); we drop these four judges from the subsequent analysis.

probability that judge i claims to have been on a judging committee with judge j if the judges were not, in fact, on a committee together. For judges on a committee together, the probability increases by 35.7 percentage points. Column 2 shows a highly significant effect on the probability of having spoken since the conclusion of the Aspire Competition. The magnitude of this effect is about 16%; on average, each judge has spoken to approximately one of his or her committee peers. Sharing a committee also increased the probability of having discussed management practices; we find significant positive effects on the probability of having discussed export strategies (column 3), labor management (column 4) and innovation (column 5).

< Table 7 here. >

4.2 Perceptions of business networks

Our experiment significantly changed the probability of judges having spoken — but did it affect judges' general perceptions of their business networks? To test this, we estimate equation 2, sharpened q-values, then the standard p-values, then corrections for the FWER. We estimate on various measures of participants' perceptions of their business networks; results are reported in Appendix 2. We find no effect of being a committee judge on any of these measures.[23] This immediately suggests that our generated network links between firm managers are unlikely to have large diffusion effects. We caused reasonably large increases in the probability of managers remembering each other — and the probability of having discussed relevant management practices — but this did not translate into changes in managers' perceptions of their business networks (nor, crucially, in their perception of the ability of those networks to help the firm).

[23] Across the four tables, three outcomes are either significant or marginally significant — but the p-values increase substantially when correcting for multiple inference.

4.3 Diffusion of management practices

We now test directly for diffusion in management practices, by estimating equation 3. To do this, we group our measures of management practices into four families: (i) formalisation, (ii) labour management, (iii) relations with clients and suppliers and (iv) innovation.

We find some evidence of diffusion, though limited. Table 8 shows a significant positive diffusion of being registered for VAT (column 1) and of having a bank current account (column 3); we estimate that having a committee peer with VAT registration at baseline increased the probability of VAT registration at follow-up by about 7 percentage points, and that having a committee peer with a bank current account at baseline increased the probability of having a bank current account by about 4 percentage points at follow-up. We strongly reject a null hypothesis of imitation for VAT registration; rather, this appears to follow a 'diffusion of innovation' pattern, in which firms are more likely to register if their peers have done so, but no less likely to register if their peers have not done so.

< Table 8 here. >

Tables 9, 10 and 11 respectively report measures of diffusion for relations with clients and suppliers, labour management and of innovation. After correcting for multiple inference, we find no significant evidence of diffusion in any of these outcomes.

< Table 9 here. >

< Table 10 here. >

< Table 11 here. >

4.4 Diffusion heterogeneity by firm size and firm sector

Our main specification finds only limited evidence of diffusion. But could this result be driven by heterogeneous effects? It may be that practices diffuse strongly among firms that are similar, while the average diffusion effect remains small. To test this, we consider two key measures of firm similarity: size and sector. We bifurcate our sample at the median firm size (four permanent employees); we denote firms with more than four employees as ‘large’ and firms with four or fewer as ‘small’. We repeat the estimations in Tables 8 to 11, estimating separately for ‘small’ firms and ‘large’. For each specification, we interact the sum of peers adopting and the sum of peers not adopting with our binary measure of size.

Our results do not substantially change the conclusions from Tables 8 to 10. In our primary specification, we found significant positive diffusion for VAT registration; Tables 12 and 13 show that this positive diffusion appears reasonably uniform across large and small firms, with diffusion both from large and small peer firms. Our primary specification showed significant positive diffusion of having a bank current account; we now find (Table 12, column 3) that this is driven by the adoption decisions of large firms, reacting both to large and to small peers. We now also find a significant positive diffusion of having an external auditor, for small firms; we estimate that a small firm is about 4 percentage points more likely to use an external auditor if a small peer does so, and about 2 percentage points more likely if a large peer does so (column 2, Table 13).

< Table 12 here. >

< Table 13 here. >

Tables 14 and 15 test measures of relations with clients and suppliers, disaggregating by firm size. We find a large and highly significant diffusion of advertising, from small firms to large firms: a large firm is about 23 percentage points more likely to advertise at follow-up as a result of having a small peer firm that had advertised at baseline (column 1, Table 14). We also find a large and significant *negative* diffusion of having sales paid after delivery; a large firm is approximately 10 percentage points less likely to accept payment after delivery if a small peer firm does so (column 5, Table 14). We find no significant diffusion effects for small firms (Table 15).

< Table 14 here. >

< Table 15 here. >

Tables 16 and 17 test for diffusion of various measures of firm innovation, disaggregated by firm size. As with formalisation, we find large and significant diffusion effects from small firms to large: this is true in the case of introducing new products (a large firm is 10 percentage points more likely to do this if a small peer firm has done so previously), and changing production processes (where the magnitude is 7 percentage points). We find no significant effects for diffusion to small firms (though note that, for change of production processes, the magnitude of the estimated effect for diffusion from small firms to small firms is almost identical to the magnitude from small firms to large firms).

< Table 16 here. >

< Table 17 here. >

In Appendix 2, we disaggregate by size for measures of labour management; we find no significant diffusion effects. Appendix 2 also tests whether diffusion is stronger between two firms that are in the same sector; we find no evidence of this.

4.5 Diffusion and the probability of having spoken

We have found some evidence — though limited — of diffusion of management practices. So how does such diffusion occur? One possibility is that our experiment facilitated diffusion simply by having placed entrepreneurs on a committee together: entrepreneurs then choose with whom they wish to speak, and diffusion occurs through having spoken. Alternatively, it may be that diffusion needed more — that it required not merely for us to place judges on a committee together, but also to prompt judges to speak with each other. In some sense, the former mechanism is more complex: it suggests that managers *choose* optimally with whom they will speak, on the basis of some characteristics observable to each other. In contrast, the latter mechanism is more deterministic: it suggests that diffusion occurred through the relationships that we created, rather than through the relationships that judges chose.

To distinguish between these two mechanisms, we return to the dyadic data — and, for the first time in the paper, we exploit the random distribution of factsheets. Table 18 uses a dyadic Linear Probability Model (analogous to equation 1). It tests how the factsheets influenced the probability of judge i remembering judge j, having spoken to judge j since the Aspire Competition, and the probability of having discussed management practices. We estimate this probability as a function of (i) the factsheets that judge j received (which we expect to have little effect, if any), and (ii) whether judges i and j received the same factsheet. We find that having randomly received the same factsheet increased significantly the probability of having spoken since the competition (column 2), and the probability of having discussed both labor management and innovation (columns 4 and 5); these effects are all approximately of a magnitude of 5 percentage points.

< Table 18 here. >

Our random distribution of factsheets therefore generated random variation in the probability of having spoken — above the variation we generated by the formation of the judging committees. We can exploit this random variation to distinguish between our two hypothesised mechanisms for diffusion. To do this, we generate a predicted probability of having spoken from column 2 of Table 18. We now run a diffusion estimation in which we interact baseline peer characteristics with (i) the predicted probability of having spoken (which we denote $\widehat{\text{spoken}}$) and (ii) a dummy for whether judge i reports having spoken to judge j, *less* the predicted probability $\widehat{\text{spoken}}$. If diffusion occurs via self-selected conversations, we should expect this second term to be non-zero. In contrast, if diffusion occurs through conversations that we induced by the distribution of factsheets, we expect the first term to be non-zero.[24] We estimate on the six measures for which, in the primary specifications, we obtained a sharpened q

[24] For this section, we are therefore making the simplifying assumption that diffusion from firm j to firm i only occurs if the manager of i reports having spoken to the manager of firm j.

value of less than 0.2.[25] We report sharpened q-values and standard p-values; we calculate the standard p-values using a wild bootstrap procedure, in which we repeat both the dyadic first stage and the probit second stage.[26]

The results are reported in Table 19. In each case, we find that it is the interaction with the predicted measure of having spoken — rather than the interaction with the 'residual' — that is larger, and that has both the smaller p-value and the smaller sharpened q. (Note, however, that the estimates are not significant after we disaggregate in this way.) It appears, therefore, that the diffusion we observed is explained more through variation that we induced in the probability of having spoken, rather than by variation caused by managers' own decision to seek out peers whose expertise might benefit their firms.

< Table 19 here. >

5 Conclusions

In this paper, we report results from the first field experiment designed to vary exogenously firms' network of peers. Our results present a stark contrast to findings from earlier studies of network diffusion — in particular, studies of adolescent health and of student academic performance. On the whole, we find only limited evidence of diffusion in management practices — despite the fact that our experiment induced a large and highly significant change in the probability of network link formation between managers. For the sample as a whole, we find evidence of positive diffusion of VAT registration and of having a bank current account. When we disaggregate by firm size, we find some evidence of positive diffusion of having an external auditor (to small firms, from small peers), of advertising (to large firms, from small

[25] Of course, this means that our outcomes are chosen on the basis of their earlier significance. That is exactly the point: in this section, we are interested in exploring the mechanisms for diffusion *for those outcomes that were earlier significant, or marginally significant*.

