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Skill Based Management: Evidence from Manufacturing Firms

Andy Feng
Anna Valero

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

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Abstract
This paper investigates the link between management practices and workforce skills in manufacturing firms, exploiting geographical variation in the supply of human capital. Skills measures are constructed using newly compiled data on universities and regional labour markets across 19 countries. Consistent with management practices being complementary with skills, we show that firms further away from universities employ fewer skilled workers and are worse managed, even after controlling for a rich set of observables and fixed effects. Analysis using regional skill premia suggests that variation in the price of skill drives these relationships.

Key words: management practices, human capital, universities, complementarities
JEL Codes: I23; I26; J24; L2; M2

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Andy Feng, Ministry of Trade and Industry, Government of Singapore. Anna Valero, Centre for Economic Performance, London School of Economics.

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There have been major advances in the measurement and analysis of management practices in recent years. Survey data have established the importance of management practices in explaining differentials in productivity between and within countries and sectors (Bloom and Van Reenen, 2007; Bloom *et al.*, 2014b). Recent analysis has estimated that across countries, management explains on average around 30 per cent of the gap in total factor productivity with the United States (Bloom *et al.*, 2016), and experimental evidence from Indian textile plants has shown that management plays a causal role in this regard (Bloom *et al.*, 2013).[1] However, less is known about why firms adopt different management practices (Bloom *et al.*, 2019). Given that management practices are so important for firm performance, and can be measured and benchmarked across firms, why do we not see all firms adopting best practice?

Motivated by previously documented associations between plant level management practices and skills (see for example Bloom and Van Reenen, 2007; Bloom *et al.*, 2014b), this paper uses data from the World Management Survey (WMS) on manufacturing plants to test the hypothesis that human capital and management practices are complements. We construct a new dataset across 19 countries related to plant and region-level skill availability, and in "factor demand" equations (Brynjolfsson and Milgrom, 2013), find robust evidence that firms facing more abundant (and cheaper) skills have higher management scores, ceteris paribus. This supports the hypothesis that modern management practices and a skilled workforce are complementary, consistent with a skilled workforce increasing the marginal benefit or lowering the marginal cost associated with good management practices, so that firms facing a skill-abundant workforce employ more skilled labour and have better management practices in equilibrium. In this sense, good management practices - adopted as a consequence of the channel studied here - are examples of "skill biased management".

Assuming that labour markets are local in nature (Moretti, 2011), we construct two main measures of local or regional skill supply. The first measure is the plant specific distance to nearest university. We calculate this as a drive time using geocoded information on WMS plants (across regions in 19 countries) and universities from the World Higher Education Database (WHED) - an international listing of higher education institutions. The second measure of skill supply is the regional skill premium. To calculate this we obtain labour force micro data in 13 countries, which allow us to run wage regressions and estimate the wage premium for university graduates at the subnational region level.

We hypothesise that universities increase the supply of skills, and hence reduce the price of skills;

[1] Much of this literature is focused on interviewing middle managers to understand organisational structures and day to day processes within firms. There have also been major advances in the measurement of CEO behaviour (Bandiera *et al.*, 2017). While CEO behaviour and management practices are correlated with each other, they also appear to be independently correlated with firm performance.

and that this is the mechanism through which we might expect the distance measure to be related to firm human capital and management practices. In support of this, we show that regions with higher university density (universities normalised by population) have a higher degree share and lower skill premium. This is a new finding that suggests that skill is expensive when it is relatively scarce in a location and cheap when it is abundant.

In the firm level analysis, we find a robust relationship between distance (drive time), firm level human capital and management practices: firms further from universities have fewer skilled workers and managers, and are on average worse managed. We control for firm and geographic characteristics, and country, time and industry fixed effects. We include region fixed effects to control for unobservable characteristics at the subnational level that are related to university presence and the management of firms. In the absence of an instrument for university location using this rich international dataset, we cannot rule out the possibility that the results are driven by better managed firms choosing locations close to universities, though we partially address this concern by showing that there is no differential effect for firms which are founded after their nearest university, and by considering within firm variation as an extension to the skill premium analysis. We note however, that if our results are driven by better managed firms making such locational decisions, they are still supportive of a complementarity between better management and skills.

Next, we replace distance to nearest university with the regional skill premium in our regressions and show that firms facing higher skill premia in the region in which they are located employ significantly less skilled workers and are significantly worse managed. We find that these results are stronger when we exclude capital regions, where we might expect demand shocks or other unobservables that raise both the skill premium and management practices are more prevalent. Moreover, firms in capital cities are more likely to be able to recruit from wider areas (due to commuting patterns or inward migration).

We explore whether our results are heterogeneous by observable firm characteristics, noting that the assumption that labour markets are local may depend on firm type. We find that the relationships between management practices and both university distance and regional skill premia are stronger for single-plant firms compared to plants that are part of multinationals or multi-plant domestic firms. This is intuitive, since these types of firms are likely to be less reliant on the local environment when recruiting staff and setting management practices. Plants that are part of larger multinational enterprises may be able to attract workers from other regions or countries due to their stronger brand, and might also move staff between locations (Choudhury, 2017). Moreover, management practices in such firms might be set centrally at the company headquarters, which may be in a different region or even country. In contrast, in the distance analysis there is no evidence of heterogeneity with respect to observable university characteristics, including subject mix. In particular, the results are not driven by universities offering business type courses. This suggests that the university effect is more likely to operate via their role as producers of general human capital, rather than as providers of consultancy services or training for local firms which we might expect to be more prevalent in business schools.

Our main regressions are estimated using surveyed firms as a cross section. A subset of firms in the WMS were re-interviewed during the sample period which allows us to estimate how changes in firm level human capital and skill prices affect management practices (there is not enough variation in the number of universities over this short time frame to use the distance measure in the panel). While this specification is demanding on the data, there remains a robust positive relationship between firm level changes in human capital and management practices, and a negative relationship between changes in regional skill premia and firm management practices.

The focus in this paper is on testing for complementarities by estimating demand equations (Brynjolfsson and Milgrom, 2013). However, on a subsample of plants where performance data are available we also examine whether there is evidence that a more highly skilled workforce increases the marginal benefit of adopting modern management practices. This is tested using interactions between workforce skills and management practices in performance equations (Brynjolfsson and Milgrom, 2013). We estimate simple production functions including firm degree share, and then external skills measures (distance to university and regional skill premium) and their interaction with management practices. Here we find more tentative evidence of complementarities in the case of single plant firms only, consistent with the finding that plant-specific locational measures of skill supply appear more relevant in such cases.

In general, a complementarity between worker skills and management practices may seem intuitive. The surveyed management practices closely resemble the complementary characteristics of "modern manufacturing" discussed by Milgrom and Roberts (1990) and Roberts (1995). Highly skilled, cross trained workers are listed alongside (among other things) lean production techniques, performance tracking and communications as features of the modern firm (Roberts, 1995). A more educated workforce is more likely to show initiative and be able to effectively implement complex, flexible and more decentralised production practices. On the other hand, one could also argue that certain management practices and skilled workers could be substitutes. In the presence of a highly skilled workforce, there may be less need for constant performance tracking and communicating - more able workers could just be left to get on with their jobs. Of course, there may be heterogeneity in these relationships for different types of management practices but our results show that skills and management are, on average, not substitute inputs to production. Shedding light on this issue empirically is therefore valuable for helping managers and policy makers understand best how to improve management practices and hence productivity.

This paper contributes to the literature that seeks to explain the differences in management practices that are observed across firms. In a series of papers, Bloom, Sadun, Van Reenen and co-authors have shown that education of both managers and workers are strongly correlated with management scores (Bloom and Van Reenen, 2007, 2010; Bloom *et al.*, 2014b). Using Census Bureau survey data on plants in the US, Bloom *et al.* (2017a) show that plants within counties with "quasi-random" land grant colleges (Moretti, 2004) have significantly higher management scores, and the same can be said for counties with a higher college share in the working age population.[2] Bender *et al.* (2016) use matched employer-employee data in Germany to show that better managed firms recruit and retain skilled workers.[3] We contribute to this literature by using newly collated international measures of skills which are external to the firm. Our empirical strategy of using distance to universities has been used widely in the labour economics and innovation literatures.[4] This paper is the first, to our knowledge, that relates distance to universities to firm management.[5]

More generally, we contribute to the evidence on organisational complementarities and skill biased technology. A theoretical framework for thinking about organisational complementarities is set out by Milgrom and Roberts (1990), and Brynjolfsson and Milgrom (2013) give an overview of the theory and empirics of organisational complementarities.[6] Much of the empirical literature has focused on testing whether different types of organisational practices are optimally implemented together (for example Ichniowski *et al.*, 1997; Bresnahan *et al.*, 2002; Black and Lynch, 2001, 2004). Our work using regional skill premia uses a similar approach to Caroli and Van Reenen (2001) who find evidence of skill-biased organisational change. There is compelling evidence that management can be thought of as an organisational technology (Bloom *et al.*, 2016), creating a link to the skill-biased technical change literature. In models of endogenous technology adoption (Basu and Weil, 1998; Zeira, 1998;

[2] Together with human capital, this paper explores three other drivers of management practices - competition, business environment and learning spillovers - and finds that together they account for about a third of the variation in management practices.

[3] Using administrative data from Portugal Queiro (2016) finds that firms with educated managers have better performance, and suggests that the mechanism for this involves educated managers being more likely to introduce new technologies.

[4] See for example, Card (1995) that relates distance to university to individual level enrollment at university. Examples of papers that relate proximity to universities to firm innovation include Anselin *et al.* (1997), Henderson *et al.* (1998) and Belenzon and Schankerman (2013)

[5] The WHED data in this paper have also been employed by Bloom *et al.* (2017b), who relate distance to university to hospital management practices. In contrast with our findings, they show that hospitals closer to universities with both business and medical schools are better managed, but that there are no effects for universities with only one of these departments, or neither. This suggests that specialist knowledge or training of managers (medical and MBA) is more important in the management of hospitals. Our results support a more of a general human capital effect, as university proximity is associated with a higher share of both managers and workers with a degree and better management practices, with no heterogeneity by broad university subject areas.

[6] Ennen and Richter (2010) also give review of the management, economics and other related literatures.

Caselli, 1999), which are tested using time series data in (Beaudry and Green, 2003, 2005), when a major technology becomes available, it is not adopted immediately by all agents. Instead it is adopted in environments where complementary factors are plentiful and cheap. Beaudry *et al.* (2010) find that US cities with low skill premia adopted computers more intensively, and Garicano and Heaton (2010) find evidence of complementarity between IT and skilled workers in US police departments. Our contribution to this literature is to provide empirical evidence that management practices are complementary with human capital based on an international sample of manufacturing firms, and newly collated data on universities and labour markets.

1 Data

1.1 Overview of Data Sources

We use data from three main sources, the key features of which are described in this section (for further details see the Data Appendix). Survey data on management practices and skills in manufacturing plants are obtained from the World Management Survey (WMS). The unit of observation is the manufacturing plant (referred to interchangeably as the firm in this paper). WMS questions relate to the management practices at a particular plant surveyed (rather than the head office, which might differ in the case of multi-plant firms).[7] Therefore the WMS gives a measure of management practices at a particular location, which makes the spatial approach taken in this paper appropriate. The measure of management practices is the standardised WMS management score, which is based on the average score that a plant achieves across 18 practices (broadly relating to operations, monitoring, targets and people management). It has been shown that management scores are positively and robustly correlated with performance (e.g. Bloom and Van Reenen, 2007; Bloom *et al.*, 2014b, 2016), a relationship that holds across countries, sectors and types of firm. We therefore interpret a higher management score as "better" management. The share of the workforce with a university degree is our measure of human capital - this is available for the total workforce, and managers/non-managers separately. In the distance analysis, we use data from surveys conducted between 2004 and 2010 across 19 countries, as a pooled cross section.

Information on universities across countries is sourced from the World Higher Education Database (WHED), which provides data on the location and other university characteristics (such as subjects or level of study offered, and founding date). See Valero and Van Reenen (2019) for a full description of the data. We geocode universities and plants, by mapping their postcodes to geographic coordinates.

[7] The analysis in this paper is at the plant level and we are clear when we explore heterogeneity across plants that are single-plant firms versus those that are part of multi-plant domestic or multinational enterprises

This enables us to calculate the main distance measure by estimating drive times between each plant and its nearest university (based on google maps). We favour drive time instead of a straight line distance because it accounts for natural geographic features. Given that the analysis in this paper is based on an international sample with differing geographies across countries, this helps to account for distance in a consistent manner. Alternative distance measures are explored in the robustness.

Analysis of the relationships between regional skill premia, firm human capital and management practices is conducted on a subsample of 13 countries where we were able to access international labour force survey (or equivalent) data sources.[8] Skill premia are estimated using wage regressions, where log wages are regressed on education, experience, experience squared and gender, by region. Our preferred specification includes a dummy variable to indicate whether or not an individual has a degree, and the estimated skill premium is the coefficient on this dummy. Available observations in regions are pooled over the years where data were available, and year fixed effects included in the regressions. We also compute the regional degree share and a raw wage ratio (the log ratio of skilled wages to unskilled wages), measures that were available for additional countries as ready-made regional aggregates.[9] Retrieving the skill premium from regional wage regressions is preferred as this controls for other factors that might differ across groups and regions.

The key geographic control is population density at the location of the plant (within 100km), which is based on data from the Center for International Earth Science (CIESIN) data. Other regional data were obtained from Gennaioli *et al.* (2013). In addition to average years of education, and college share which is used to sense check the supply of skills data collected from surveys, there are also other covariates such as as temperature, inverse distance to coast and oil per capita and population.