[26] For this algorithm, we use the sample cluster definition as in the earlier specifications — namely, we cluster by committee and, for clustering purposes, treat non-committee judges as each forming their own committee.

peers), of introducing new products (to large firms, from small peers), and changing production processes (to large firms, from small peers). We find negative diffusion of having sales paid after delivery (to large firms, from small peers). Such diffusion appears to be a combination of 'diffusion of innovation' and simple imitation. We find no effect on other outcomes, and no effect on managers' perceptions of business networks.

There may be several reasons that we do not find more evidence of diffusion. Of course, it may be that diffusion among firm managers requires more time, or a stronger network treatment. Nonetheless, our experiment induced large variation in network links — so why did managers not use this as an opportunity to adopt new management practices? There may be several strategic reasons. First, entrepreneurs may face clear incentives *not* to encourage technology adoption by peers who could then compete away their profit (Foster and Rosenzweig, 1995). Additionally, peer relationships may be a mechanism for the diffusion not only of tales of success, but also of entrepreneurial horror stories — for example, stories of firms that tried and failed at exporting, or at introducing new products. Finally, managers may feel sufficiently set in their existing practices — or sufficiently wary of experimentation — not to see a need to learn from other managers' experiences (Callander and Matouschek, 2013). For all of these reasons, business networks need not provide a basis for reducing the heterogeneity of either management practices or productivity outcomes between competing firms.

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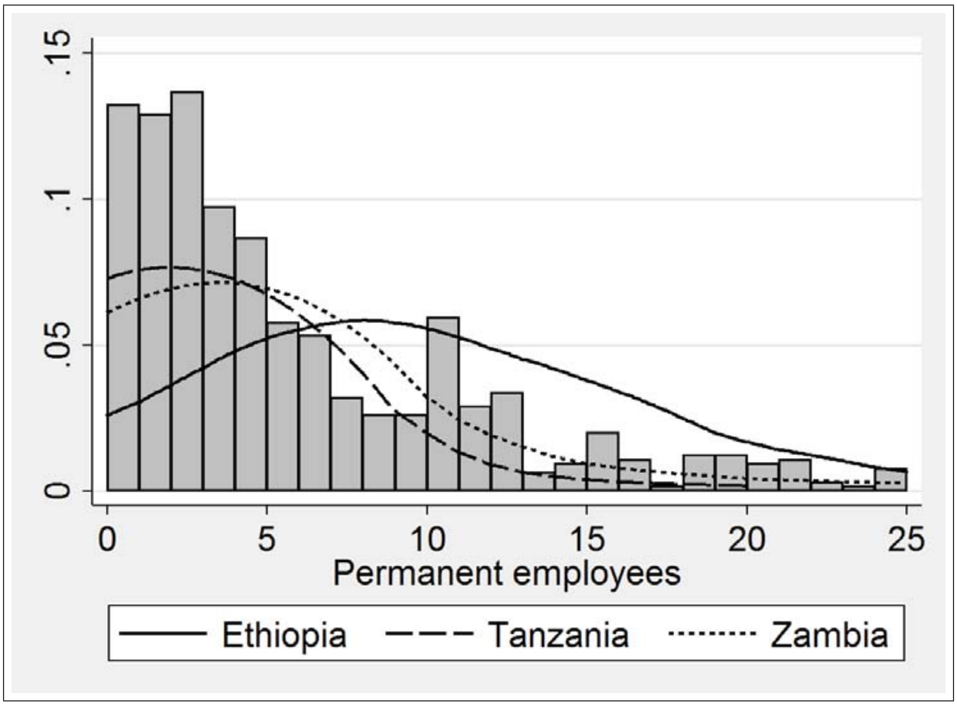
Figures and tables (main text)

Figure 1: **Size distribution of sampled firms**



This figure shows the size distribution of the sampled firms. We show the histogram across all firms, with kernel density plots by country (for which we use a bandwidth of 4 for each kernel). For graphical clarity, we have truncated the firm size above at 25; a total of 21 firms had more than 25 permanent employees at baseline.

Table 1: **Sector of manufacturing**

	ETHIOPIA		TANZANIA		ZAMBIA	
FOOD PROCESSING	53	**21%**	21	**8%**	38	**14%**
GARMENTS	48	**19%**	58	**22%**	65	**25%**
LEATHER PRODUCTS	49	**20%**	37	**14%**	42	**16%**
METAL PRODUCTS	46	**18%**	50	**19%**	61	**23%**
WOOD PRODUCTS	54	**22%**	96	**37%**	57	**22%**
TOTAL	**250**	100%	**262**	100%	**263**	100%

Table 2: **Management seniority**

	ETHIOPIA	TANZANIA	ZAMBIA	
OWNER AND MANAGER	94	91	109	294
PRESIDENT / MANAGER	93	100	76	269
VICE PRESIDENT / DEPUTY MANAGER	23	0	5	28
DEPARTMENT HEAD	9	37	17	63
ACCOUNTS / FINANCE / ADMINISTRATION	17	0	0	17
OTHER	2	1	4	7
	238	229	211	678

Table 3: **Covariate balance: Committee judges versus non-committee judges**

	COMMITTEE JUDGE			NON-COMMITTEE JUDGE			Equality (p)	
	N	Mean	Std.Dev	N	Mean	Std.Dev	Mean	Distr.
Total permanent employees	237	5.768	8.560	100	6.950	7.761	**0.235**	**0.037****
Dummy: Owner is female	237	0.169	0.375	98	0.204	0.405	**0.445**	**1.000**
Owner's age (years)	236	38.432	8.737	99	38.000	9.805	**0.691**	**0.925**
Dummy: Firm registered	237	0.502	0.501	100	0.570	0.498	**0.256**	**0.874**
Dummy: Production uses electricity	237	0.793	0.406	100	0.760	0.429	**0.500**	**1.000**
Number of local competitors	232	20.203	49.022	98	18.969	37.242	**0.823**	**0.223**
Number of friends in business	223	11.242	18.151	96	9.635	11.243	**0.423**	**0.988**
Number of regular suppliers	231	4.693	4.734	99	4.677	6.040	**0.980**	**0.854**
Dummy: Firm exports	237	0.051	0.220	100	0.050	0.219	**0.981**	**1.000**
Number of product types	234	6.885	11.415	99	7.646	22.918	**0.686**	**0.852**
Dummy: Acquired machinery	231	0.385	0.488	99	0.515	0.502	**0.029****	**0.178**
Dummy: Bank account	237	0.506	0.501	99	0.515	0.502	**0.883**	**1.000**

*'**Mean equality** (p)' reports the p-value from a two-sample t test with equal variances.*
*'**Distr. equality** (p)' reports the p-value from a two-sample Kolmogorov-Smirnov test (calculated exactly).*
***Confidence:* '$*$': 90%; '$**$': 95%; '$***$': 99%.**

Table 4: **Covariate balance: Participants versus non-participants**

	PARTICIPANT			NON-PARTICIPANT			Equality (p)	
	N	Mean	Std.Dev	N	Mean	Std.Dev	Mean	Distr.
Total permanent employees	337	6.119	8.337	343	7.703	12.611	**0.054***	**0.427**
Dummy: Owner is female	335	0.179	0.384	336	0.149	0.356	**0.290**	**0.996**
Owner's age (years)	335	38.304	9.053	333	39.465	10.651	**0.129**	**0.366**
Dummy: Firm registered	337	0.522	0.500	340	0.535	0.499	**0.734**	**1.000**
Dummy: Production uses electricity	337	0.783	0.413	343	0.764	0.425	**0.544**	**1.000**
Number of local competitors	330	19.836	45.788	330	18.827	45.436	**0.776**	**0.300**
Number of friends in business	319	10.759	16.380	325	9.305	12.190	**0.201**	**0.967**
Number of regular suppliers	330	4.688	5.151	329	5.003	8.555	**0.567**	**0.516**
Dummy: Firm exports	337	0.050	0.219	343	0.070	0.255	**0.286**	**1.000**
Number of product types	333	7.111	15.704	338	5.796	7.454	**0.165**	**0.638**
Dummy: Acquired machinery	330	0.424	0.495	326	0.485	0.501	**0.121**	**0.557**
Dummy: Bank account	336	0.509	0.501	337	0.507	0.501	**0.969**	**1.000**