1.2 Descriptive Statistics

A summary of the key variables used in our analysis is provided in the Data Appendix. The mean management score in our sample is just under 3. In the average plant, 15 per cent of the total workforce have a degree. This is closer to 60 per cent looking only at managers, and 10 per cent for non-managers. In our regressions we take the natural log of the degree share, and add one so that zero observations are kept in the sample. We control for plant and firm employment, plant age and MNE status.[10] Just under half of plants are part of a multinational enterprise, and 59 per cent have more than one production site (multi-unit production). In our analysis, we consider multi-plant firms those that are

[8] For more details on the data sources see Table A9 in the Appendix.

[9] Microdata were obtained for 14 countries, and ready-made regional aggregates for an additional 4 countries. Our main analysis sample is based on 13 countries where reliable wage data were available, and the wider samples are included in robustness.

[10] Missing values are imputed and a dummy to indicate missing status is included in regressions.

either part of a multinational, or have multi-unit domestic production. 50 per cent of the plants are part of a large firm (which we define as having over 300 employees), and 28 per cent are listed. 40 per cent of the workforce of the average plant is in a union.

The average distance (drive time) to the nearest university is 0.45 hours. Figure 1 plots the histogram of driving times in 10 minute bins which is clearly skewed to the right. In the robustness, we experiment with using the natural log of the drive time, and exclude observations that are in the same postcode as universities (and hence have a drive time of zero). Locational features are controlled for by including longitude, latitude and average population density within a 100km radius of the plant. The average plant in our sample is in a region where the skill premium is 0.57, 19 per cent of the workforce have a degree and there are just under four universities per million people.

Country-level descriptive statistics on the sample on which we conduct our analysis are also reported in the Appendix. The United States has the highest management scores on average, though there is also substantial within-country variation. The highest degree share is in Japan, where 32 per cent of the workforce of the average plant are university graduates. The skill premia appear of reasonable magnitude compared to estimates from the literature.[11] There is also variation in the mean distances and skill premia across countries.

In this paper our focus is on finer grained analysis based on variation within countries or regions. The region in this analysis is equivalent to a US state or NUTS1-2 regions in Europe, and our sample contains 314 such regions across the 19 countries listed.[12]

2 Conceptual Framework and Empirical Strategy

2.1 Conceptual Framework

By their nature, it is reasonable to hypothesise that modern management practices and human capital are complements. Milgrom and Roberts (1990) and Roberts (1995) analysed "modern manufacturing" and argued that, given that there are complementarities among organisational practices, a range of practices may need to be implemented together for a particular technological advance to raise efficiency. A highly skilled workforce with transferrable skills is listed as one of the features of modern manufacturing.

The management practices scores in the WMS closely resemble Roberts' modern manufacturing. A well-managed firm is defined as one that has successfully implemented modern manufacturing

[11] For example, see Strauss and de la Maisonneuve (2007) for OECD country estimates.

[12] In the Appendix we report the number of regions in each country and show that there is substantial within-region variation.

techniques; and one that is "continuously monitoring and trying to improve its processes, setting comprehensive and stretching targets, and promoting high-performing employees and fixing (by training or exit) underperforming employees" (Bloom *et al.*, 2012).

A simple framework helps illustrate one path to our empirical strategy. We assume a neoclassical production function in a static environment. $Y = F(A, M, H)$ where output Y is some function of technology and human capital inputs H with $\partial Y/\partial H > 0$ and $\partial Y^2/\partial H^2 < 0$.[13] We distinguish between production technology A and management technology M (Lucas, 1978). It is assumed that performance is increasing continuously in the level of management quality[14], so $\partial Y/\partial M > 0$ and $\partial Y^2/\partial M^2 < 0$. Human capital-management complementarity, which we refer to as "skill biased management", implies a positive cross derivative: $\partial Y^2/\partial M \partial H > 0$. It follows therefore that in equilibrium, the firm's managerial technology is an increasing function of human capital:

$$M = G(H, A, \eta) \quad (1)$$

We interpret Equation 1 as a demand equation in a complementarity framework (see for example Bresnahan *et al.*, 2002), but other interpretations are possible.[15] This framework captures the fact that conditioning on firm level human capital, there is variation across firms in management practices due to other technologies, information frictions, optimisation errors or other idiosyncratic factors (η).

While our core analysis is focused on "demand equations" as represented in Equation 1, we also estimate production functions including levels of H (or a shifter of this), M and their interaction. The levels reflect the extent to which the firm has successfully adopted modern management practices and the degree to which the firm uses more highly skilled labour; while the interaction term will reflect complementarity (a positive cross-derivative implies a positive coefficient on the interaction term).

2.2 Empirical Strategy

Suppose we estimated the following using OLS:

$$M_i = \beta_0 + \beta_1 H_i + \beta_2 X_i + u_i \quad (2)$$

[13] We abstract from standard capital and labour for ease of notation.

[14] See Bloom *et al.* (2016) for a full description of management as a technology, which is modelled as an intangible capital stock, and evidence to support this view.

[15] If we interpret equation 1 as a production function, better management is "produced" by higher skilled managers or workers. An alternative interpretation (Nelson and Phelps, 1966) is that managers and workers of higher skill are able to draw and adapt random management technology from a better distribution. An interpretation closer to Lucas (1978) is that skilled managers are matched with better workers.

where for firm i, M is the management score, H is the level of human capital, X is observable firm characteristics including size and industry, and u is an idiosyncratic error term. A number of endogeneity issues arise. First, there are issues of omitted variables bias, the sign of which will depend on the nature of the omitted technologies A. For example, if information technologies that facilitate better management practices are positively correlated with skills, the bias would be positive. But if communication technologies that facilitate better management practices lead to a reduction in worker skills, the bias would be negative.[16] Intangible assets such as brand or firm culture may also be embodied in this unobserved technology, and such assets are also likely to be correlated with both management practices and worker skills. Second, observed correlations between management practices and skills might reflect reverse causality, if workers with higher human capital choose to work in better managed firms. We therefore need to find exogenous variation in workforce skills to be able to make a causal claim about the relationship between skills and management practices.

Our empirical strategy uses variation in the skill environments faced by firms, in a world with frictions that prevent the skill price equalising across space.[17] It can be described schematically as follows:

$$Universities_k \rightarrow Skill\ Supply_k \rightarrow Skill\ Price_k \rightarrow H_{ik} \rightarrow\ M_{ik}$$

where the first arrow represents the relationship between the spatial presence of universities and supply of human capital (measured as the share of the workforce with a degree in a region k), which we hypothesise will be positive. This rests on the assumption that student mobility is imperfect after graduation, so that at least some graduates stay and contribute to the local labour market. This seems reasonable based on observations in the US and the UK.[18] The share of skilled labour in the region can be expected to affect the relative skill price (skill premium), which we hypothesise will affect the hiring decisions of firms. All else equal, we would expect that a higher skill premium would result in a lower degree share in the firm (H_{ik}) since skilled labour is more expensive relative to unskilled labour. Finally, skill biased management would imply that there is a positive relationship between firm level human capital and the adoption of complementary management practices.

Our empirical approach to estimating these relationships is largely dictated by data availability and issues of aggregation. We begin by aggregating to the region level (equivalent to a US

[16] Bloom *et al.* (2014a) find that improvements in information technologies lead to decentralisation, while improvements in communication technologies have the opposite effect.

[17] In the absence of frictions, the price of skill would equalise (via the law of one price). In such a world, university presence should have no effect on skill shares in a local area. In reality, frictions and the inelastic supply of non-tradables such as land limit the extent of price equalisation - see for example, Roback (1988) and Glaeser and Gottlieb (2009).

[18] For example, Kodrzycki (2001) looks at NSLY data in the US and finds that over two-thirds of college graduates remain in the same state post graduation. Data from the UK Higher Education Statistics Authority shows that a high fraction of first degree graduates in a region remain in the same region for work. In 2004-05, this fraction was 61 per cent.

state), and linking university presence in a region with regional skills and prices ($Universities_k \rightarrow Skill\ Supply_k, Skill\ Price_k$). We then estimate the reduced form relationship between university presence and firm skills and management practices ($Universities_{ik} \rightarrow H_{ik}, M_{ik}$), calculating a firm specific distance measure between each firm and its closest university. In this analysis we are able to examine within region variation, so that unobservable factors that affect regional skills and firm outcomes are controlled for. To get more information on the mechanism and explore the effects of relative skill prices, we estimate the associations between regional skill prices, firm skills and management practices ($Skill\ Price_k \rightarrow H_{ik}, M_{ik}$).

2.2.1 Distance to University, Firm Skills and Management Practices

Our reduced form analysis examines the relationships between firm skills and management practices and distance to closest university. We estimate:

$$Y_{ijkct} = \alpha_1 Dist_{ijkct} + X'_{ijkct}\alpha_2 + \phi_j + \xi_k + \tau_t + \varepsilon_{ijkct} \tag{3}$$

for firm i in sector j, region k, country c and survey year t. The outcome variable $Y \in \{M, H\}$. The distance variable, $Dist$, is measured as the drive time to the nearest university in hours. We expect α_1 to be negative, firms closer to universities should have a higher degree share and be better managed, due to their improved access to skills.

We include a number of firm controls, X, that have been shown to matter for management practices (see for example Bloom and Van Reenen, 2007; Bloom *et al.*, 2016), and are likely to be related to skill share in the firm too. These include firm size, age and ownership status - we also include industry fixed effects ϕ_j. To pick up any differences over the years in which the WMS surveys are conducted, we include year dummies τ_t. ε_{ijkct} is the error term, which we cluster at the region level to allow for heteroskedasticity and correlation between firms in the same region. In the robustness we show that results are unchanged if we allow for more general spatial correlation.

To address concerns regarding location specific factors which may confound our estimates we do several things. First, we include regional fixed effects (ξ_k). We also control for geographic characteristics which may be correlated with both skills and the management of firms: in particular population density within 100km of the plant (also, longitude and latitude).

There are two main concerns around this estimation strategy. First, we may worry that well managed firms are endogenously located close to universities. To partially address this we examine universities founded after the firms were founded and show our results are similar. It seems less likely that there would be issues of reverse causality (that universities choose locations close to medium sized manufacturing firms - those surveyed in the WMS - with higher management scores), or firms endogenously choosing locations on the basis of future university openings.

Second, we may worry about the interpretation of a relationship between distance to universities and management practices. Such a relationship could be due to the diffusion of information or advice from universities to surrounding firms, for example via consultancy services, managerial training or access to more specialised inputs - rather than through an effect on the supply of skills as our diagram suggests. In practice, both mechanisms are likely to be at play, but if non human capital routes were more important we would expect that universities with certain subject mixes may have more of an effect - in particular, business, economics, finance, or even engineering and sciences. We are able to filter such universities, and show that they do not drive our results.[19]

2.2.2 Regional Skill Premia, Firm Skills and Management Practices

We now turn to our analysis of how firm human capital and management practices respond to the relative price of skills they face. The purpose of this part of the analysis is to provide evidence that firms respond to regional skill prices.

The regressions are similar to Equation 3, but the distance term is replaced by the skill premium. In this spatial analysis, skill premia (the log ratio of skilled wages to unskilled wages) need to be calculated based on a locational unit - and in line with the literature (see for example Caroli and Van Reenen, 2001; Gennaioli *et al.*, 2013) and what is feasible from a data perspective (see next section) we choose the subnational region, equivalent to a US state. We use the average skill premium over the period 2005-2010. Our main measure is the coefficient on a degree dummy from wage regressions, which is an estimate of the skill premium having controlled for other factors (such as worker experience). We expect that the coefficient on the skill premium will be negative: firms facing a higher skill premium will have lower human capital and be worse managed if skill biased management holds.

Since the skill premium varies at the regional level, we are unable to include region fixed effects in these regressions, but we do include country dummies. These regressions are weighted using the population in a region divided by the population in the country to reduce the effects of outliers in low population regions (for which labour force data is likely to be less reliable), and standard errors are clustered at the region level as before.

[19] Under the caveats above and the (strong) assumption that the exclusion restriction holds, i.e. that universities affect management only via their impact on the supply of skills, we also estimate the relationship between firm skills and management using the distance measure as an instrument for firm skills.

3 Results

3.1 Basic Relationships

A number of correlations motivate the analysis in this paper. The firm level correlation between degree share and management practices has been established in the literature (Bloom and Van Reenen, 2007; Bloom *et al.*, 2014b) and is the starting point for this study. Figure 2 plots the correlation between average management scores of firms within 20 equally sized bins in terms of degree share (absorbing country fixed effects, though results are not sensitive to this), showing a positive and precise relationship.[20] This strong relationship exists for both managers and non managers as shown in Table 1 which reports the regression equivalent.[21] A Wald test on the coefficients on managers and workers in column (4) shows that these are not significantly different from each other, and we keep our focus on total workforce skills in the analysis that will follow.

Figure 3 is a visualisation of the basic correlations between distance to nearest university, management practices and firm degree share, absorbing country fixed effects. This shows that firms that are further from their closest university tend to have lower management scores and a lower degree share.[22]

Finally, a key assumption in our regional skill premium analysis is that a higher price of skills in a region reflects lower supply and we therefore expect a negative correlation between the regional skill premium and degree share. We find that this is indeed the case (see Appendix Figure A1) and that the correlation is stronger when we omit capital regions. This seems intuitive, as demand shocks and other unobservables that raise both the skill premium and the supply of skilled workers may be considered more likely in hubs of economic activity.[23]

3.2 Main Results

3.2.1 Universities, Regional Skills and Skill Premia

We begin with some region level analysis to support the first causal link hypothesised in Section 2; the relationship between the location of universities, skill supply and skill premia. Table 2 shows that the

[20] These relationships are as strong using the unlogged degree share, but we use the natural log since this provides a better fit to the data (the equivalent plot of the unlogged degree share reveals a non-linearity in the relationship).

[21] The relationship between firm skills and management practices remains highly significant and of similar order of magnitude when a full set of controls are included, as can be seen in column (2) of Appendix Table A12.

[22] These graphs show that there are some outlier observations in remote regions. These are spread across countries with larger landmass, including Argentina, Australia, Canada, Chile, China and India. We retain these in the analysis, even though dropping them strengthens the relationships. When we construct our distance measures, we winsorise the distances of very remote plants to the regional maximum, see the Data Appendix for more details. Our regression results are robust to dropping such cases.

[23] To reflect this, our regional regressions that follow include a dummy variable indicating regions that contain a capital city.

correlations between regional university density (number of universities per million people), degree share and the estimated skill premium are significant and of the expected sign. Column (1) controls only for country dummies, and column (2) adds geographic controls. This analysis suggests that a one per cent rise in university density is associated with a 0.2 per cent higher degree share and a 0.03 per cent lower skill premium.[24]

3.2.2 Distance to University, Firm Skills and Management Practices

Next we report the reduced from relationships between firm management practices, degree share and distance to university (Table 3). The dependent variable in Panel A is the standardised management score. Column (1) includes country and year dummies plus survey controls to reduce noise in the data. The relationship between management scores and distance is negative and significant. Column (2) adds region fixed effects which have little impact on the main coefficient. In column (3), industry dummies and firm controls (as reported) are added and these reduce the magnitude of the coefficient slightly to -0.05. Column (4) adds geographic controls (population density, longitude and latitude, not reported here) none of which are significant, and the our coefficient is unchanged. Column (4) is the core specification, and implies that plants that are an extra hour of drive time away from their closest university (which is roughly two standard deviations) have on average 0.05 standard deviations worse management practices. In the next section we show that this result is robust to alternative specifications and sample selection.

Panel B reports regressions of firm level degree share on distance to university. Again, there is a significant and negative correlation between distance and degree share of -0.16 (column (1)). This decreases slightly in magnitude as we add controls in the order discussed previously. The result in column (4) implies that an extra hour of driving time reduces the log degree share by 0.12, representing over a tenth of the standard deviation across firms.[25]

The results of the core specifications (Table 3, column (4)) are depicted in Figure 4. This analysis suggests that, within regions, firms located close to universities have both higher human capital and higher management scores. While we cannot rule out the possibility that better managed firms are locating near to universities, or universities are providing other support that raises management practices, we go some way towards addressing these concerns in the analysis that follows.

[24] In further analysis, not reported here, consistent relationships are found with alternative measures of skills including the simple log wage ratio and variables sourced from Gennaioli *et al.* (2013): their estimate of college share and average years of education.

[25] We also estimated column (4) for managers and non-managers separately and found that the effect is negative and highly significant for both (the coefficient on distance for degree share of managers is -0.087, and the coefficient for non managers is -0.12, both are significant at the 1 per cent level).

3.2.3 Regional Skill Premia, Firm Skills and Management Practices

We have seen that regions with higher university density tend to have lower skill premia. In this section we provide evidence to suggest that the mechanism underlying the relationship between distance to university, skills and management practices is, at least in part, via the role of universities in increasing the supply and reducing the price of skills in their local area.

The relationships between regional skill premia and firm management practices and human capital are reported in Table 4 on the subsample of countries where labour force data were collected. The dependent variable in Panel A is the standardised management score. Column (1) controls only for country and year fixed effects, and shows that management scores are negatively and significantly related to regional skill premia. Column (2) adds 2 digit industry dummies and firm controls (consistent with our previous analysis) which reduces the coefficient. The addition of plant level geographic controls (longitude, latitude and population density) in column (3) increases significance.[26] Column (4) adds survey controls and our coefficient is slightly reduced.[27] The coefficient of -0.74 implies that a one per cent rise in the degree premium leads to a 0.0074 standard deviation reduction in management scores. To assess the magnitude of this effect, we apply it to the variation between US states. It implies that a one standard deviation rise in the skill premium reduces management scores by -0.04 standard deviations, representing 15 per cent of the cross-state variation.[28] Column (5) reports the result when capital regions are dropped, the relationship is now stronger and significant at the 1 per cent level, suggesting that unobservables that raise management practices and also raise the skill premium are more prevalent in capital regions.

The relationship between skill premia and degree share is less precisely estimated (Panel B), but still negative. In fact our coefficient gets stronger and more precise as geographic controls are added, in particular the capital region dummy. In column (4), the coefficient is -0.821, and significant at the 5 per cent level. As in Panel (A), excluding capital regions altogether increases the magnitude of the effect and its significance.

[26] We show that the core specification, column (4) is robust also to the addition of regional geographic controls in the robustness (see Appendix Table A11, panel C).

[27] Here we exclude the analyst dummies. This model using region-level variation has fewer effective degrees of freedom and we find that the analyst dummies have a large effect, reducing the magnitude of the coefficient and raising the standard errors (see robustness tests in Appendix Table A11 row (9)). We therefore leave them out of this core specification.

[28] The cross-state standard deviation of the degree premium in the US is 0.058. -0.7 x 0.058 = -0.04, which is 15 per cent of the cross region standard deviation in management scores (0.28).

3.3 Robustness and Heterogeneity

3.3.1 Summary of Robustness Tests

The results so far provide strong evidence that distance to university and regional skill premia matter for firm management practices. We test the robustness of the relationships between management practices and both the distance and skill premium measures, and the results are detailed in Appendix B. First, we show that the distance results are robust to different specification assumptions with respect to the clustering of standard errors, allowing non linearities in the distance measure, including additional geographic controls (in particular local population density), or more detailed fixed effects. We experiment with different distance measures that do not take geographical features into account (driving distance, straight line distance and the number of universities within a 100km radius). With driving / straight line distance, the coefficient takes the expected sign but precision is lost, while there are positive and significant relationships between management practices and the quantity of universities. We also add more granular fixed effects to the regressions. The distance coefficient remains negative and significant on the inclusion of country - year dummies, and region-industry dummies, but significance is lost in some of the more demanding specifications, for example using county or city level fixed effects. Results are robust to different sample choices.

Analogue robustness tests are carried out on our regional skill premium regressions (using the full sample that includes capital regions). These show that the sign of the relationship between skill premia and management practices is robust to different assumptions on specification and sample, but the significance of these results is lost in some cases. In particular, when standard errors are clustered at the country level, or when the regressions are unweighted (more noise is expected as skill premia are likely to be worse measured in less populous regions where sample sizes are smaller). In addition, we explore whether the expected relationships exist for alternative measures of regional skills such as a raw regional wage ratio or various quantity measures (such as degree share or regional years of education). In general, the coefficients on these measures are of the expected sign but they tend not to be significant. These measures are likely to provide a more noisy measure of the supply of skills in the labour market: the raw wage ratio does not correct for years of experience and gender; quantity based measures such as college share do not reflect how the market values skills; and an additional year of education means different things in different contexts or stages of education.[29]

[29] Indeed, the fact that our management regressions are not robust to quantity measures is consistent with Caroli and Van Reenen (2001), where the main measure of skills supply is the skill premium.

3.3.2 Heterogeneity Across Firm or University Type

We explore whether there is heterogeneity across observable characteristics of firms and universities to gain a better understanding of the mechanisms driving our results. We find evidence of heterogeneity in effects between plants that belong to multi-plant enterprises (defined as either being part of multinational firms or firms that have more than one production site domestically) and those that are single-plant firms. This appears to be the case in both the distance and skill premium specifications (Table 5). Column (1) shows our distance regression with a dummy for multi-plant firms.[30] In column (2) we add an interaction term between distance and the multi-plant dummy. This is positive but not significant, but the effect for single-plant firms is slightly larger. In columns (3) and (4) we replicate columns (1) and (2) on the sample for which skill premia are available. The average effect across all plants on the reduced sample is similar in this sample (0.056 compared to 0.050 in the full sample), but the effect of distance in single-plant firms is double the size (-0.11) and significant at the 1 per cent level, and the interaction term is larger and more significant (the p value is 0.102). Columns (5) and (6) show that similarly the skill premium has a stronger relationship with management practices in single plant firms, now the interaction term is significant at the 5 per cent level.

The finding that these relationships appear to be stronger in single-plant firms is intuitive as we might expect such firms to be more sensitive to their local labour markets. Plants that are part of a domestic multi-plant or multi-national firms are likely to have access to wider national or even international labour markets due to their ability to transfer staff internally or recruit staff from further afield due to a stronger or better known "brand". The relevant skills price for such firms is therefore not necessarily the regional skill premium; or at least we might expect that the regional skill premium is a worse-measured estimate of the effective skills price in such cases. A separate but related point is that in larger, multi-unit firms, management practices and processes might be set centrally at their headquarters. This could imply that managers in constituent plants are constrained in choosing the optimal management practices for their particular setting based on the availability of a complementary skilled workforce; i.e. that optimisation errors are more likely in these plants.[31]

Second, in the university distance analysis, we investigate whether specific types of university are driving the results. Heterogeneity across universities may tell us something about the mechanism through which universities impact on local firms. If we find stronger effects for universities with business departments, this could imply that it is the managerial skills that are important for the

[30] We vary our previous regressions here slightly by including a multi-plant dummy rather than only the MNE dummy from before.

[31] We explore heterogeneity across other firm characteristics including ownership, size and union representation, and in general there is no evidence of this in the distance specifications. On the other hand, consistent with the multi-unit results in the skill premium analysis, there are positive and significant interaction terms with a large firm dummy and listed status.

management of firms rather than general human capital. Furthermore, we might worry that the effects we have found are due to universities providing consulting services or other support to local firms rather than the provision of human capital, and stronger effects universities with business departments could suggest this type of mechanism is at work. The results show that there is no evidence of heterogeneity for universities offering business type courses or any other subject type (law and social sciences, medicine and science or arts and humanities), suggesting that universities affect firm management via their effect on general human capital rather than through the teaching of any particular discipline (see Table A5 in the Appendix).

We also examine whether the distance effect is stronger where the nearest university was founded before the plant. If better managed firms have based location decisions on the proximity to existing universities, then we may expect a stronger coefficient when we look at observations where the nearest university was founded before the plant. In fact, we find that there is no differential effect in such cases.

Finally, we check whether the relationships between management practices and skills measures that we have found exist for all the types of management practices scored in the WMS, or whether skills are more important for a subset of these. We run our distance and skill premium regressions with the standardised scores for each of the four different management practice groupings as dependent variables: operations, monitoring, targeting and people management (see Appendix Table A6). We find that the negative relationship with both the distance and skill premia measures applies across all practice groupings. This is consistent with the empirical fact that management practices within firms are correlated: a firm that scores highly on one managerial question will tend to score highly on all of them (Bloom *et al.*, 2014b). The coefficients vary in magnitude and significance across the two specifications and this is not driven by the different samples. In particular, distance to university appears to have the strongest relationship with Targeting, while the skill premium appears to be more strongly related to People Management and Monitoring. The stronger relationship between the skill premium and People Management, in particular, is intuitive as when skills are relatively more expensive, it is optimal for firms to do more to recruit and retain talent.

3.3.3 Distance to University as an Instrument

Based on the reduced form analysis we have presented, showing a robust relationship between management practices and distance to nearest university, we revisit the endogenous relationship between firm level degree share and management practices and estimate IV regressions using distance to nearest university as an instrument. The first stage therefore is equivalent to the specification in

Panel B, column (4) from Table 3. The results are in the Appendix. Overall this analysis does not suggest that OLS overestimates the relationship between firm skills and management practices as we might expect.[32] However, we treat these results with caution, as they rely not only on the exogeneity of university location, but also on the assumption that universities affect the management of firms only via their impact on firm degree share (rather than through direct consultancy, training services or other externalities), which is unlikely to hold in practice.

3.4 Extensions

3.4.1 Panel Estimates

The core results in this paper are based on cross sectional analysis, and while we have addressed concerns regarding identification to the extent possible, we cannot entirely rule out that the results are driven by other omitted variables or endogenous plant location. Therefore it is valuable to examine whether our relationships survive when variation is within firm. A subset of firms in a subset of countries (eleven of our sample of 19) were re-interviewed during the sample period (2005-2010).

We begin by examining whether our firm level relationship between degree share and management practices survives when we estimate a differenced regression (Table 6). Column (1) is the same specification as in the endogenous OLS regressions in Table 1 column (1) where only country and year fixed effects are controlled for, estimated on the more recent observation in the panel sample for comparison. Column (2) includes firm, industry, geography and noise controls. Columns (3) and (4) then replicate the first two columns but include the average annual change in management practices and degree share between survey waves instead of the levels. These results suggest that there is a positive bias in OLS estimates, and that plant specific unobservables are likely to be positively correlated with both skills and management practices.