*'**Mean equality** (p)' reports the p-value from a two-sample t test with equal variances.*
*'**Distr. equality** (p)' reports the p-value from a two-sample Kolmogorov-Smirnov test (calculated exactly).*
***Confidence:* '$*$': 90%; '$**$': 95%; '$***$': 99%.**

Table 5: **Assignment to treatment: Committee and non-committee judges**

	PANEL JUDGE	NON-PANEL JUDGE	NON-PARTICIPANT
ETHIOPIA	86	40	112
TANZANIA	90	44	124
ZAMBIA	63	22	158
	239	106	394

Table 6: **Assignment to treatment: Judging committees**

	A	**B**	**C**	**D**	**E**	**F**	**G**	**H**	**I**	**J**	**K**	**L**	**M**	**N**	**O**	**P**	**TOTAL**
ETHIOPIA	6	6	6	6	5	5	5	5	6	5	3	6	5	6	5	6	**86**
TANZANIA	6	5	6	6	6	6	5	5	6	6	6	4	6	6	6	5	**90**
ZAMBIA	4	4	4	5	5	6	6	4	4	3	3	3	3	5	[2]	[2]	**63**

Table 7: **Results: Creation of network links**

	(1)	(2)	(3)	(4)	(5)
				discussion topics	
	remembers	spoken since	exports	labor	innovation
Dummy: Same panel	**0.357**	**0.161**	**0.030**	**0.065**	**0.118**
	(0.024)***	(0.016)***	(0.010)***	(0.010)***	(0.014)***
Constant	0.025	0.013	0.003	0.006	0.010
	(0.003)***	(0.002)***	(0.001)***	(0.001)***	(0.002)***
Observations	9602	9602	9602	9602	9602

The unit of observation is a dyadic response. Parentheses show standard errors, allowing for dyadic clustering.
'Remembers' is a dummy for 'Were you on a judging panel with this person?'.
'Spoken since' is a dummy for 'Have you spoken to this person since the Aspire Competition awards ceremony?'.
'Exports' is a dummy for 'Did you discuss export strategies?'.
'Labor' is a dummy for 'Did you discuss labor management?'.
'Innovation' is a dummy for 'Did you discuss innovation and business advice?'.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 8: **Diffusion results: Formalisation**

	(1)	(2)	(3)	(4)
Sum of peers adopting	**0.066**	**0.016**	**0.044**	**0.029**
	[0.015]**	**[0.258]**	**[0.081]***	**[0.258]**
	(0.004)***	(0.409)	(0.050)**	(0.341)
	{0.049}*	{0.487}	{0.175}	{0.487}
Sum of peers <u>not</u> adopting	**0.003**	**0.008**	**-0.022**	**-0.022**
	[0.669]	**[0.669]**	**[0.669]**	**[0.669]**
	(0.757)	(0.372)	(0.200)	(0.110)
	{0.769}	{0.661}	{0.548}	{0.472}
Controls	✓	✓	✓	✓
Observations	333	326	329	326
H_0: Imitation (p)	0.005***	0.277	0.367	0.826
Baseline adoption	8%	16%	42%	32%

Outcome variables:
1: Whether the firm is registered for VAT ('missing' = 'no')
2: Whether the firm's financial statements are certified by external auditor.
3: Whether the firm has a bank current account.
4: Whether the firm has a savings account.

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 9: **Diffusion results: Relations with clients and suppliers**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sum of peers adopting	**0.043**	**0.086**	**-0.007**	**0.021**	**-0.010**	**-0.003**	**-0.090**
	[0.166]	**[0.166]**	**[0.651]**	**[0.215]**	**[0.648]**	**[0.651]**	**[0.166]**
	(0.041)**	(0.033)**	(0.793)	(0.141)	(0.655)	(0.919)	(0.084)*
	{0.276}	{0.276}	{0.893}	{0.501}	{0.893}	{0.893}	{0.415}
Sum of peers not adopting	**-0.022**	**0.009**	**-0.019**	**0.025**	**0.006**	**0.001**	**0.001**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.095)*	(0.444)	(0.144)	(0.333)	(0.732)	(0.920)	(0.854)
	{0.745}	{0.950}	{0.766}	{0.935}	{0.950}	{0.950}	{0.950}
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	325	324	323	327	327	329	328
H_0: Imitation (p)	0.354	0.017**	0.329	0.090*	0.895	0.937	0.087*
Baseline adoption	34%	13%	25%	65%	39%	3%	5%

Outcome variables:

1: Whether the firm has advertised in the past 6 months

2: Whether the firm pays any purchases before delivery

3: Whether the firm pays any purchases after delivery

4: Whether the firm has any sales paid before delivery

5: Whether the firm has any sales paid after delivery

6: Whether the firm imports

7: Whether the firm exports

Coefficients show the estimated mean marginal effect.

'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.

'( )' show standard p-values, allowing for clustering by committee.

'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.

Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 10: **Diffusion results: Innovation**

	(1)	(2)	(3)
Sum of peers adopting	**0.017**	**0.020**	**-0.049**
	[0.507]	**[0.507]**	**[0.181]**
	(0.505)	(0.346)	(0.051)*
	{0.467}	{0.467}	{0.134}
Sum of peers not adopting	**0.013**	**-0.008**	**0.008**
	[1.000]	**[1.000]**	**[1.000]**
	(0.411)	(0.550)	(0.351)
	{0.571}	{0.571}	{0.571}
Controls	✓	✓	✓
Observations	324	328	328
H_0: Imitation (p)	0.249	0.587	0.127
Baseline adoption	42%	27%	19%

Outcome variables:

1: Whether the firm has introduced new products in the past year

2: Whether the firm has changed its production processes in the past year (e.g. layout)

3: Whether the firm has changed its product delivery methods in the past year

(Note: The baseline questions for these estimations referred to the last three financial years.)

Coefficients show the estimated mean marginal effect.

'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.

'( )' show standard p-values, allowing for clustering by committee.

'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.

Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 11: **Diffusion results: Labour management**

	(1)	(2)	(3)	(4)	(5)	(6)
Sum of peers adopting	**0.032**	**-0.043**	**0.010**	**0.015**	**-0.012**	**-0.008**
	[1.000]	**[0.447]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.372)	(0.051)*	(0.746)	(0.437)	(0.532)	(0.705)
	{0.729}	{0.363}	{0.729}	{0.729}	{0.729}	{0.729}
Sum of peers <u>not</u> adopting	**0.003**	**-0.011**	**-0.003**	**0.003**	**0.009**	**0.008**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.709)	(0.298)	(0.889)	(0.881)	(0.582)	(0.598)
	{0.905}	{0.871}	{0.905}	{0.905}	{0.905}	{0.905}
Controls	✓	✓	✓	✓	✓	✓
Observations	326	327	325	314	316	320
H_0: Imitation (p)	0.345	0.018**	0.808	0.468	0.925	0.989
Baseline adoption	9%	36%	42%	56%	43%	34%

Outcome variables:

1: Whether the firm provides housing for any employees

2: Whether the firm provides free/subsidised meals for any production workers

3: Whether the firm provides toilets with running water for any production workers

4: Whether the firm hires production workers without recommendation/referral

5: Whether the average production worker has more than 7 years' education

6: Whether entry-level production workers receive more than 1 month's training

Coefficients show the estimated mean marginal effect.

'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.

'( )' show standard p-values, allowing for clustering by committee.

'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.

Significance: †: $p < 0.15$, *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 12: **Diffusion results for 'large' firms: Formalisation**

	(1)	(2)	(3)	(4)
Sum of small peers adopting	**0.103**	**0.290**	**0.074**	**0.109**
	[0.412]	**[0.412]**	**[0.412]**	**[0.412]**
	(0.291)	(0.147)	(0.275)	(0.170)
	{0.267}	{0.267}	{0.267}	{0.267}
Sum of small peers <u>not</u> adopting	**0.026**	**0.037**	**-0.073**	**-0.042**
	[0.142]	**[0.142]**	**[0.081]***	**[0.142]**
	(0.121)	(0.133)	(0.019)**	(0.165)
	{0.268}	{0.268}	{0.151}	{0.268}
Sum of large peers adopting	**0.119**	**-0.030**	**0.086**	**0.035**
	[0.047]**	**[0.303]**	**[0.029]****	**[0.303]**
	(0.030)**	(0.464)	(0.007)***	(0.445)
	{0.266}	{0.534}	{0.154}	{0.534}
Sum of large peers <u>not</u> adopting	**0.007**	**0.061**	**-0.072**	**0.039**
	[0.810]	**[0.810]**	**[0.810]**	**[0.810]**
	(0.761)	(0.127)	(0.299)	(0.336)
	{0.752}	{0.554}	{0.613}	{0.613}
Controls	✓	✓	✓	✓
Observations	136	132	134	134
H_0: Imitation, small firms (p)	0.020**	0.574	0.837	0.132
H_0: Imitation, large firms (p)	0.197	0.103	0.986	0.386

Outcome variables:
1: Whether the firm is registered for VAT ('missing' = 'no')
2: Whether the firm's financial statements are certified by external auditor.
3: Whether the firm has a bank current account.
4: Whether the firm has a savings account.

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 13: **Diffusion results for ‘small’ firms: Formalisation**

	(1)	(2)	(3)	(4)
Sum of small peers adopting	**0.069**	**0.044**	**0.033**	**0.059**
	[0.116]	**[0.086]***	**[0.183]**	**[0.238]**
	(0.069)*	(0.020)**	(0.231)	(0.384)
	{0.464}	{0.281}	{0.650}	{0.650}
Sum of small peers <u>not</u> adopting	**-0.008**	**0.002**	**0.036**	**-0.034**
	[0.521]	**[0.658]**	**[0.337]**	**[0.337]**
	(0.513)	(0.793)	(0.126)	(0.078)*
	{0.846}	{0.846}	{0.532}	{0.441}
Sum of large peers adopting	**0.038**	**0.024**	**0.006**	**0.057**
	[0.155]	**[0.010]****	**[0.652]**	**[0.246]**
	(0.089)*	(0.002)**	(0.885)	(0.296)
	{0.410}	{0.081}*	{0.890}	{0.516}
Sum of large peers <u>not</u> adopting	**0.025**	**-0.020**	**-0.078**	**0.041**
	[0.583]	**[0.583]**	**[0.583]**	**[0.583]**
	(0.368)	(0.112)	(0.200)	(0.359)
	{0.489}	{0.489}	{0.489}	{0.489}
Controls	✓	✓	✓	✓
Observations	197	194	195	192
H_0: Imitation, small firms (p)	0.133	0.035**	0.048**	0.723
H_0: Imitation, large firms (p)	0.154	0.813	0.331	0.175

Outcome variables:
1: Whether the firm is registered for VAT (‘missing’ = ‘no’)
2: Whether the firm’s financial statements are certified by external auditor.
3: Whether the firm has a bank current account.
4: Whether the firm has a savings account.

Coefficients show the estimated mean marginal effect.
‘[ ]’ show the ‘sharpened’ False Discovery Rate adjusted q-values.
‘( )’ show standard p-values, allowing for clustering by committee.
‘{ }’ show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 14: **Diffusion results for 'large' firms: Relations with clients and suppliers**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sum of small peers adopting	**0.233**	**-0.018**	**0.065**	**0.028**	**-0.096**	**0.018**	**-0.013**
	[0.001]***	**[1.000]**	**[0.700]**	**[0.948]**	**[0.037]****	**[1.000]**	**[1.000]**
	(0.000)***	(0.686)	(0.247)	(0.389)	(0.012)***	(0.829)	(0.759)
	{0.023}**	{0.185}	{0.185}	{0.185}	{0.134}	{0.185}	{0.185}
Sum of small peers <u>not</u> adopting	**-0.001**	**0.013**	**-0.027**	**-0.026**	**0.014**	**0.010**	**0.008**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.965)	(0.469)	(0.380)	(0.558)	(0.742)	(0.546)	(0.348)
	{0.979}	{0.945}	{0.945}	{0.945}	{0.945}	{0.945}	{0.945}
Sum of large peers adopting	**-0.013**	**0.113**	**0.011**	**0.047**	**-0.017**	**-0.018**	
	[1.000]	**[0.920]**	**[1.000]**	**[0.920]**	**[1.000]**	**[1.000]**	
	(0.695)	(0.119)	(0.829)	(0.160)	(0.636)	(0.713)	
	{0.829}	{0.652}	{0.843}	{0.671}	{0.829}	{0.829}	
Sum of large peers <u>not</u> adopting	**0.009**	**-0.001**	**-0.117**	**0.035**	**0.010**	**-0.011**	**-0.006**
	[1.000]	**[1.000]**	**[0.011]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.861)	(0.953)	(0.001)***	(0.396)	(0.766)	(0.539)	(0.712)
	{0.951}	{0.951}	{0.079}*	{0.951}	{0.951}	{0.951}	{0.951}
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	133	133	133	135	135	134	133
H_0: Imitation, small firms (p)	0.000***	0.906	0.499	0.963	0.125	0.738	0.907
H_0: Imitation, large firms (p)	0.938	0.139	0.041**	0.108	0.892	0.565	0.712

Outcome variables:
1: Whether the firm has advertised in the past 6 months
2: Whether the firm pays any purchases before delivery
3: Whether the firm pays any purchases after delivery
4: Whether the firm has any sales paid before delivery
5: Whether the firm has any sales paid after delivery
6: Whether the firm imports
7: Whether the firm exports

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 15: **Diffusion results for 'small' firms: Relations with clients and suppliers**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sum of small peers adopting	**0.027**	**0.112**	**-0.009**	**0.012**	**-0.007**	**0.078**	**-0.141**
	[0.720]	**[0.333]**	**[0.925]**	**[0.785]**	**[0.925]**	**[0.333]**	**[0.343]**
	(0.418)	(0.073)*	(0.836)	(0.560)	(0.841)	(0.036)**	(0.132)
	{0.838}	{0.455}	{0.838}	{0.838}	{0.838}	{0.372}	{0.561}
Sum of small peers <u>not</u> adopting	**-0.029**	**0.026**	**0.007**	**-0.047**	**0.019**	**-0.003**	**0.002**
	[0.627]	**[0.914]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.055)*	(0.159)	(0.683)	(0.386)	(0.462)	(0.647)	(0.828)
	{0.535}	{0.769}	{0.835}	{0.835}	{0.835}	{0.835}	{0.835}
Sum of large peers adopting	**0.019**	**0.163**	**-0.072**	**0.046**	**0.075**		
	[0.548]	**[0.548]**	**[0.548]**	**[0.548]**	**[0.548]**		
	(0.591)	(0.098)*	(0.152)	(0.283)	(0.235)		
	{0.576}	{0.478}	{0.488}	{0.488}	{0.488}		
Sum of large peers <u>not</u> adopting	**-0.022**	**-0.050**	**-0.006**	**0.109**	**-0.022**	**0.020**	**-0.001**
	[1.000]	**[1.000]**	**[1.000]**	**[0.190]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.551)	(0.186)	(0.857)	(0.023)**	(0.652)	(0.310)	(0.962)
	{0.966}	{0.822}	{0.966}	{0.260}	{0.966}	{0.882}	{0.966}
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	192	191	190	192	192	174	180
H_0: Imitation, small firms (p)	0.966	0.021**	0.968	0.527	0.795	0.041**	0.133
H_0: Imitation, large firms (p)	0.954	0.286	0.237	0.022**	0.529	0.310	0.962

Outcome variables:
1: Whether the firm has advertised in the past 6 months
2: Whether the firm pays any purchases before delivery
3: Whether the firm pays any purchases after delivery
4: Whether the firm has any sales paid before delivery
5: Whether the firm has any sales paid after delivery
6: Whether the firm imports
7: Whether the firm exports

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 16: **Diffusion results for ‘large’ firms: Innovation**

	(1)	(2)	(3)
Sum of small peers adopting	**0.101**	**0.073**	**-0.013**
	[0.051]*	**[0.051]***	**[0.387]**
	(0.025)**	(0.032)**	(0.837)
	{0.154}	{0.154}	{0.846}
Sum of small peers <u>not</u> adopting	**0.034**	**-0.019**	**-0.003**
	[1.000]	**[1.000]**	**[1.000]**
	(0.314)	(0.466)	(0.926)
	{0.707}	{0.780}	{0.925}
Sum of large peers adopting	**-0.061**	**-0.029**	**-0.122**
	[0.234]	**[0.397]**	**[0.163]**
	(0.189)	(0.571)	(0.046)**
	{0.492}	{0.686}	{0.240}
Sum of large peers <u>not</u> adopting	**0.020**	**-0.068**	**0.022**
	[0.752]	**[0.338]**	**[0.752]**
	(0.643)	(0.084)*	(0.439)
	{0.686}	{0.280}	{0.686}
Controls	✓	✓	✓
Observations	134	134	135
H_0: Imitation, small firms (p)	0.006***	0.172	0.804
H_0: Imitation, large firms (p)	0.492	0.094*	0.099*

Outcome variables:
1: Whether the firm has introduced new products in the past year
2: Whether the firm has changed its production processes in the past year (e.g. layout)
3: Whether the firm has changed its product delivery methods in the past year
(Note: The baseline questions for these estimations referred to the last three financial years.)