Moving now to the regional skill premium analysis in Panel B, we also find evidence that the effects we found in the main analysis (Table 2) are not driven entirely by unobserved factors. Here columns (1) and (2) follow the cross sectional analysis on the reduced panel sample, but use a simple wage ratio as our time varying measure of the skill premium[33], for the nine countries in the panel

[32] In fact the IV results suggest that OLS estimates are biased downwards. In general, we anticipate an upward bias due to unobservables such as effective strategy or leadership that are likely to be positively correlated with both a higher skilled workforce and better management practices. However, a negative bias could occur if for example, communication technologies that are complementary with management practices, and raise management scores when employed, also reduced the requirement for skilled workers. It could also be the case that OLS results are attenuated due to measurement error in firm human capital which is a survey response, or reflect LATE effects whereby the relationships between firm level human capital and management practices are stronger for firms for whom distance to university is an important determinant of skilled workforce composition.

[33] We use this measure rather than the degree dummy coefficient from regional regressions on micro labour force data used in the cross section as there were insufficient observations in some region-year cells to calculate the latter measure robustly on an annual basis.

where annual wage ratio data were available.[34] We find a significant negative relationship between changes in management scores and the skill premium which becomes stronger once controls are added.[35]

3.4.2 Performance Equations

On the subsample of firms where financial data are available, we estimate simple production functions including firm degree share, and then separately in a reduced form approach, the external skills measures (distance to university and regional skill premium); and their interaction with management practices. Interacting the external measures which are proxies for the price of skills faced by the plants allows us to examine whether the marginal benefit of adopting modern management practices is higher when skills are cheaper. The results of this analysis are in the Appendix. In summary, we find more tentative evidence of complementarities in the case of single plant firms only, consistent with the finding that plant-specific locational measures of skill supply appear more relevant for such firms. These results provide additional suggestive evidence for complementarities to support our core analysis.

4 Conclusions

We have presented robust evidence that skills and management practices are complements using a newly analysed dataset on international universities and newly collated data on international subnational skill prices. Our proxy for skills access at the firm level is a measure of distance to closest university. Firms closer to universities have both higher degree share and management scores. These results can help us to understand one of the channels through which universities affect regional economic performance (Valero and Van Reenen, 2019). Using our estimates of regional skill premia, we provide evidence that universities might shift the supply and relative price of skills, which we then show are related to firm human capital and management scores. In extensions to our main analysis we also show that our results survive when variation is within plant, and provide some more tentative evidence of complementarities using the performance equations approach.

Complementarity between productivity enhancing management practices and general human capital is relevant for policymakers seeking ways to improve management in lagging firms, and productivity in general for two main reasons. First, complementarity implies that policies to raise

[34] These are France, Germany, Greece, Italy, Japan, Poland, Sweden, UK and US. Japan and Poland were not included in our core cross section analysis, as we were not able to obtain the microdata to run wage regressions. However, ready-made regional average wages (for skilled and unskilled workers respectively) were purchased from the statistical agencies in these countries. We note that the results in this table are very similar when Japan and Poland are excluded.

[35] Consistent with the cross sectional analysis, the coefficients are more negative when capital regions are excluded.

human capital do not only raise productivity via a direct impact on worker skills, but also via an indirect effect as firms with a skilled workforce are more likely to adopt better management practices. Second, it implies that the payoffs from implementing polices to raise general human capital and policies specifically aimed at improving management practices (such as managerial training) are higher when such polices are implemented together. Similarly, the evidence presented in this paper suggests that managers seeking to implement or maximise the effectiveness of modern management practices should ensure that they recruit sufficiently skilled workers and managers.

There are a number of directions for future work. First, the measure of firm level human capital used in this paper (degree share) does not account for skills acquired from vocational education or on-the-job training. It would be valuable to understand better the specific types of skill that are relevant with respect to modern management practices, and how these can best be acquired. Second, the analysis in this paper is based on the manufacturing sector and similar work could be carried out to explore whether there is evidence of complementarities in the service sectors which dominate as a share of GDP in advanced economies like the US and UK. Finally, it would be interesting to consider how workforce skills might complement different manager types (Bandiera *et al.*, 2017), and how these interact with management practices as determinants of firm performance.

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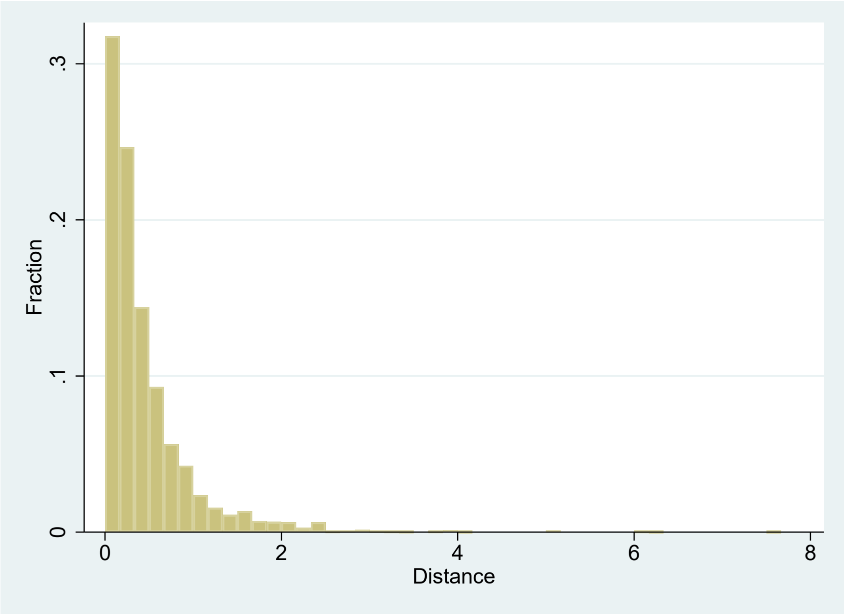
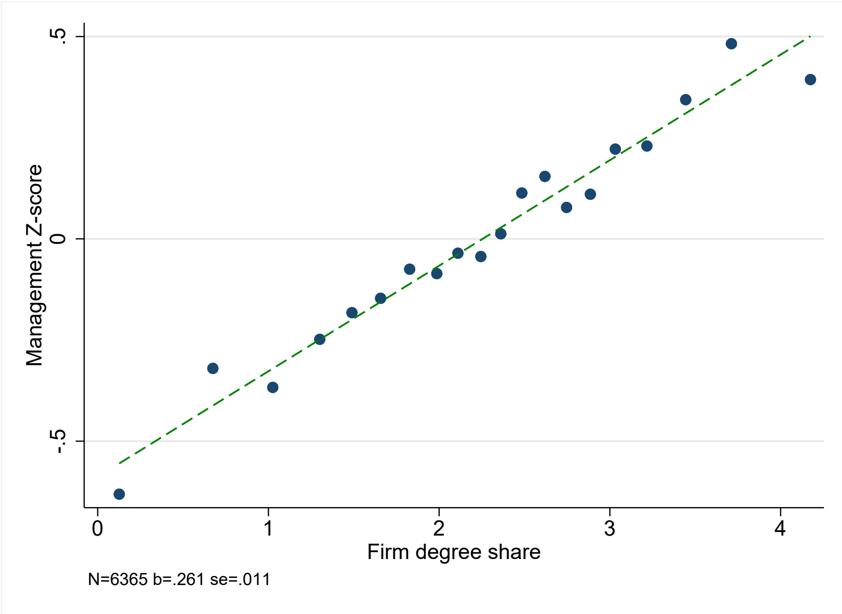
Figure 1: Histogram of Distance Measure



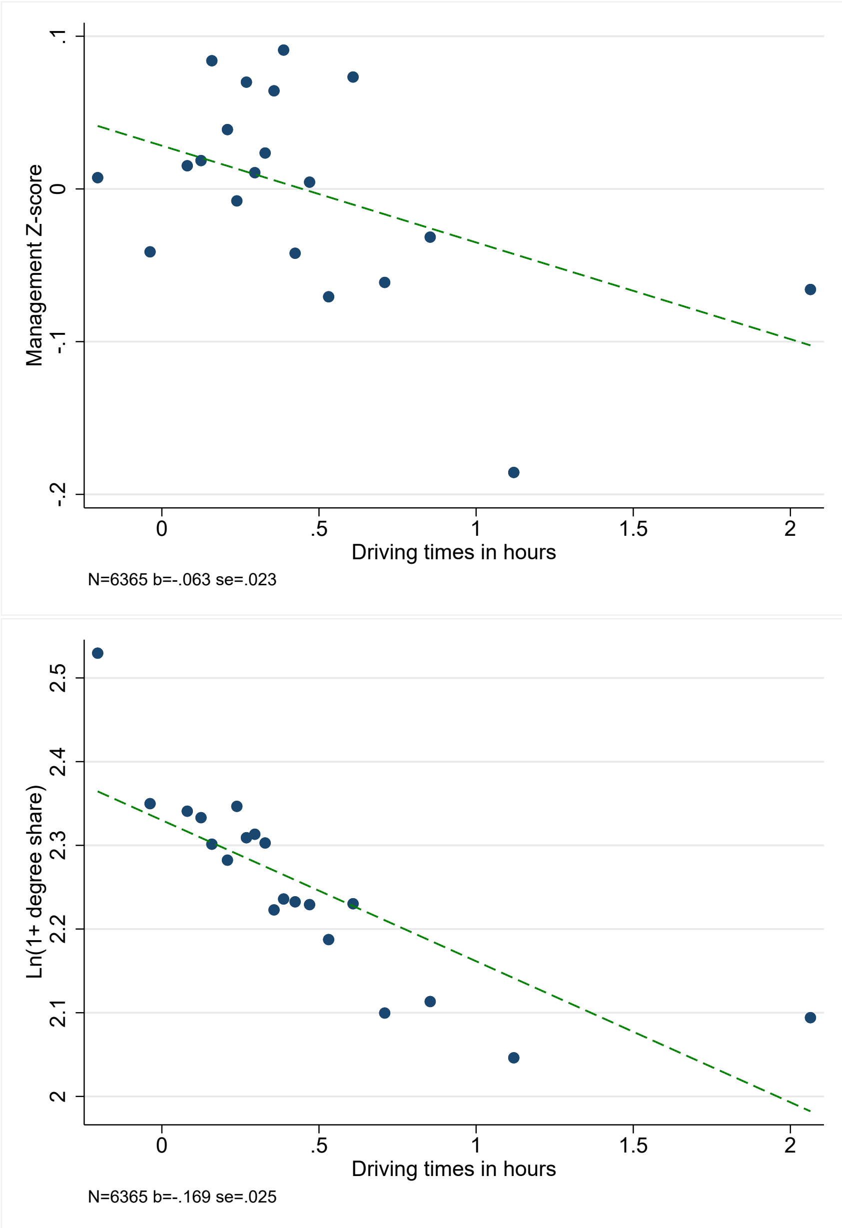
NOTES: N=6,363, observations split into 10 minute bins. Distance is measured as the drive time (in hours) between a plant and its nearest university.

Figure 2: Firm skills and management practices



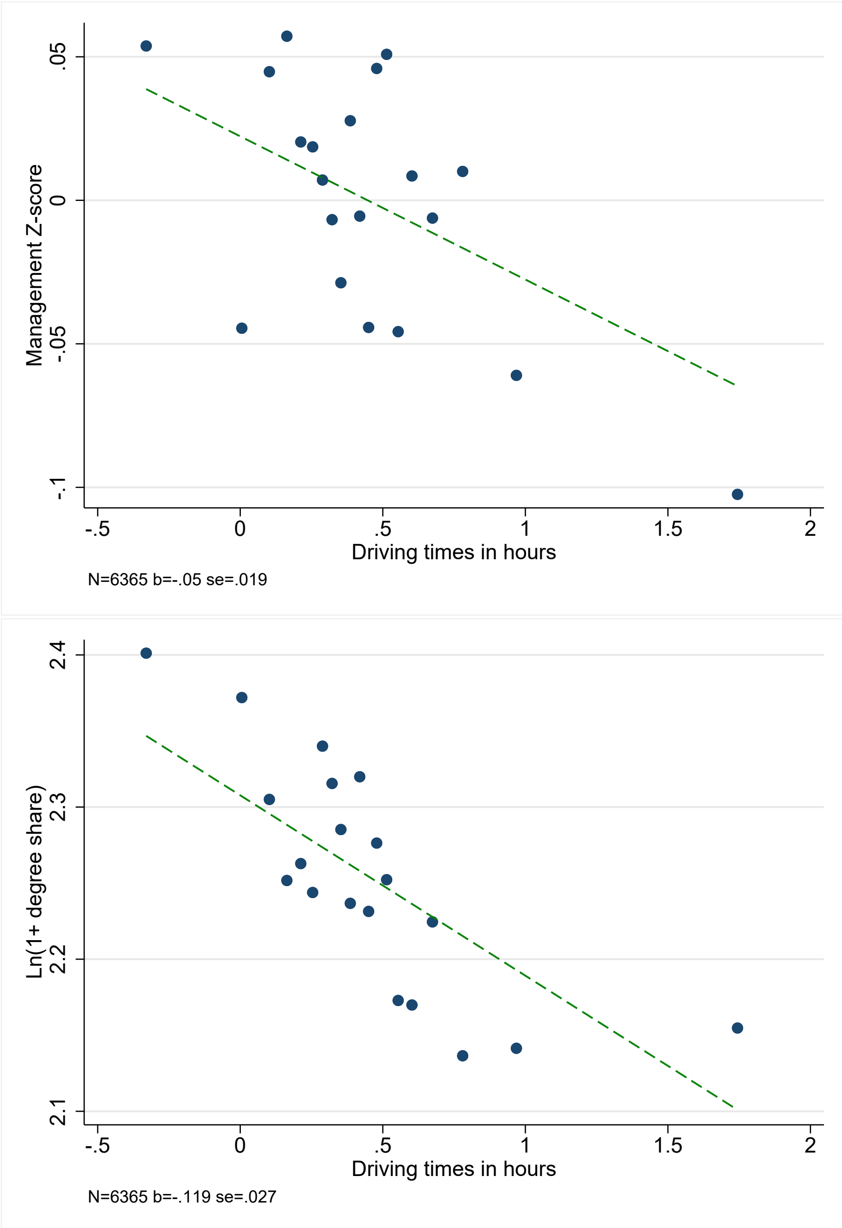
NOTES: Scatter plot of average firm management practices on average Ln(1+degree share) within 20 evenly sized bins. Variation is within country. The solid line represents the line of best fit.