Coefficients show the estimated mean marginal effect.
‘[ ]’ show the ‘sharpened’ False Discovery Rate adjusted q-values.
‘( )’ show standard p-values, allowing for clustering by committee.
‘{ }’ show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 17: **Diffusion results for ‘small’ firms: Innovation**

	(1)	(2)	(3)
Sum of small peers adopting	**0.013**	**0.069**	**-0.039**
	[0.889]	**[0.131]**	**[0.458]**
	(0.710)	(0.038)**	(0.314)
	{0.754}	{0.160}	{0.604}
Sum of small peers <u>not</u> adopting	**-0.006**	**0.006**	**0.003**
	[1.000]	**[1.000]**	**[1.000]**
	(0.750)	(0.762)	(0.808)
	{0.821}	{0.821}	{0.821}
Sum of large peers adopting	**0.037**	**-0.078**	**-0.035**
	[0.823]	**[0.823]**	**[0.823]**
	(0.451)	(0.185)	(0.373)
	{0.441}	{0.441}	{0.441}
Sum of large peers <u>not</u> adopting	**0.033**	**0.029**	**0.026**
	[0.912]	**[0.912]**	**[0.912]**
	(0.477)	(0.338)	(0.221)
	{0.606}	{0.606}	{0.595}
Controls	✓	✓	✓
Observations	190	194	193
H_0: Imitation, small firms (p)	0.850	0.037**	0.381
H_0: Imitation, large firms (p)	0.269	0.425	0.838

Outcome variables:
1: Whether the firm has introduced new products in the past year
2: Whether the firm has changed its production processes in the past year (e.g. layout)
3: Whether the firm has changed its product delivery methods in the past year
(Note: The baseline questions for these estimations referred to the last three financial years.)

Coefficients show the estimated mean marginal effect.
‘[ ]’ show the ‘sharpened’ False Discovery Rate adjusted q-values.
‘( )’ show standard p-values, allowing for clustering by committee.
‘{ }’ show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 18: **Results: Creation of network links: Effect of receiving the same factsheet**

	(1)	(2)	(3)	(4)	(5)
			discussion topics		
	remembers	spoken since	exports	labor	innovation
Dummy: Received the same sheet	**0.013**	**0.067****	**0.011**	**0.042****	**0.053***
	(0.037)	(0.033)	(0.013)	(0.021)	(0.028)
CSAE sheet	0.084**	0.029	-0.027**	-0.007	0.024
	(0.034)	(0.026)	(0.012)	(0.016)	(0.022)
Exports sheet	0.027	0.043*	0.007	-0.006	0.024
	(0.036)	(0.023)	(0.013)	(0.015)	(0.023)
Innovation sheet	0.040	0.015	0.016	0.040**	0.039*
	(0.037)	(0.028)	(0.012)	(0.017)	(0.024)
Labor sheet	-0.012	-0.038	-0.018*	-0.024*	-0.040*
	(0.034)	(0.024)	(0.011)	(0.013)	(0.021)
Constant	0.327***	0.134***	0.037***	0.056***	0.093***
	(0.036)	(0.020)	(0.011)	(0.012)	(0.015)
Observations	976	976	976	976	976

The unit of observation is a dyadic response. Parentheses show standard errors, allowing for dyadic clustering.
'Remembers' is a dummy for 'Were you on a judging panel with this person?'.
'Spoken since' is a dummy for 'Have you spoken to this person since the Aspire Competition awards ceremony?'.
'Exports' is a dummy for 'Did you discuss export strategies?'.
'Labor' is a dummy for 'Did you discuss labor management?'.
'Innovation' is a dummy for 'Did you discuss innovation and business advice?'.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 19: **Results: Selected outcomes and the probability of having spoken**

	(1)	(2)	(3)	(4)	(5)	(6)
Σ **(peer adopting** $\times$ $\widehat{\textbf{spoken}}$**)**	**0.379**	**0.213**	**0.254**	**0.369**	**-0.868**	**-0.300**
	[0.282]	**[0.282]**	**[0.282]**	**[0.282]**	**[0.282]**	**[0.282]**
	(0.162)	(0.105)	(0.057)*	(0.183)	(0.358)	(0.121)
Σ **[peer adopting** $\times$ **(spoken** $-\widehat{\textbf{spoken}}$**)]**	0.003	0.034	0.070	0.036	0.129	0.079
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.988)	(0.493)	(0.166)	(0.840)	(0.616)	(0.557)
Controls	✓	✓	✓	✓	✓	✓
Observations	333	329	325	324	328	328
Baseline adoption	8%	42%	34%	13%	5%	19%

Outcome variables:
1: Whether the firm is registered for VAT (‘missing’ = ‘no’)
2: Whether the firm has a bank current account
3: Whether the firm has advertised in the past 6 months
4: Whether the firm pays any purchases before delivery
5: Whether the firm exports
6: Whether the firm has changed its product delivery methods in the past year

‘[ ]’ show the ‘sharpened’ False Discovery Rate adjusted q-values.
‘( )’ show standard p-values, allowing for clustering by committee.
Significance: †: $p < 0.15$, *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Appendix 1: Further details on the experiment protocol

Advertising

Figure 2 shows the poster used in Zambia. This poster was translated into Amharic and Swahili and displayed in public places in Addis Ababa, Dar es Salaam and Lusaka. The content and stye of the poster formed the basis for other advertising run on radio and on Facebook.

In all three countries, applicants were able to apply by submitting a hard copy application form; in Tanzania and Zambia, applicants were also given the option of applying online.

Factsheets

Figures 3 to 6 show the English versions of the four factsheets distributed in each country. As noted, the factsheets relate to the Centre for the Study of African Economies, exporting, innovation and labour management.

Table 20 shows the structure of factsheet assignment. Each committee judge and each non-committee judge was randomly assigned to a row in this table, so that all rows were filled before assigning judges to any new positions. This ensured that, so far as possible, two-thirds of judges received factsheets and one-third did not; it also ensures that, so far as possible, each possible pair of factsheets was assigned the same number of times.

Figure 2: **Advertising for aspiring entrepreneurs: Zambian poster**

ASPIRE

Do you aspire to be a successful entrepreneur?

Do you aspire to start your own business?

Do you have a **business idea** that needs support?

If so, **apply for the chance to win US$1,000** to help you to start your own business!

The Centre for the Study of African Economies (University of Oxford, UK) is interested in learning about the growth of new business ideas in Zambia. We are running a business ideas competition for aspiring young entrepreneurs, and we want you to apply!

Who: Applications are open to any aspiring entrepreneur aged 18 – 25, male or female. (Note that you may be required to provide proof of your age.)
What: In July and August, we will be running a competition to reward aspiring entrepreneurs. You can win the chance to present and explain your idea to a group of Zambian business leaders. Those with the best project win US$1,000!
How: Apply online at **www.csae.ox.ac.uk/aspire/zambia**. There is **no application cost**.
When: It's with immediate effect and applications close on 22 July at 6pm.

TO WIN

US$1,000!!

Figure 3: **Factsheet: The Centre for the Study of African Economies**

The Centre for the Study
of African Economies

Did you know...?

CSAE is celebrating 25 years of studying economic issues in Africa

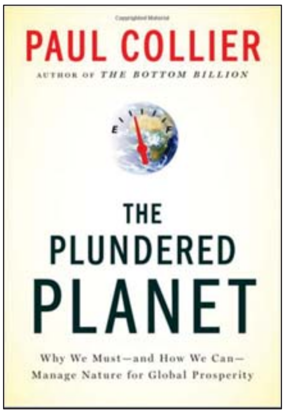
CSAE was founded at the University of Oxford in 1986. This year, CSAE hosted its 25th Anniversary Conference, on the theme of '**Economic Development in Africa**'. There were **270 presentations** and almost **400 participants**.

Paul Collier, the CSAE Director, has just published a new book

In his latest book '**The Plundered Planet**', Professor Collier argues that countries can ensure equitable development by using technological innovation, environmental protection and better government regulation. Professor Collier is one of the promoters of the **Natural Resource Charter**, a set of principles for governments and societies to use wisely the development opportunities created by natural resources.

Professor Paul Collier

'The Plundered Planet'



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Videos from the 25th Anniversary Conference are available at http://www.csae.ox.ac.uk/conferences/.

Marcel Fafchamps
Professor of Development Economics
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Simon Quinn
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Figure 4: **Factsheet: Exports**

CSAE 25 YEARS — CENTRE FOR THE STUDY OF AFRICAN ECONOMIES

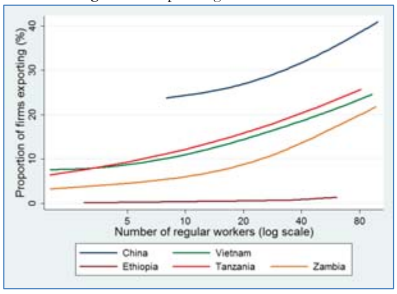
Asia-Africa Study Factsheet

UNIVERSITY OF OXFORD

Did you know...?

Fact 1: African firms could export more

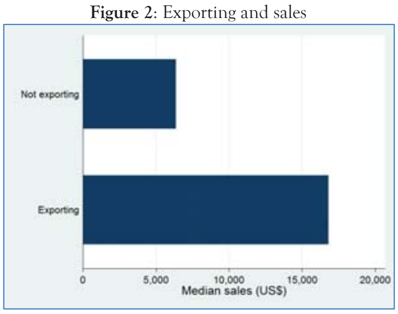
Figure 1: Exporting and firm size



Research shows that **Chinese** firms are more likely to export than firms of a similar size in Africa. **Figure 1** illustrates this. This suggests that more African firms could **follow the Chinese example** by exporting.

Fact 2: Firms that export have higher sales

Figure 2: Exporting and sales



Exporting is an important way by which a firm can increase its market. **Figure 2** shows the median sales for African exporters and non-exporters. **On average, exporting firms sell much more.**

Here are some steps that a firm can take to start exporting:

- ✓ **Identifying export opportunities** (for example, by learning about foreign markets, or by finding local export agencies);
- ✓ Discussing exporting opportunities with a **bank or other finance organisation**;
- ✓ Obtaining any **necessary export permits** from government authorities;
- ✓ **Discussing exporting strategies with other firms** that export successfully.

We appreciate your participation in the study and we hope that you find this information useful.*

Marcel Fafchamps	**Simon Quinn**
Professor of Development Economics	Post-doctoral researcher
University of Oxford	University of Oxford

* Your firm was surveyed last year by the Centre for the Study of African Economies at the University of Oxford (UK). This was part of a research project to learn about African competitiveness in manufacturing. The study covered China, Vietnam, Ethiopia, Tanzania and Zambia. Many firm managers asked us to pass on results from the study, to help improve their firm's performance.

Figure 5: **Factsheet: Innovation**

csae 25 YEARS CENTRE FOR THE STUDY OF AFRICAN ECONOMIES

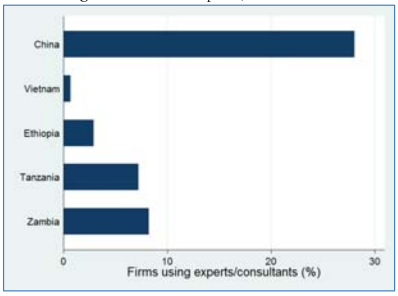
Asia-Africa Study Factsheet

UNIVERSITY OF OXFORD

Did you know…?

Fact 1: African firms could use experts and consultants more

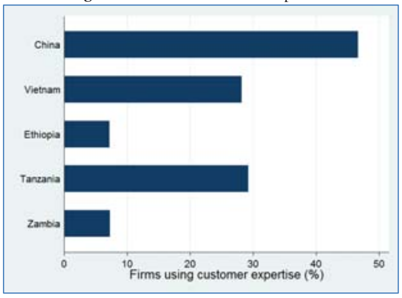
Figure 1: Use of experts/consultants



Research shows that **Chinese** firms are much more likely than firms in Africa to use **experts/consultants** to develop new products and to introduce new production processes. This is illustrated in **Figure 1**. This suggests that more African firms could **follow the Chinese example**.

Fact 2: African firms could use customer expertise more

Figure 2: Use of customer expertise



Customers can be an important source of ideas and technological expertise. **Figure 2** shows that Chinese firms are more likely to use the expertise of their customers for developing new products.

Here are some steps that a firm can take to innovate more successfully:

- ✓ Finding **consulting firms** that can advise on introducing new products or processes;
- ✓ Speaking to **suppliers of machines and equipment** about other firms and their innovations;
- ✓ Discussing potential innovations with **customers**;
- ✓ Joining a **business association**;
- ✓ **Discussing innovation strategies with other firms** that innovate successfully.

We appreciate your participation in the study and we hope that you find this information useful.*

Marcel Fafchamps	**Simon Quinn**
Professor of Development Economics	Post-doctoral researcher
University of Oxford	University of Oxford

* Your firm was surveyed last year by the Centre for the Study of African Economies at the University of Oxford (UK). This was part of a research project to learn about African competitiveness in manufacturing. The study covered China, Vietnam, Ethiopia, Tanzania and Zambia. Many firm managers asked us to pass on results from the study, to help improve their firm's performance.

Figure 6: **Factsheet: Labour management**

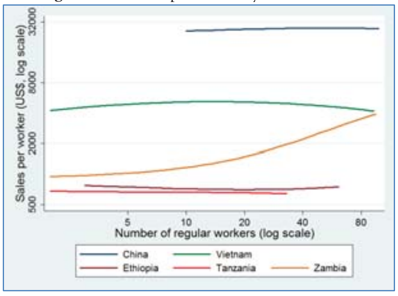
Asia-Africa Study Factsheet

Did you know…?

Fact 1: <u>Chinese firms produce more per worker than African firms</u>

Research shows that Chinese and Vietnamese firms produce substantially more per worker than firms in Ethiopia, Tanzania or Zambia.

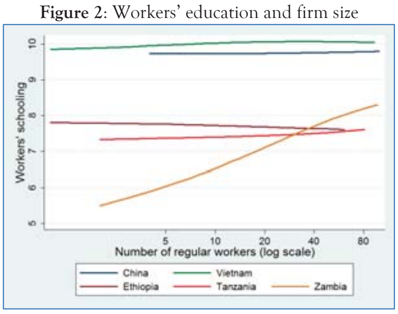
Figure 1: Labour productivity and firm size



Fact 2: <u>Asian firms hire more educated production workers</u>

Chinese and Vietnamese firms have a more highly educated production workforce. **Figure 2** compares the average education of entry-level production workers. This suggests that more African firms could **follow the Chinese example**.

Figure 2: Workers' education and firm size



Here are some steps that a firm can take to produce more per worker:

- ✓ Offering **on-the-job training or vocational training**;
- ✓ Relying on more educated workers to **supervise production**;
- ✓ Introducing **double or triple work shifts**;
- ✓ Boosting employee morale by offering **eating areas, private lockers and clean toilets**;
- ✓ **Discussing labour management strategies with other firms**.

We appreciate your participation in the study and we hope that you find this information useful.*

Marcel Fafchamps
Professor of Development Economics
University of Oxford

Simon Quinn
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University of Oxford

* Your firm was surveyed last year by the Centre for the Study of African Economies at the University of Oxford (UK). This was part of a research project to learn about African competitiveness in manufacturing. The study covered China, Vietnam, Ethiopia, Tanzania and Zambia. Many firm managers asked us to pass on results from the study, to help improve their firm's performance.

Table 20: **Structure of factsheet assignment**

	FACT SHEETS			
	CSAE	EXPORTS	INNOVATION	LABOUR
$\alpha \cdot 1$	✓	✓		
$\alpha \cdot 2$		✓	✓	
$\alpha \cdot 3$			✓	✓
$\alpha \cdot 4$	✓			✓
$\alpha \cdot 5$				
$\alpha \cdot 6$				
$\beta \cdot 1$	✓	✓		
$\beta \cdot 2$		✓		✓
$\beta \cdot 3$			✓	✓
$\beta \cdot 4$	✓		✓	
$\beta \cdot 5$				
$\beta \cdot 6$				
$\gamma \cdot 1$	✓		✓	
$\gamma \cdot 2$		✓	✓	
$\gamma \cdot 3$		✓		✓
$\gamma \cdot 4$	✓			✓
$\gamma \cdot 5$				
$\gamma \cdot 6$				
$\delta \cdot 1$	✓		✓	
$\delta \cdot 2$			✓	✓
$\delta \cdot 3$		✓		✓
$\delta \cdot 4$	✓	✓		
$\delta \cdot 5$				
$\delta \cdot 6$				
$\varepsilon \cdot 1$	✓			✓
$\varepsilon \cdot 2$		✓		✓
$\varepsilon \cdot 3$		✓	✓	
$\varepsilon \cdot 4$	✓		✓	
$\varepsilon \cdot 5$				
$\varepsilon \cdot 6$				
$\zeta \cdot 1$	✓			✓
$\zeta \cdot 2$			✓	✓
$\zeta \cdot 3$		✓	✓	
$\zeta \cdot 4$	✓	✓		
$\zeta \cdot 5$				
$\zeta \cdot 6$				

Appendix 2: Additional estimation results

Perceptions of business networks

Table 21 tests for measures of the number of friends (specifically, whether the respondent has friends or relatives in various positions, and the total number of friends and relatives in business in other firms). Table 22 tests characteristics of friends (including the respondents' perceptions of their friends' experience, firm size, frequency of speaking, and whether the respondents' friends know each other). Table 23 tests whether respondents have friends who would help with various aspects of doing business; Table 24 tests whether the respondent has ever helped any of his her friends or relatives in doing business.