Figure 3: Distance to University, Management Scores and Degree Share, Basic Correlations



NOTES: Scatter plots of average management Z-score and degree share on average travel time within 20 evenly sized bins. Variation is within country. The solid line represents the line of best fit.

Figure 4: Distance to University, Management Scores and Degree Share, Main Results



NOTES: Scatter plots of average management Z-score and degree share on average travel time within 20 evenly sized bins. Controls and fixed effects are absorbed as per Table 3 column (4). The solid line represents the line of best fit.

Table 1: Firm Skills and Management Practices, Basic Regressions

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)
Ln(1+degree share)	0.262***			
	(0.015)			
Ln(1+degree share), managers		0.207***		0.138***
		(0.013)		(0.011)
Ln(1+degree share), non managers			0.198***	0.156***
			(0.010)	(0.010)
Observations	6365	6365	6365	6365

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses (for consistency with later analysis). All columns include country and year dummies.

Table 2: Regional Skills and Universities

	(1)	(2)
A: Dependent variable is Ln(region degree share)		
Ln(1+universities per million)	0.196***	0.180***
	(0.037)	(0.027)
Panel B: Dependent variable is skill premium in region		
Ln(1+universities per million)	-0.027*	-0.032**
	(0.016)	(0.014)
Observations	208	208
Country dummies	yes	yes
Geographic controls	no	yes

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with robust standard errors in parentheses. All columns contain country dummies. The unit of observation is a region. Geographic controls include the regional average of the plant level geographic controls: population density within 100km, longitude and latitude, and region level variables: capital region dummy, temperature, inverse distance to the coast, Ln(oil production) and Ln(population).

Table 3: Distance to University, Plant Management and Skills

	(1)	(2)	(3)	(4)
A: Dependent variable is Management Z-score				
Distance	-0.067***	-0.070***	-0.049***	-0.050***
	(0.018)	(0.019)	(0.018)	(0.019)
Ln(employment, plant)			0.200***	0.200***
			(0.017)	(0.017)
Ln(employment, firm)			0.072***	0.073***
			(0.013)	(0.013)
Ln(plant age)			-0.030**	-0.029**
			(0.014)	(0.014)
MNE			0.389***	0.389***
			(0.031)	(0.031)
B: Dependent variable is Ln(1+Degree Share)				
Distance	-0.160***	-0.144***	-0.113***	-0.119***
	(0.029)	(0.029)	(0.027)	(0.027)
Ln(employment, plant)			0.061***	0.059***
			(0.019)	(0.019)
Ln(employment, firm)			0.019	0.019
			(0.017)	(0.017)
Ln(plant age)			-0.015	-0.015
			(0.018)	(0.018)
MNE			0.234***	0.235***
			(0.032)	(0.032)
Observations	6365	6365	6365	6365
Number of clusters	314	314	314	314
Region dummies	no	yes	yes	yes
Industry dummies	no	no	yes	yes
Geography controls	no	no	no	yes

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. See Table A1 for a description of the key variables. All columns include country dummies, year dummies, and survey controls for interviewer gender, interviewee job tenure, interviewee seniority, interview reliability, interview day of week, time and duration, and dummy variables for the analyst conducting the interview. Missing values are mean-coded, and dummies included to indicate where this is the case. Geography controls include population density, longitude and latitude.

Table 4: Regional Skill Premia, Plant Management and Skills

	(1)	(2)	(3)	(4)	(5)
A: Dependent variable is Management Z-score					
Skill Premium	-1.027**	-0.667*	-0.800**	-0.737**	-0.925***
	(0.481)	(0.371)	(0.363)	(0.349)	(0.258)
Ln(employment, plant)		0.274***	0.275***	0.241***	0.254***
		(0.029)	(0.030)	(0.028)	(0.032)
Ln(employment, firm)		0.081***	0.082***	0.062***	0.053***
		(0.017)	(0.016)	(0.017)	(0.020)
Ln(plant age)		-0.025	-0.026	-0.037*	-0.031*
		(0.019)	(0.018)	(0.021)	(0.018)
MNE		0.521***	0.517***	0.467***	0.388***
		(0.051)	(0.051)	(0.050)	(0.050)
capital			0.060	0.061	
			(0.054)	(0.048)	
B: Dependent variable is Ln(1+Degree Share)					
Skill Premium	-0.651	-0.580	-0.798**	-0.833**	-0.911***
	(0.493)	(0.400)	(0.354)	(0.343)	(0.281)
Ln(employment, plant)		0.078**	0.080**	0.075**	0.065***
		(0.035)	(0.035)	(0.036)	(0.023)
Ln(employment, firm)		0.016	0.017	0.011	0.015
		(0.020)	(0.020)	(0.019)	(0.019)
Ln(plant age)		-0.000	-0.002	-0.001	0.016
		(0.026)	(0.026)	(0.026)	(0.022)
MNE		0.356***	0.349***	0.337***	0.300***
		(0.045)	(0.045)	(0.046)	(0.047)
capital			0.128**	0.136***	
			(0.051)	(0.049)	
Observations	4555	4555	4555	4555	3881
Number of clusters	208	208	208	208	198
Industry dummies	no	yes	yes	yes	yes
Geographic controls	no	no	yes	yes	yes
Survey controls	no	no	no	yes	yes
Capital regions	yes	yes	yes	yes	no

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Regressions are weighted using population in the region as a share of country population. All columns include country and year dummies. Industry dummies are 2 digit SIC code, geography and survey controls as before (but excluding the analyst dummies) (see Table 3). See Table A1 for a description of the key variables.

Table 5: Heterogeneity by Multi-plant Status

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)	(5)	(6)
Distance	-0.050***	-0.058*	-0.056**	-0.110***		
	(0.019)	(0.034)	(0.022)	(0.037)		
Distance X Multi-plant		0.012		0.080		
		(0.043)		(0.049)		
Skill premium					-0.708*	-1.024**
					(0.376)	(0.399)
Skill premium X Multi-plant						0.411**
						(0.163)
Multi-plant	0.267***	0.261***	0.317***	0.280***	0.400***	0.152
	(0.031)	(0.036)	(0.038)	(0.045)	(0.043)	(0.127)
Observations	6365	6365	4555	4555	4555	4555
Number of clusters	314	314	208	208	208	208

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. *Multi* is a dummy denoting multi-plant status, which we define as a plant that either belongs to a multinational enterprise, or a domestic multi-plant firm.

Table 6: Panel Regressions

	(1)	(2)	(3)	(4)
Dependent variable	zman	zman	d zman	d zman
A: Firm human capital				
ln(1+degree share)	0.207***	0.133***		
	(0.0251)	(0.0275)		
d ln(1+degree share)			0.0521**	0.0663**
			(0.0257)	(0.0259)
Observations	1310	1310	1310	1310
Number of clusters	204	204	204	204
B: Regional wage ratio				
ln(wage ratio)	-0.155	-0.649*		
	(0.392)	(0.334)		
d ln(wage ratio)			-0.683**	-0.890***
			(0.291)	(0.313)
Observations	1017	1017	1017	1017
Number of clusters	162	162	162	162
year dummies	yes	yes	yes	yes
country dummies	yes	yes	yes	yes
controls	no	yes	no	yes

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Sample includes all firms that were interviewed in more than one wave over the period 2005-2010, in their latest observation. Differenced variables are calculated as average annual differences. All columns include country and year dummies. Controls include industry, firm, geography and noise controls as in core specifications. The regressions in Panel A include region fixed effects.

A Data Appendix

A World Management Survey

We use WMS survey waves conducted between 2004 and 2010, across 19 countries. These countries are: Argentina, Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Italy, Japan, Mexico, New Zealand, Poland, Portugal, Sweden, United Kingdom and United States. Ireland was also surveyed, but it is excluded from our analysis because it does not use post codes and hence it was not possible to accurately identify the location of the firms.

Here we describe the key features of the data and how it is used in this paper. Further details on the survey methodology is found in Bloom and Van Reenen (2007) (see also Bloom *et al.* (2016) for more recent updates) and at the WMS website (http://worldmanagementsurvey.org/).

The WMS Sample

The sampling frame in the WMS was based on firm-level accounting databases, which provide sufficient information on companies to conduct stratified telephone surveys (company name, address and a size indicator). The sampling frame was all firms with a manufacturing primary industry code with between 50 and 5000 employees on average over the most recent three years of data prior to the survey.[1]

Scoring Management

The survey evaluation tool defines 18 management practices in four broad areas. Each is scored from 1 (worst) to 5 (best practices). Table A7 lists the 18 dimensions and the nature of questions asked. These areas were developed together with an international consulting firm as processes that, if adopted, should be expected to raise performance. Innovative steps were taken to maximise the quality of data: in particular the use of a "double-blind" interview method to reduce biases; open ended questions, and careful selection of interviewers and interviewees. Internal validity is tested by re-interviewing (with a different interviewer and interviewee) a sub-sample of firms. There was a positive and highly significant correlation between the scores from first and second interviews. The validity of the interpretation of high management scores as "good" management practices is supported by the existence of strong positive associations between management scores the scores with observable measures of firm performance: including sales, profitability and survival probability, within and across countries. We normalise the management score to a mean zero, standard deviation one Z-score - across all countries and firms in the sample.

[1] In Japan and China, this was 150-5000 since the database used, BVD Oriana, only samples firms with more than 150 employees.

Other Variables from WMS

In order to geocode the plants, we required post codes. Detailed plant location data (other than region) were not collected in the original surveys. A separate project was conducted during 2011 to collect post-codes of the plants in the survey. This project was able to yield a 97.5 per cent response from the sampled firms.

Information on plant-level skills was collected in the surveys. Interviewees were asked what share of the total workforce, managers and non managers had degrees.

Consistent with Bloom and Van Reenen (2007) and subsequent papers, we used a number of other variables as controls, and for heterogeneity analysis. These include: number of employees in the plant and firm, plant age, MNE status, listed status, whether the plant belongs to a multi-plant firm, union representation and 2 digit SIC industry codes. We also add survey controls in our regressions to reduce noise. These include the gender, tenure and seniority of the manager who responded, the day of the week and hour of the interview, the duration of the interview, a measure of interviewee reliability as coded by the interviewer, and dummy variables to indicate the interviewer.

Missing values for plant employment, firm employment and interview noise controls were imputed using the average of these variables and a dummy variable is included in regressions where this is the case. For plant age, we followed the following imputation strategy. We first use firm age if that was available. Otherwise, we "hot-decked" plant age using regressions of plant founding dates on all other regressors for the sample that was not missing plant age.[2] We experimented with a simpler strategy of using the region average plant age and found similar results.

Financial data used in the performance regressions were sourced from accounting databases, as described, for example, in Bloom and Van Reenen (2007).

B World Higher Education Database

The World Higher Education Database (WHED) is a database of higher education institutions around the world compiled by the International Association of Universities, in collaboration with UNESCO.[3] The WHED can be accessed online for a fee, and we obtained underlying data as at 2010. The key information relevant for this study includes: details on location, founding date and academic divisions (for example business, social sciences, law, medicine, science, arts and humanities). A full description of this database is available in Valero and Van Reenen (2019).

[2] The full list of covariates is the same as that used in our core regressions.
[3] For more information see: http://www.whed.net/home.php

C Geographic Data

Our empirical strategy requires measurement of the distance between plants and universities. Based on their postcodes, we geocoded plants and universities using the GeoPostcodes database. Drive times and distances between plants and universities were then calculated using google maps. Additional geographic information was then added using GIS software.

GeoPostcodes Database

The GeoPostcodes database is a commercial website providing data on the region, city, longitude and latitude of postal codes in countries.[4] We purchased country-level databases for 18 of our countries in March 2012.[5] We use this database to match postal codes to geographic coordinates and regions. In Table A8 we show the geocoding success rates across countries for WMS plants and WHED universities. On average, there are high levels of success- with a 96 per cent match for plants and 95 per cent match for universities.

A fraction of plants and universities appear to be in the same postcode and thus have the same geographic coordinates (this affects 10 per cent of the plants). This could be due to postcodes being fairly large geographies in certain cases or measurement errors in the postcodes. In robustness checks we exclude these plants and find similar results.

Google Drive Times

We calculate the drive times between each plant and its nearest university. This was done using the `traveltime` command in stata.[6] This command uses the geographic coordinates of two points and uses google maps to calculate the drive time (in hours) between them. A corresponding driving distance (in km) is also calculated. To minimise computing times we limited the search of the nearest university within a 100km Euclidean radius of each plant. Where a plant did not have a university within this radius, we find the nearest university at any distance and winsorised the resulting drive times using the regional maximum. This was done to minimise outlier bias.[7]

Drive times in google maps are calculated using information from GPS-enabled devices of users. To ensure that seasonality or varying traffic conditions were not affecting our results, we calculated another set of drive times several months later. The correlation between the two measures was 0.95.

CIESIN Population Data

[4] For more information, see: http://www.geopostcodes.com/UK

[5] In the UK we used the `geocode` command in stata to geocode the plants and universities. Information on this command is available at https://ideas.repec.org/c/boc/bocode/s457450.html, it uses googlemaps to geocode postal codes

[6] Information on `traveltime` can be found here: http://ideas.repec.org/c/boc/bocode/s457449.html

[7] This affected 1.4 per cent of the sample. In robustness checks we exclude these isolated plants from the analysis and find no difference in results. It should be noted that for a fraction of the plants and universities that shared postcodes, the resulting google drive time would be reported as zero. In the robustness checks we excluded these plants and find no significant difference in results.

We control for population density at the location of the plant. The Center for International Earth Science Information Network (CIESIN) provides the Gridded Population of the World (GPW) that depicts the distribution of population across the world in 2000.[8] We use GIS software to spatially intersect each plant with population density data from the CIESIN within a 100km buffer and find the average population density (1000 people per square km, within country) within that buffer.[9]

D Regional Labour Force Data

Labour force data were obtained for 18 countries in the survey. The sources are outlined in Table A9. Microdata were obtained for 14 countries. In most cases these were labour force or household surveys, but in the case of Germany this was administrative labour force data. Where we were able to obtain access to microdata, we ran wage regressions by region. This allowed us to estimate the wage premium for having a degree, as the coefficient on a degree dummy, once other key characteristics were controlled for (experience, experience squared and gender). The specific years for which we were able to access data varied by source, but we tried to obtain as many years as possible between 2003 and 2010. For our cross-sectional analysis, observations were pooled over years in order to maximise the number of observations in a region, and therefore we included year dummies in the wage regressions. We also calculated raw wage ratios and the percentage of the labour force with a degree. These measures of the relative price of skills, or quantity of skills are used in the robustness. We calculated yearly raw wage ratios for use with the panel of WMS firms.

In the case of China, Japan, New Zealand and Poland, it was not possible to access microdata. However, regional aggregates of wage ratios and college share were available. For China, these came from summary statistics of the 2005 census; and for the other three countries the data were prepared for this purpose by the relevant statistical offices. It was not possible to obtain data for Portugal.

E Final Analysis Sample Selection

An initial 10,163 interviews were available. Ireland was dropped because it does not use postal codes, and hence we could not establish the exact location of the plants (161 observations). A further 415 observations had missing or mis-reported postal codes. As mentioned previously, a few plants were interviewed multiple times either during follow up waves or during the same wave as a second interview for validity checks. In our core sample for cross sectional analysis, we keep the most recent interview of the plant (which involves dropping 2,396 observations), however, our results are robust

[8] Data are available here: http://sedac.ciesin.columbia.edu/data/collection/gpw-v3. Population density is represented as centroids in a features file. These centroids correspond to the smallest geography available for the country. For example in the US, this is the Census block group.

[9] We also checked the robustness of results with varying buffer sizes including using only the nearest centroid.

to keeping all interviews for each plant and running a pooled cross section. We drop 784 observations with missing observations of firm level degree share which is the key (endogenous) explanatory variable; and 42 observations that are singletons in a particular region. This results in a final analysis sample of 6,365 plants for our analysis using distance to universities.

For consistency, the sample we use for the regional analysis is a subsample of this, consisting of 4,555 plants in the 13 countries for which we were able to calculate what we consider to be reliable regional skill premia from regional wage regressions. The final sample for the regional analysis drops an additional six observations in two regions (Arica y Parinacota and Los Rios in Chile which both became operational in 2007) where population data were not available in our regional dataset (we use regional population data from Gennaioli *et al.* (2013) to calculate weights for the regional regressions). We exclude India, where the sample sizes in the source data (NSS) by region were often small and likely to give unreliable estimates - in particular in some states there were very few observations in the manufacturing sector, or with degree level education. We include India in the robustness (see Table A11, row (17) and our coefficient on the skill premium is dampened slightly but remains highly significant). Results are robust to alternative sample specification, including keeping observations where firm level degree share is missing, keeping all survey waves or using the raw wage ratio which was available for more countries as a ready-made regional aggregate.

B Robustness Tests on Core Results

We report the main experiments on our core distance specification Table A10. The sample of 6,365 plants is used unless otherwise stated. In Panel A we check the standard errors, clustering at the country level, university level (Cameron *et al.*, 2011) and allowing a spatial aspect using Conley standard errors (Fetzer, 2014; Hsiang, 2010). None of these adjustments affect the significance of the result.

We might worry that the distribution of drive times is skewed to the right, as shown in Figure 1 and that a simple linear relationship between drive times and management practices is not the best representation of the data. In Panel B, we allow for non linearities in distance. First show that taking logs does not affect the sign or significance of the result. A quadratic in drive time a slightly larger coefficient, and higher order polynomials raise the standard errors, but the coefficient on drive time remains negative and of similar order of magnitude. We then include a number of additional geographic controls (Panel C). Adding a quartic in geography controls leads to a loss of significance though the magnitude of our coefficient remains similar, and including measures of population density has little impact. We experiment with different distance measures that do not take geographical features into account (driving distance, straight line distance and number of universities within a 100km radius). With driving / straight line distance, the coefficient takes the expected sign but significance is lost, while there are positive and significant relationships between management practices and the quantity of universities (the coefficient is the same if a radius of 50km is used, but it is now significant at the 5 per cent level).

Next we show that our result is not sensitive to sample selection. Keeping all survey waves increases noise, but the magnitude of the coefficient is unchanged. The same goes for dropping observations so that the sample is consistent with that used for the regional analysis, and excluding firms with the same postal code as their closest university. Dropping winsorised observations strengthens the result, and dropping capital regions has no effect.

Panel F uses more granular fixed effects. First, we include country-year fixed effects and this does not change our result. We then turn to more demanding specifications, comparing observations in increasingly smaller cells - first region-sector, then county and finally city - dropping cells with only one observation. Significance is lost but the sign of the relationship is still negative. Finally, we show that using 3 digit industry dummies instead of 2 digit has no effect on the magnitude or significance of our main result.

Analogue robustness checks on the skill premium regressions are in Table A11. In general, the sign of the relationship is robust to different assumptions, but the significance of the relationship is lost in some cases. In particular, when standard errors are clustered at the country level (Panel A), or when regressions are unweighted (Panel B). More noise is to be expected in the data unweighted by some measure of population, as skill premia are likely to be worse measured in less populous regions within a country. In Panel C, additional controls are included and in general, the results remain significant. In particular, the inclusion of local population density does not affect the size or significance of the coefficient on degree premium.

We also explore whether the expected relationships exist for alternative measures of regional skills, such as raw regional wage ratios or various quantity measures such as regional degree share or years of education. In general, the signs are as expected, but results not significant in these other measures.

Finally, in Panel E we show that the result is robust to alternative sample choices: keeping all survey waves, keeping India and firms with missing degree share.

C IV Regressions

In this section we describe the results of IV regressions where firm human capital is instrumented by distance to nearest university: i.e. the first stage is equivalent to specification in Panel B, column

(4) from Table 3. The results are summarised in Table A12. Column (1) gives the correlation between total workforce degree share and management practices, controlling for country and year dummies which we saw in Table 1. The magnitude of the coefficient falls slightly on the inclusion of the full set of controls (column (2)). Column (3) reports the IV regression, where degree share is instrumented with drive time. The first stage F-statistic is of a large magnitude (19.7) and so we do not appear to have a problem of weak instruments (Staiger and Stock, 1997; Stock *et al.*, 2012).

We also provide some evidence that attempts to address concerns regarding exclusion and the exogeneity of university location. To address the concern that universities affect management channels other than human capital we explore whether universities with business departments have a direct effect on management practices (both a main effect and interacted with distance[10]), see Table A13. The excluded instrument for firm human capital is now the distance to universities without business departments. Business departments do not appear to have a direct effect on management, and the IV coefficient is of similar magnitude. We carry out an equivalent exercise for nearest universities founded before the plant, where now the excluded instrument is the distance to nearest universities founded after the plant; and find no effect of pre-existing universities on management practices which is inconsistent with a view that better managed firms endogenously locate near to universities.

D Performance Equations

On the subsample of plants where financial information is available, we estimate simple production functions, interacting the management score with the different skills variables in turn: firm degree share (Table A14), distance and skill premium (Table A15).

Each table follows the same format. Column (1) is a simple regression of the natural log of sales on labour, capital, firm and industry controls. We include 2 digit sic dummies and full noise controls, hours worked, plant age and dummies for missing values. The firm degree share and distance analyses also include region fixed effects. We mean-code missing values of capital and employees, and include a dummy to indicate this. [11] We also include the relevant skills variable, in relative terms, versus the country median so, for example, the relative distance term is zero for a plant at that is at the country median distance from nearest university. Column (2) then includes the interaction between management practices and the relative skills variable. Columns (3) and (4) then repeat the first two

[10] This is a form of the over-identification test, and a similar strategy is used by Card (1995) when estimating the returns to schooling. He allows distance to have a direct effect, and uses distance interacted with family variables as the excluded instrument for college education

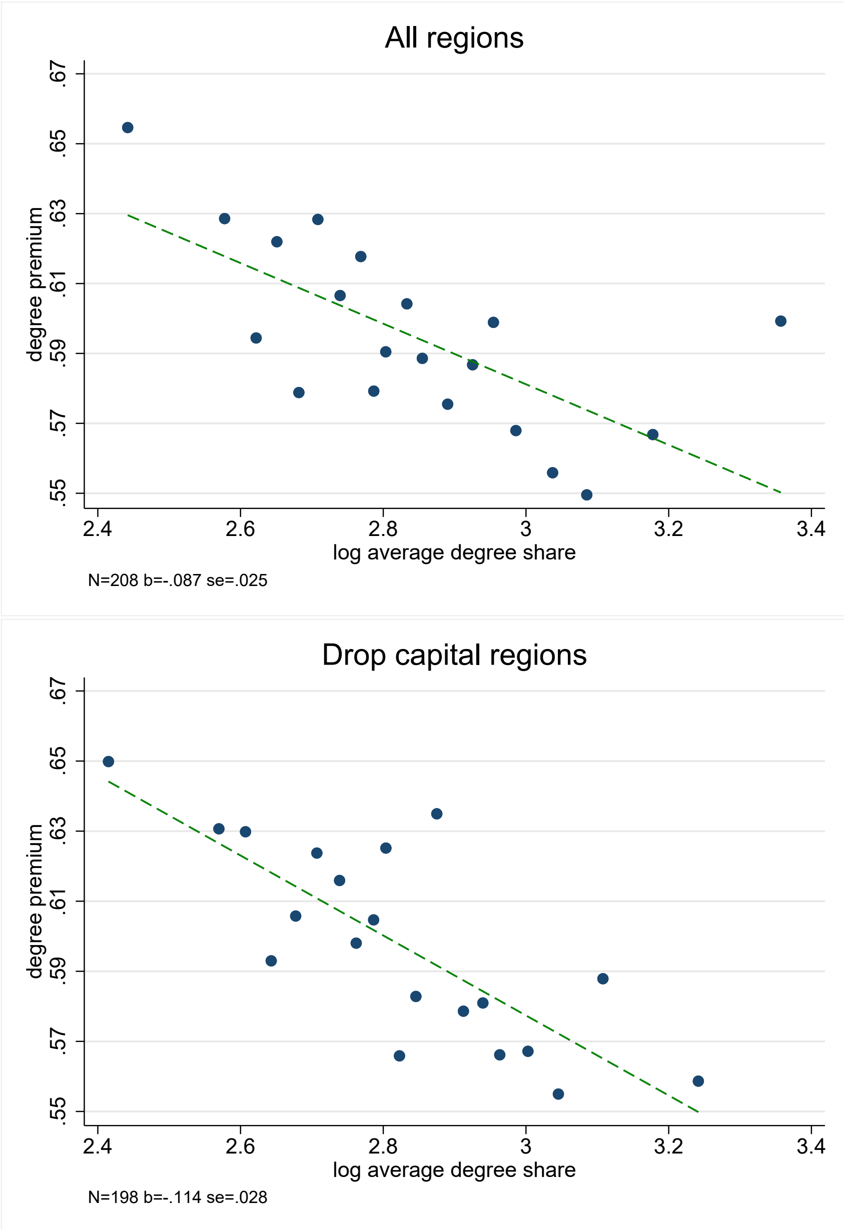
[11] Capital is missing for 24% of the sample, and employment is missing for 3% of the sample. Results are robust to dropping these observations - in fact the interaction term with firm degree share becomes larger in magnitude and significant at the 10 per cent level. Materials are not included here, as this variable is missing for 75% of the sample.

columns but on the sample of single plant firms; and (5) and (6) for multi-plant.

For single-plant firms only, the signs of the interaction terms are as would be expected under the hypothesis that skills and management practices are complements: positive for firm level human capital; and negative for distance and the skill premium for which higher values imply that the skill price is higher. However, only the distance interaction is significant at conventional levels (5%), see Table A15 Panel A, column (4). This analysis therefore provides additional suggestive evidence to support our main findings.

E Appendix Figures

Figure A1: Regional skill Premium and Degree Share



NOTES: Scatter plots of average regional skill premium on average regional degree share within 20 evenly sized bins. Variation is within country. The solid line represents the line of best fit.