< Table 21 here. >
< Table 22 here. >
< Table 23 here. >
< Table 24 here. >

Disaggregation by size and sector

Tables 25 and 26 disaggregate by size for measures of labour management; as in Table 11, we find no significant diffusion effects.

< Table 25 here. >
< Table 26 here. >

Tables 27 to 30 test whether diffusion is stronger between two firms that are in the same sector. We find no evidence of this across any of the outcomes considered.

< Table 27 here. >
< Table 28 here. >
< Table 29 here. >
< Table 30 here. >

Table 21: **Results: Number of friends**

	(1)	(2)	(3)	(4)	(5)	(6)
Dummy: Committee judge	**-0.067**	**-0.012**	**-0.084**	**0.034**	**-0.400**	**0.089**
	[0.427]	**[0.689]**	**[0.427]**	**[0.427]**	**[0.689]**	**[0.427]**
	(0.230)	(0.829)	(0.100)	(0.272)	(0.689)	(0.097)*
	{0.627}	{0.842}	{0.439}	{0.627}	{0.842}	{0.439}
Session dummies	✓	✓	✓	✓	✓	✓
Observations	330	330	329	330	330	327

Outcome variables:
1: Whether the respondent has friends or relatives working as bank officials.
2: Whether the respondent has friends or relatives who are elected officials / political party officials.
3: Whether the respondent has friends or relatives who are working for the government.
4: Whether the respondent has friends or relatives who are in business in other firms.
5: Number of friends and relatives who are in business in other firms.
6: Whether the respondent has friends or relatives in the same sector.

'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 22: **Results: Characteristics of friends**

	(1)	(2)	(3)	(4)	(5)
Dummy: Committee judge	**0.017**	**0.070**	**0.010**	**-0.020**	**-0.033**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.767)	(0.231)	(0.845)	(0.712)	(0.545)
	{0.875}	{0.729}	{0.875}	{0.875}	{0.875}
Session dummies	✓	✓	✓	✓	✓
Observations	330	329	329	321	321

Outcome variables:
1: On average, business friends/relatives are more experienced than the respondent.
2: On average, business friends/relatives work in a larger firm than the respondent.
3: On average, the respondent speaks at least weekly with his/her business friends/relatives.
4: Some of the respondent's business friends/relatives know each other.
5: All of the respondent's business friends/relatives know each other.

'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 23: **Results: Friends who could help**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dummy: Committee judge	**0.010**	**-0.105**	**0.008**	**-0.026**	**-0.016**	**-0.001**	**0.045**	**0.023**
	[1.000]	**[0.550]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.843)	(0.044)**	(0.887)	(0.647)	(0.779)	(0.986)	(0.427)	(0.682)
	{0.988}	{0.274}	{0.988}	{0.988}	{0.988}	{0.993}	{0.954}	{0.988}
Session dummies	✓	✓	✓	✓	✓	✓	✓	✓
Observations	327	327	325	328	328	328	328	328

Outcome variables:

Respondent has at least one friend/relative in business who could…

1: …help to identify sources of raw materials domestically.

2: …help to identify sources of raw materials in another country.

3: …help to identify new markets for your products.

4: …help to secure external finance for the firm.

5: …help to identify and recruit skilled workers for the firm.

6: …provide valuable technological information about which machinery/equipment to purchase for the firm.

7: …help to obtain information on where to buy second-hand machinery/equipment.

8: …provide information about how to operate and repair machinery/equipment.

'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.

'( )' show standard p-values, allowing for clustering by committee.

'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.

Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 24: **Results: Friends whom the respondent has helped**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dummy: Committee judge	**0.081**	**0.073**	**0.012**	**-0.000**	**0.006**	**0.016**	**0.085**	**-0.019**
	[0.868]	**[0.868]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[0.868]**	**[1.000]**
	(0.157)	(0.174)	(0.824)	(1.000)	(0.918)	(0.789)	(0.145)	(0.761)
	{0.638}	{0.638}	{0.993}	{0.994}	{0.993}	{0.993}	{0.629}	{0.993}
Session dummies	✓	✓	✓	✓	✓	✓	✓	✓
Observations	327	327	326	328	327	296	328	325

Outcome variables:

Respondent has helped at least one friend/relative in business . . .

1: . . . to identify sources of raw materials domestically.

2: . . . to identify sources of raw materials in another country.

3: . . . to identify new markets for your products.

4: . . . to secure external finance for the firm.

5: . . . to identify and recruit skilled workers for the firm.

6: . . . by providing valuable technological information about which machinery/equipment to purchase for the firm.

7: . . . to obtain information on where to buy second-hand machinery/equipment.

8: . . . by providing information about how to operate and repair machinery/equipment.

‘[ ]’ show the ‘sharpened’ False Discovery Rate adjusted q-values.

‘( )’ show standard p-values, allowing for clustering by committee.

‘{ }’ show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.

Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 25: **Diffusion results for 'large' firms: Labour management**

	(1)	(2)	(3)	(4)	(5)	(6)
Sum of small peers adopting	**0.021**	**-0.052**	**0.111**	**0.064**	**-0.002**	**0.149**
	[0.939]	**[0.347]**	**[0.265]**	**[0.265]**	**[0.944]**	**[0.265]**
	(0.806)	(0.343)	(0.088)*	(0.118)	(0.971)	(0.039)**
	{0.931}	{0.742}	{0.466}	{0.466}	{0.977}	{0.311}
Sum of small peers <u>not</u> adopting	**0.007**	**-0.037**	**-0.032**	**0.024**	**-0.016**	**0.020**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.674)	(0.125)	(0.431)	(0.597)	(0.694)	(0.550)
	{0.703}	{0.664}	{0.703}	{0.703}	{0.703}	{0.703}
Sum of large peers adopting	**0.013**	**-0.021**	**0.044**	**0.001**	**-0.031**	**-0.196**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[0.434]**
	(0.869)	(0.799)	(0.267)	(0.970)	(0.466)	(0.050)*
	{0.963}	{0.963}	{0.844}	{0.971}	{0.924}	{0.393}
Sum of large peers <u>not</u> adopting	**-0.019**	**0.017**	**0.027**	**-0.093**	**0.040**	**0.034**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.401)	(0.321)	(0.539)	(0.121)	(0.568)	(0.374)
	{0.614}	{0.614}	{0.614}	{0.614}	{0.614}	{0.614}
Controls	✓	✓	✓	✓	✓	✓
Observations	135	135	134	123	131	131
H_0: Imitation, small firms (p)	0.743	0.135	0.191	0.114	0.760	0.038**
H_0: Imitation, large firms (p)	0.941	0.970	0.139	0.168	0.886	0.089*

Outcome variables:
1: Whether the firm provides housing for any employees
2: Whether the firm provides free/subsidised meals for any production workers
3: Whether the firm provides toilets with running water for any production workers
4: Whether the firm hires production workers without recommendation/referral
5: Whether the average production worker has more than 7 years' education
6: Whether entry-level production workers receive more than 1 month's training

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 26: **Diffusion results for ‘small’ firms: Labour management**