F Appendix Tables

Table A1: Descriptive Statistics

	Mean	S.D	Min	Max	Count
WMS variables					
Management Score	2.93	0.67	1	4.89	6365
Management Z-Score	0	1.00	-2.89	2.94	6365
Degree share	14.8	16.7	0	100	6365
Degree share, managers	58.1	34.0	0	100	6365
Degree share, non managers	10.4	16.3	0	100	6365
Ln(1+degree share)	2.25	1.05	0	4.62	6365
Ln(employment, plant)	5.10	0.96	0	8.99	6365
Missing Ln(employment, plant)	0.017	0.13	0	1	6365
Ln(employment, firm)	5.83	1.11	0	11.1	6365
Missing Ln(employment, firm)	0.0016	0.040	0	1	6365
Ln(plant age)	3.40	0.79	0	6.28	6365
Missing Ln(plant age)	0.44	0.50	0	1	6365
MNE	0.46	0.50	0	1	6365
Multiunit production	0.59	0.49	0	1	6365
Large Firm (>300 employees)	0.50	0.50	0	1	6365
Public listed	0.28	0.45	0	1	6365
Union (percent)	39.8	39.4	0	100	6365
Google Maps and GIS calculations					
Distance	0.45	0.54	0	7.55	6365
Latitude	23.3	32.7	-54.8	65.7	6365
Longitude	8.01	78.1	-127.5	176.9	6365
Avg pop density	1.34	1.88	0	16.0	6365
Regional Skills Variables					
Skill Premium	0.57	0.22	0.26	1.25	4561
Regional Degree Share	18.6	8.01	0.11	52.7	6191
universities per million people in 2005	3.97	3.43	0	30.6	6365

NOTES: *Management score* is the average of all 18 WMS management scores. *Management Z-score* is the standardised score. *Degree share*, *degree share (managers)* and *degree share (non managers)* are the plant-level percentages of total workforce, managers and non-managers with degrees, respectively. *Ln(1+degree share)* is the natural log of 1+ the total workforce degree share. Missing values of firm, plant employment and plant age are mean coded and an indicator shown. *Union* is the percentage of the workforce that is unionised. *Distance* is the google driving time in hours from the plant to the nearest university (full description in the Data Appendix). *Longitude* and *Latitude* are geographic coordinates of the plant location corresponding to its postal code. *Avg pop density* is the average population density within a 100km radius of the plant calculated using GIS software. *Skill premium* is the coefficient on a degree dummy, recovered from regional wage regressions. *Regional degree share* is the percentage of regional population with a degree. *Universities per million people* is the number of universities in a region in 2005, divided by the population. Appendix Table A3 summarises additional variables used in our analysis and robustness checks.

Table A2: Summary of Data at the Country Level

	# plants	Management Z-score		Degree Share (%)		Distance (hours)		Skill Premium	
		Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Argentina	232	-0.27	1.06	10.09	12.11	0.52	0.90	0.68	0.07
Australia	400	0.07	0.86	11.97	14.12	0.53	0.60	0.29	0.03
Brazil	519	-0.34	1.01	11.00	12.60	0.22	0.34	0.95	0.06
Canada	371	0.35	0.93	11.58	13.77	0.63	0.83	0.40	0.05
Chile	264	-0.28	0.93	14.17	13.56	0.78	0.72	0.83	0.09
China	509	-0.32	0.70	10.35	13.06	0.74	0.76	-	-
France	255	0.11	0.80	13.57	15.58	0.63	0.46	0.39	0.03
Germany	292	0.47	0.84	13.91	14.74	0.36	0.22	0.60	0.03
Greece	174	-0.41	1.24	17.36	16.10	0.46	0.47	0.32	0.02
India	648	-0.56	1.04	20.65	21.61	0.35	0.47	-	-
Italy	170	0.15	0.91	14.86	14.59	0.59	0.32	0.45	0.07
Japan	97	0.46	0.85	31.78	21.38	0.11	0.25	-	-
Mexico	179	-0.00	1.06	22.48	21.49	0.16	0.15	0.96	0.09
New Zealand	143	-0.14	0.83	11.37	14.44	0.40	0.43	-	-
Poland	233	-0.04	0.95	20.20	17.83	0.32	0.31	-	-
Portugal	174	-0.25	0.91	9.36	9.88	0.30	0.19	-	-
Sweden	246	0.45	0.79	15.37	17.34	0.61	0.48	0.34	0.03
United Kingdom	786	0.10	0.97	12.28	15.73	0.42	0.42	0.54	0.03
United States	673	0.59	0.92	19.12	18.81	0.31	0.28	0.58	0.06

NOTES: N=6,363. *Management Z-score* is the standardised simple average of all 18 management questions from the World Management Survey. Degree share is the plant-level percentage of total workforce, with a degree. *Distance* is the drive time in hours from the plant to the nearest university. *Skill premium* is the coefficient on a degree dummy from regional wage regressions.

Table A3: Additional Descriptive Statistics

	Mean	S.D	Min	Max	Count
WHED characteristics					
Uni has business finance	0.62	0.48	0	1	6365
Uni has law or social sciences	0.74	0.44	0	1	6365
Uni has medicine or science	0.76	0.43	0	1	6365
Uni has arts humanities	0.72	0.45	0	1	6365
Uni has all listed depts	0.15	0.36	0	1	6365
University founding	1941.8	98.5	1088	2011	6365
Missing founding	0.054	0.23	0	1	6365
University founded before plant	0.60	0.49	0	1	6365
Google maps and GIS calculations					
Driving distance	0.27	0.52	0	13.5	6365
Straightline distance	0.22	0.57	0	35.7	6365
No. of universities within 100km	34.3	55.3	0	441	6365
No. of universities within 50km	19.4	38.1	0	316	6365
Avg pop density within 50km radius	1.69	2.51	0	20.9	6365
Avg pop density nearest centroid	3.00	7.29	0	84.9	6365
Plant and university share postal code	0.11	0.31	0	1	6365
Distances are winsorized	0.016	0.13	0	1	6365
Regional skills variables					
Log of average regional wage ratio	0.65	0.33	0.17	2.02	5543
Mincer years of education coefficient	0.10	0.039	0.033	0.21	4561
average years of education, Gennaioli et al.(2013)	9.20	2.83	3.02	12.8	6331
Average regional degree share, Gennaioli et al.(2013)	0.20	0.13	0.016	0.50	6357
Additional variables for productivity					
Ln(Sales)	10.5	1.74	0	16.6	4835
Ln(Capital)	9.48	1.79	-1.85	16.0	4835
Missing Capital	0.24	0.43	0	1	4835
Ln(Employees)	5.74	1.08	0	12.5	4835
Missing Employees	0.035	0.18	0	1	4835
Ln(Hours)	3.76	0.12	3.56	4.38	4835
Missing Hours	0.0081	0.089	0	1	4835

NOTES: The subject variables are dummies indicate provision at nearest university. *University founding* gives founding year. *Driving distance* is the google driving distance ('00km) to nearest university. *Straightline distance* is the straight line distance ('00km) to nearest university. *No. universities within 100km (50km)* is a count within the given radius. *Avg pop density within 50km radius* and nearest centroid are calculated using GIS software. An indicator is created for plants and universities that share a postcode, and for plants with no university within 100km radius (distance is winsorised to regional maximum). *ln(average regional wage ratio)* is based on calculation from microdata or ready-made data as shown in Table A9.*Mincer years of education coefficient* is recovered from regional wage regressions. *Average years of education* and *average college share* are measures of skills quantities, obtained from Gennaioli *et al.* (2013). The productivity sample is conditioned on plants with non-missing sales. Missing values of capital or employees are mean coded. Financial data are sourced from accounting databases. Hours worked is a survey question.

Table A4: Within Region Variation

	Regions	Difference 90th−10th Percentile Plant, Median region Management Z-score	Degree share (%)	Distance (hours)
Argentina	15	2.20	1.70	0.42
Australia	6	2.13	2.74	1.77
Brazil	19	2.50	2.56	0.72
Canada	9	2.39	2.40	1.30
Chile	14	1.85	1.56	0.61
China	26	1.66	2.56	1.40
France	20	2.06	2.25	0.83
Germany	15	2.05	2.27	0.50
Greece	9	2.88	2.55	0.70
India	22	2.52	2.08	0.68
Italy	13	2.46	2.09	0.70
Japan	19	1.61	1.55	0.00
Mexico	19	2.31	2.02	0.19
New Zealand	10	1.77	2.55	0.84
Poland	16	2.44	2.16	0.74
Portugal	11	2.29	2.31	0.48
Sweden	19	1.90	2.50	0.87
United Kingdom	12	2.54	3.07	0.56
United States	40	2.18	2.58	0.55

NOTES: Number of regions=314. This table shows region-level variation in Management Z-score, Degree Share and Distance variables, by country.

Table A5: Heterogeneity by University Characteristics

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)	(5)	(6)
Subject is:	Bus	Law, Soc. Sci	Med, Sci	Arts, Hum.	All listed	
Distance	-0.052*	0.002	-0.008	-0.033	-0.041*	-0.073***
	(0.029)	(0.051)	(0.051)	(0.046)	(0.021)	(0.027)
Distance x "subject"	0.003	-0.060	-0.049	-0.019	-0.051	
	(0.032)	(0.051)	(0.053)	(0.047)	(0.046)	
subject	0.002	0.045	0.024	-0.000	0.025	
	(0.029)	(0.029)	(0.034)	(0.035)	(0.035)	
Distance x before						0.041
						(0.039)
Before						-0.003
						(0.028)
Observations	6,365	6,365	6,365	6,365	6,365	6,365
Number of clusters	314	314	314	314	314	314

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Column (1) reproduces the core specification in Table 3, Panel A, column (4).

Table A6: Effects of Skills on Different Management Practice Groupings

Dependent Variable	(1) zman	(2) zops	(3) zmonitor	(4) ztarget	(5) zpeople
Panel A: Distance					
Distance	-0.050***	-0.041*	-0.036	-0.065***	-0.031
	(0.019)	(0.023)	(0.023)	(0.022)	(0.022)
Observations	6,365	6,353	6,365	6,365	6,365
Number of clusters	314	314	314	314	314
Panel B: Distance (constrained sample)					
Distance	-0.053**	-0.051*	-0.037	-0.062**	-0.040
	(0.022)	(0.027)	(0.028)	(0.027)	(0.028)
Observations	4,555	4,552	4,555	4,555	4,555
Number of clusters	208	208	208	208	208
Panel C: Skill Premium					
Skill Premium	-0.737**	-0.441	-0.726**	-0.294	-0.940**
	(0.349)	(0.294)	(0.328)	(0.298)	(0.417)
Observations	4,555	4,552	4,555	4,555	4,555
Number of clusters	208	208	208	208	208

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Column (1) contains the specifications: Panel A, column (4) of Table 3, and Panel A, column (4) of Table 4. Columns (2) to (5) replicate this for different management practice groupings as the dependent variable.

Table A7: WMS Management Practices

Categories	Score from 1 to 5 based on:
Operations	
1) Introduction of modern manufacturing techniques	What aspects of manufacturing have been formally introduced, including just-in-time delivery from suppliers, autonomation, flexible manpower, support systems, attitudes, and behavior?
2) Rationale for introduction of modern manufacturing techniques	Were modern manufacturing techniques adopted just because others were using them, or are they linked to meeting business objectives like reducing costs and improving quality?
Monitoring	
3) Process problem documentation	Are process improvements made only when problems arise, or are they actively sought out for continuous improvement as part of a normal business process?
4) Performance tracking	Is tracking ad hoc and incomplete, or is performance continually tracked and communicated to all staff?
5) Performance review	Is performance reviewed infrequently and only on a success/failure scale, or is performance reviewed continually with an expectation of continuous improvement?
6) Performance dialogue	In review/performance conversations, to what extent is the purpose, data, agenda, and follow-up steps (like coaching) clear to all parties?
7) Consequence management	To what extent does failure to achieve agreed objectives carry consequences, which can include retraining or reassignment to other jobs?
Targeting	
8) Target balance	Are the goals exclusively financial, or is there a balance of financial and non financial targets?
9) Target interconnection	Are goals based on accounting value, or are they based on shareholder value in a way that works through business units and ultimately is connected to individual performance expectations?
10) Target time horizon	Does top management focus mainly on the short term, or does it visualise short-term targets as a "staircase" toward the main focus on long-term goals?
11) Targets are stretching	Are goals too easy to achieve, especially for some "sacred" cows areas of the firm, or are goals demanding but attainable for all parts of the firm?
12) Performance clarity	Are performance measures ill-defined, poorly understood, and private, or are they well-defined, clearly communicated, and made public?
People Management	
13) Managing human capital	To what extent are senior managers evaluated and held accountable for attracting, retaining, and developing talent throughout the organisation?
14) Rewarding high performance	To what extent are people in the firm rewarded equally irrespective of performance level, or are rewards related to performance and effort?
15) Removing poor performers	Are poor performers rarely removed, or are they retrained and/or moved into different roles or out of the company as soon as the weakness is identified?
16) Promoting high performers	Are people promoted mainly on the basis of tenure, or does the firm actively identify, develop, and promote its top performers?
17) Attracting human capital	Do competitors offer stronger reasons for talented people to join their companies, or does a firm provide a wide range of reasons to encourage talented people to join?
18) Retaining human capital	Does the firm do relatively little to retain top talent or do whatever it takes to retain top talent when they look likely to leave?

NOTES: This table is taken from Bloom and Van Reenen (2010).

Table A8: Geocoding Success Rates for Plants in WMS and Universities in WHED

	WMS		WHED	
	No. plants	Geocode rate	No. universities	Geocode rate
Argentina	249	0.95	95	0.95
Australia	452	0.95	44	1
Brazil	591	0.94	1852	0.90
Canada	419	1	146	1
Chile	372	0.89	88	1
China	763	0.92	548	0.98
France	639	0.97	281	1.00
Germany	672	0.99	339	1
Greece	272	0.96	38	0.97
India	936	0.97	559	0.99
Italy	314	0.98	93	0.94
Japan	176	0.97	696	0.92
Mexico	190	0.99	1322	0.93
New Zealand	150	0.97	23	1
Poland	364	1	408	1.00
Portugal	311	1.00	114	0.86
Sweden	404	0.98	38	1
United Kingdom	1381	0.94	174	0.99
United States	1347	0.95	2184	1.00

NOTES: This table shows the geocoding success rates for WMS plants and WHED universities using the GeoPostcodes database. The 9081 universities represent the population of universities in the WHED database for the relevant countries

Table A9: Labour Force Survey Data Sources

Country	Source	Years used
Microdata:		
Argentina	Permanent Household Survey (EPH), Insituto Nacional de Estadística y Censos (INDEC)	2008-10
Australia	HILDA Survey, Melbourne Institute	2005-10
Brazil	National Household Sample Survey (PNAD), Instituto Brasileiro de Geografia e Estatística (IBGE)	2003-2009
Canada	Labour Force Survey, Statistics Canada	2003-2010
Chile	National Socioeconomic Characterization Survey (CASEN), Ministry of Social development	2006, 09
France	Enquete Emploi, Institute National de la Statistique et des Etudes Economiques (INSEE), Centre Maurice Halbwachs	2003-2010
Germany	Sample of Integrated Labour Market Biographies (SIAB), Research Data Centre (FDZ) of the Germany Federal Employment Agency (BA) at the Institute for Employment Research (IAB)	2003-10
Greece	Labour Force Survey, Hellenic Statistical Authority (ELSTAT)	2003-10
India	National Sample Survey, Employment and Unemployment	2004, 06, 08
Italy	Historical Database of the Survey of Italian Household Budgets	2004, 06, 08, 10
Mexico	National Income and Expenditure Survey (ENIGH), Instituto Nacional de Estadística y Geografía (INEGI)	2006, 08, 10
Sweden	Regional Aggregates obtained from analysis at Jonkoping University, using Statistics Sweden microdata (MONA)	2005, 07, 08, 10
UK	UK Labour Force Survey, UK Data Service	2003-10
US	IPUMS-CPS	2003-10
Regional data:		
China	China 2005 Census	2005
Japan	National Statistics Centre, Ministry of Internal Affairs and Communications	2006-10
New Zealand	Statistics New Zealand	2003-10
Poland	Central Statistical Office, Poland	2004, 06, 08, 10

NOTES: Citation requirements for Canada, France and Germany follow. *Canada:* The analysis on Canada is based on Statistics Canada Microdata file: Labour Force Survey, which contains anonymized data collected from 1987 to 2010. All computations on these microdata were prepared by the authors, and the responsibility for the use and interpretation of these data is entirely with the authors. *France:* Sources cited as Emploi (en continu) - série 2003 - 2012 (version production et recherche) - [fichier électronique], INSEE [producteur], Centre Maurice Halbwachs (CMH) [diffuseur], and Emploi (en continu) - série 2003-2012 - () [fichier électronique], INSEE [producteur], Centre Maurice Halbwachs (CMH) [diffuseur] *Germany:* This study uses the factually anonymous Sample of Integrated Labour Market Biographies (version 1975-2010). Data access was provided via a Scientific Use File supplied by the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB).

Table A10: Robustness on Distance Regressions

	Specification	Coefficient on Distance	(S.E.)
(1)	Benchmark	-0.050***	(0.019)
	A. Checking standard errors		
(2)	Cluster at country	-0.050**	(0.021)
(3)	Cluster at university	-0.050***	(0.019)
(4)	Conley standard errors, 100km	-0.050***	(0.018)
	B. Non Linearities in distance		
(5)	Ln(1+driving time)	-0.104***	(0.039)
(6)	Quadratic in driving time	-0.081**	(0.035)
(7)	Cubic in driving time	-0.099*	(0.055)
(8)	Quartic in driving time	-0.120*	(0.073)
	C. Additional geography controls		
(9)	Quartic in geography controls (joint p-value <0.01)	-0.037*	(0.020)
(10)	Average population density within 50km	-0.051***	(0.018)
(11)	Average population density nearest centroid	-0.057***	(0.018)
	D. Different distance measures		
(12)	Driving distance ('00km)	-0.050*	(0.028)
(13)	Straight line distance ('00km)	-0.026	(0.020)
(14)	Ln(1+universities within 100km)	0.024*	(0.014)
	E. Sample		
(15)	Keep all waves (N=8,075)	-0.041**	(0.018)
(16)	Skill premium sample (N=4,555)	-0.053**	(0.022)
(17)	Exclude same postal codes (N=5,671)	-0.042**	(0.019)
(18)	Exclude winsorized (6,263)	-0.066**	(0.025)
(19)	Drop capital regions (N=5,549)	-0.051**	(0.020)
	F. Fixed effects		
(21)	Country X year fixed effects	-0.050***	(0.019)
(22)	Include 1,207 region X industry fixed effects (N=5,229)	-0.056*	(0.030)
(23)	Include 724 county fixed effects (N=4,553)	-0.045	(0.031)
(24)	Include 851 city fixed effects (N=2,756)	-0.209	(0.296)
(25)	Use 152 3 digit SIC industry dummies	-0.049***	(0.296)

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. N=6,363 unless stated otherwise. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Each row represents a different robustness check on Panel A, column (4) of Table 3.

Table A11: Robustness on Regional Skill Premium Regressions

	Specification	Coefficient on Skill Premium	(S.E.)
(1)	Benchmark	-0.737**	(0.363)
	A. Checking standard errors		
(2)	Cluster at country	-0.737	(0.421)
	B. Weighting		
(3)	WMS weights	-0.885**	(0.405)
(4)	No weights	-0.339	(0.286)
	C. Additional Controls		
(5)	Quartic in geography controls	-0.197	(0.332)
(6)	Average population density within 50km	-0.721**	(0.350)
(7)	Average population nearest centroid	-0.741**	(0.341)
(8)	Regional geographic variables	-0.659*	(0.376)
(9)	Analyst dummies	-0.331	(0.332)
(10)	Country X year fixed effects	-0.700**	(0.348)
(11)	3 digit SIC industry dummies	-0.621*	(0.353)
	D. Different measures of regional skills		
(12)	Ln(wage ratio)	-0.162	(0.228)
(13)	Mincer years of education coefficient	-1.150	(2.120)
(14)	Ln(degree share)	-0.066	(0.074)
(15)	Ln(degree share), Gennaioli et al. (2013)	-0.063	(0.087)
(16)	Ln(average years education), Gennaioli et al. (2013)	0.040	(0.271)
(17)	Ln(1+universities per million)	0.037	(0.055)
	E. Sample		
(18)	Keep all waves (N=5,651)	-0.818***	(0.311)
(19)	Keep India (N=5,201)	-0.584**	(0.254)
(20)	Keep firms with missing degree share (N=5,219)	-0.780**	(0.334)

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. N=4,553 unless stated otherwise. All columns estimated by OLS with standard errors clustered at the region level in parentheses. Each row represents a different robustness check on Panel A, column (4) of Table 4. Regional geographic variables include temperature, inverse distance to the coast, and cumulative oil production, and are sourced from Gennaioli et al (2013). WMS weights are calculated by dividing the number of plants in a region surveyed in the WMS by the number of plants in the country.

Table A12: Firm Degree Share and Management Practices with IV estimates

Dependent variable: Management Z-score	(1)	(2)	(3)
Specification:	OLS	OLS	IV
Ln(1+degree share)	0.262***	0.156***	0.421***
	(0.015)	(0.014)	(0.143)
Observations	6,365	6,365	6,365
Number of clusters	314	314	314
Region dummies	no	yes	yes
Industry dummies	no	yes	yes
Firm controls	no	yes	yes
Geography controls	no	yes	yes
Instrument			Distance
F statistic			19.70

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Standard errors clustered at the region level in parentheses. All columns include country and year dummies. Column (1) replicates column (1) in Table 1.

Table A13: Extended IV Regressions

Dependent variable: Management Z-score	(1)	(2)	(3)	(4)
Specification:	OLS	IV	OLS	IV
Ln(1+degree share)	0.155***	0.390*	0.156***	0.843**
	(0.014)	(0.226)	(0.014)	(0.399)
Distance X Business	-0.029	-0.006		
	(0.019)	(0.029)		
Uni has Business	0.011	-0.008		
	(0.025)	(0.032)		
Distance X Before			-0.004	0.087
			(0.025)	(0.074)
Uni founded before plant			0.019	-0.020
			(0.024)	(0.046)
Observations	6,365	6,365	6,365	6,365
Number of clusters	314	314	314	314
Instrument		Distance (Non-Business)		Distance (Founded After)
F statistic		11.08		7.094

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. Standard errors are clustered at the region level in parentheses. Regressions contain full set of controls, consistent with column (2) in Table A12.

Table A14: Performance Equation Regressions - Firm Degree Share

Dependent variable is Ln(Sales)	(1)	(2)	(3)	(4)	(5)	(6)
	All plants		Single-plant		Multi-plant	
Management Z-score	0.087***	0.088***	0.100*	0.115**	0.065**	0.064**
	(0.024)	(0.024)	(0.053)	(0.056)	(0.027)	(0.028)
Ln(Capital)	0.517***	0.517***	0.400***	0.399***	0.548***	0.548***
	(0.057)	(0.057)	(0.064)	(0.064)	(0.065)	(0.065)
Ln(Labour)	0.497***	0.497***	0.504***	0.502***	0.479***	0.479***
	(0.055)	(0.055)	(0.089)	(0.089)	(0.063)	(0.063)
Relative ln(1+Degree Share)	0.051***	0.051***	0.058*	0.084**	0.046**	0.046**
	(0.017)	(0.017)	(0.033)	(0.037)	(0.022)	(0.022)
Management Z-score X Rel. ln(1+Degree Share)		0.005		0.052		-0.003
		(0.017)		(0.034)		(0.020)
Observations	4835	4835	1306	1306	3529	3529
Number of clusters	303	303	239	239	292	292

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. The sample of 4,835 plants are the subsample of the 6,365 plants in our distance analysis for which sales data are non missing. Where missing, capital and labour are mean-coded and a dummy variable included to indicate this. All columns include region and year fixed effects, 2 digit sic dummies and noise controls. General plant controls include ln(average hours worked) and ln(firm age) - these are mean-coded if missing, with dummies to indicate this. Relative ln(1+Degree Share) is the natural log of plant degree share minus the natural log of country median.

Table A15: Performance Equation Regressions - External Skills Variables

Dependent variable is Ln(Sales)	(1)	(2)	(3)	(4)	(5)	(6)
	All plants		Single-plant		Multi-plant	
A: Distance						
Management Z-score	0.099***	0.098***	0.112**	0.131**	0.074***	0.066**
	(0.024)	(0.024)	(0.052)	(0.054)	(0.028)	(0.029)
Ln(Capital)	0.519***	0.519***	0.406***	0.406***	0.549***	0.550***
	(0.057)	(0.057)	(0.064)	(0.063)	(0.064)	(0.064)
Ln(Labour)	0.497***	0.497***	0.504***	0.508***	0.478***	0.478***
	(0.055)	(0.055)	(0.090)	(0.091)	(0.063)	(0.063)
Relative Distance	-0.038	-0.037	0.037	-0.085	-0.083	-0.086
	(0.037)	(0.040)	(0.054)	(0.069)	(0.055)	(0.055)
Management Z-score X Rel. Distance		0.004		-0.173**		0.081
		(0.038)		(0.076)		(0.050)
Observations	4835	4835	1306	1306	3529	3529
Number of clusters	303	303	239	239	292	292
B: Skill Premium						
Management Z-score	0.114***	0.117***	0.040	0.048	0.082**	0.084**
	(0.033)	(0.031)	(0.053)	(0.048)	(0.036)	(0.035)
Ln(Capital)	0.564***	0.563***	0.533***	0.533***	0.579***	0.578***
	(0.101)	(0.100)	(0.111)	(0.108)	(0.104)	(0.104)
Ln(Labour)	0.498***	0.499***	0.405***	0.405***	0.495***	0.497***
	(0.104)	(0.104)	(0.142)	(0.139)	(0.109)	(0.109)
Relative Skill Premium	0.252	0.262	-0.533	-1.060	0.464	0.545
	(0.490)	(0.479)	(0.808)	(1.087)	(0.576)	(0.602)
Management Z-score X Rel. Skill Premium		-0.530		-1.290		-0.495
		(0.569)		(1.243)		(0.624)
Observations	3602	3602	828	828	2774	2774
Number of clusters	203	203	160	160	196	196

NOTES: *** denotes significance at the 1% level, ** 5% level and * 10% level. All columns estimated by OLS with standard errors clustered at the region level in parentheses. The sample in Panel A is the same as in Table A14. Where missing, capital and labour are mean-coded and a dummy variable included to indicate this. All columns include region and year fixed effects, 2 digit sic dummies and noise controls. General plant controls include ln(average hours worked) and ln(firm age) - these are mean-coded if missing, with dummies to indicate this. Panel A also contains region fixed effects. Relative distance and skill premium are the natural log of each variable minus the country median.

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The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
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