	(1)	(2)	(3)	(4)	(5)	(6)
Sum of small peers adopting	**0.021**	**-0.014**	**-0.030**	**0.026**	**-0.007**	**-0.023**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.630)	(0.724)	(0.444)	(0.368)	(0.864)	(0.335)
	{0.848}	{0.848}	{0.848}	{0.848}	{0.848}	{0.848}
Sum of small peers <u>not</u> adopting	**0.006**	**-0.006**	**0.018**	**0.001**	**0.021**	**0.017**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.488)	(0.721)	(0.552)	(0.981)	(0.330)	(0.501)
	{0.926}	{0.933}	{0.926}	{0.985}	{0.908}	{0.926}
Sum of large peers adopting	**0.048**	**-0.052**	**-0.001**	**-0.064**	**-0.017**	**-0.130**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**	**[1.000]**
	(0.372)	(0.335)	(0.989)	(0.190)	(0.663)	(0.085)*
	{0.743}	{0.743}	{0.992}	{0.677}	{0.893}	{0.455}
Sum of large peers <u>not</u> adopting	**0.042**	**-0.059**	**-0.054**	**0.051**	**-0.028**	**-0.078**
	[0.139]	**[0.417]**	**[0.441]**	**[0.441]**	**[0.686]**	**[0.139]**
	(0.041)**	(0.221)	(0.343)	(0.382)	(0.610)	(0.033)**
	{0.211}	{0.626}	{0.626}	{0.626}	{0.626}	{0.211}
Controls	✓	✓	✓	✓	✓	✓
Observations	191	192	191	191	185	189
H_0: Imitation, small firms (p)	0.526	0.614	0.752	0.487	0.773	0.845
H_0: Imitation, large firms (p)	0.150	0.080*	0.486	0.867	0.522	0.010**

Outcome variables:
1: Whether the firm provides housing for any employees
2: Whether the firm provides free/subsidised meals for any production workers
3: Whether the firm provides toilets with running water for any production workers
4: Whether the firm hires production workers without recommendation/referral
5: Whether the average production worker has more than 7 years’ education
6: Whether entry-level production workers receive more than 1 month’s training

Coefficients show the estimated mean marginal effect.
‘[ ]’ show the ‘sharpened’ False Discovery Rate adjusted q-values.
‘( )’ show standard p-values, allowing for clustering by committee.
‘{ }’ show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 27: **Diffusion results and sector: Formalisation**

	(1)	(2)	(3)	(4)
Sum of peers adopting	**0.083**	**0.024**	**0.044**	**0.033**
	(0.006)***	(0.243)	(0.065)*	(0.316)
Sum of peers <u>not</u> adopting	**0.005**	**0.010**	**-0.016**	**-0.031**
	(0.596)	(0.309)	(0.420)	(0.048)**
Sum of peers adopting (same sector)	**-0.079**	**-0.073**	**0.003**	**-0.017**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**
	(0.389)	(0.205)	(0.946)	(0.741)
	{0.805}	{0.668}	{0.938}	{0.921}
Sum of peers <u>not</u> adopting (same sector)	**-0.013**	**-0.004**	**-0.020**	**0.031**
	[1.000]	**[1.000]**	**[1.000]**	**[1.000]**
	(0.451)	(0.867)	(0.511)	(0.203)
	{0.757}	{0.872}	{0.757}	{0.611}
Controls	✓	✓	✓	✓
Observations	333	326	329	326
H_0: Imitation (p)	0.006***	0.142	0.362	0.944
H_0: Imitation, same sector (p)	0.317	0.170	0.741	0.800

Outcome variables:
1: Whether the firm is registered for VAT ('missing' = 'no')
2: Whether the firm's financial statements are certified by external auditor.
3: Whether the firm has a bank current account.
4: Whether the firm has a savings account.

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 28: **Diffusion results and sector: Labour management**

	(1)	(2)	(3)	(4)	(5)	(6)
Sum of peers adopting	**0.008**	**-0.048**	**0.001**	**0.031**	**-0.029**	**-0.040**
	(0.810)	(0.067)*	(0.972)	(0.243)	(0.259)	(0.158)
Sum of peers <u>not</u> adopting	**0.001**	**-0.004**	**0.011**	**-0.019**	**0.033**	**0.019**
	(0.888)	(0.757)	(0.658)	(0.491)	(0.085)*	(0.292)
Sum of peers adopting (same sector)	**0.079**	**0.017**	**0.031**	**-0.057**	**0.069**	**0.123**
	[0.640]	**[0.880]**	**[0.880]**	**[0.640]**	**[0.640]**	**[0.348]**
	(0.301)	(0.723)	(0.555)	(0.312)	(0.276)	(0.043)**
	{0.692}	{0.753}	{0.753}	{0.692}	{0.692}	{0.301}
Sum of peers <u>not</u> adopting (same sector)	**0.006**	**-0.029**	**-0.054**	**0.064**	**-0.093**	**-0.037**
	[0.607]	**[0.568]**	**[0.432]**	**[0.432]**	**[0.051]***	**[0.568]**
	(0.755)	(0.373)	(0.181)	(0.132)	(0.008)***	(0.436)
	{0.782}	{0.721}	{0.622}	{0.605}	{0.089}*	{0.721}
Controls	✓	✓	✓	✓	✓	✓
Observations	326	327	325	314	316	320
H_0: Imitation (p)	0.781	0.056*	0.688	0.699	0.894	0.512
H_0: Imitation, same sector (p)	0.290	0.825	0.706	0.910	0.716	0.230

Outcome variables:
1: Whether the firm provides housing for any employees
2: Whether the firm provides free/subsidised meals for any production workers
3: Whether the firm provides toilets with running water for any production workers
4: Whether the firm hires production workers without recommendation/referral
5: Whether the average production worker has more than 7 years' education
6: Whether entry-level production workers receive more than 1 month's training

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 29: **Diffusion results and sector: Relations with clients and suppliers**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sum of peers adopting	**0.039**	**0.100**	**-0.015**	**0.000**	**0.000**	**0.012**	**-0.081**
	(0.104)	(0.015)**	(0.603)	(0.999)	(0.996)	(0.720)	(0.114)
Sum of peers not adopting	**-0.014**	**-0.002**	**-0.020**	**0.013**	**0.010**	**-0.006**	**0.000**
	(0.385)	(0.880)	(0.195)	(0.636)	(0.594)	(0.402)	(0.953)
Sum of peers adopting (same sector)	**0.027**	**-0.067**	**0.028**	**0.087**	**-0.032**		
	[0.722]	**[0.573]**	**[0.722]**	**[0.205]**	**[0.573]**		
	(0.524)	(0.207)	(0.490)	(0.034)**	(0.273)		
	{0.522}	{0.522}	{0.522}	{0.276}	{0.522}		
Sum of peers not adopting (same sector)	**-0.043**	**0.039**	**0.004**	**0.061**	**-0.018**	**0.023**	**0.006**
	[0.465]	**[0.465]**	**[0.903]**	**[0.465]**	**[0.902]**	**[0.465]**	**[0.902]**
	(0.271)	(0.068)*	(0.914)	(0.136)	(0.658)	(0.107)	(0.711)
	{0.710}	{0.501}	{0.920}	{0.567}	{0.915}	{0.537}	{0.915}
Controls	✓	✓	✓	✓	✓	✓	✓
Observations	325	324	323	327	327	323	318
H_0: Imitation(p)	0.374	0.017**	0.228	0.657	0.756	0.869	0.117
H_0: Imitation, same sector (p)	0.807	0.543	0.568	0.010**	0.362	0.107	0.711

Outcome variables:
1: Whether the firm has advertised in the past 6 months
2: Whether the firm pays any purchases before delivery
3: Whether the firm pays any purchases after delivery
4: Whether the firm has any sales paid before delivery
5: Whether the firm has any sales paid after delivery
6: Whether the firm imports
7: Whether the firm exports

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 30: **Diffusion results and sector: Innovation**

	(1)	(2)	(3)
Sum of peers adopting	**0.032**	**0.010**	**-0.048**
	(0.246)	(0.705)	(0.113)
Sum of peers <u>not</u> adopting	**0.014**	**-0.013**	**0.004**
	(0.409)	(0.373)	(0.670)
Sum of peers adopting (same sector)	**-0.075**	**0.032**	**-0.007**
	[0.417]	**[0.761]**	**[1.000]**
	(0.098)*	(0.432)	(0.910)
	{0.287}	{0.703}	{0.913}
Sum of peers <u>not</u> adopting (same sector)	**-0.006**	**0.021**	**0.014**
	[1.000]	**[1.000]**	**[1.000]**
	(0.843)	(0.568)	(0.348)
	{0.869}	{0.817}	{0.742}
Controls	✓	✓	✓
Observations	324	328	328
H_0: Imitation(p)	0.106	0.917	0.160
H_0: Imitation, same sector (p)	0.101	0.376	0.911

Outcome variables:
1: Whether the firm has introduced new products in the past year
2: Whether the firm has changed its production processes in the past year (e.g. layout)
3: Whether the firm has changed its product delivery methods in the past year
(Note: The baseline questions for these estimations referred to the last three financial years.)

Coefficients show the estimated mean marginal effect.
'[ ]' show the 'sharpened' False Discovery Rate adjusted q-values.
'( )' show standard p-values, allowing for clustering by committee.
'{ }' show p-values corrected for the FWER, using a Westfall-Young Stepdown Bootstrap.
Significance: *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.