Management and Human Capital Employment: an overlooked Relationship

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Management and Human Capital Employment: an overlooked Relationship

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Abstract

We look at data for Management and Skills demand of firms in existing databases and we highlight the strong positive relationship between both variables. We devise a model that explains this relationship and calibrate it in order to present quantitative results and compare those results with the estimated ones. We discover that a simple model with *Management as Technology* can replicate well the estimated influence of Management in the skills demand of firms. We also present evidence of the influence of the subitems of Management on skills' demand and discovered that aside from the talent component of Management, target and performance components greatly influence the demand for skills.

JEL classification: L2, M2, M5, O32, O33, O34.

Keywords: management practices, productivity, human capital.

1 Introduction

Differences in management practices (or management quality) has been shown to be an important determinant of differences in firms', industries' and countries' productivity levels: about a quarter of cross-country and within-country TFP gaps can be accounted for by management practices. A review article that summarizes the main results of this recent literature, which began with the article of Bloom and Van Reenen (2007), is Bloom et al. (2014). Management scores are constructed and made publicly available by the World Management Survey (WMS) – initially described in Bloom and Van Reenen (2007) – and have been widely used in this literature. A more recent description is provided in Bloom et al. (2016). The WMS questions address practices that are likely to be associated with delivering existing goods or services more efficiently, focusing on production (lean), human resources management (talent), and management of goals and performance (target and performance, respectively). Managers are the interviewees.

Higher management scores are positively and significantly associated with higher productivity, firm size, profitability, sales growth, market value, and survival. For example, Bloom et al. (2012a) use a database of 10,000 organizations across 20 countries and estimate production functions in which they regress real firm sales on the management score including controls for other inputs (e.g. labor, capital, employee education) and other covariates (e.g. firm age, noise controls, industry, country and year dummies). In the cross section their results show that a one standard deviation increase in management is associated with an increase in TFP of 15%. This relationship is monotonically increasing. The paper also discusses the possibility of nonlinear relationships on the top of the management scores distributions. Meagher and Strachan (2013) apply Bayesian techniques to the Bloom and Van Reenen (2007) data for four countries and also find that there is some convexity for high scores. They interpret this as consistent with the idea that there is complementarity between multiple managerial practices (as in Gibbons and Henderson (2013); Milgrom and Roberts (1990)). Bloom and Van Reenen (2010) discuss why management practices differ across firms and countries. Bloom et al. (2012c) extended the empirical analysis to the transition economies. Competition, multinational and private ownership, and human capital are strongly correlated with better management practices, which means, according to the authors, that more competition, openness, and education in those economies would push management practices upward. Not only manufacturing firms, but also hospitals, schools and retailing sectors have been analyzed (Bloom et al. (2012b); Bloom et al. (2015); McNally (2010). The relationship between managerial practices and R&D in explaining firm performance has recently been studied by Nemlioglu and Mallick (2017) and the authors conclude that they are complementary.

Bloom et al. (2017) devise a model that predicts a positive impact of management on firms' performance, a positive relationship between product market competition and management, and a rise in the level and a fall in the dispersion of management with firm age – all results supported empirically. The authors formalize management either as design or as capital (than can be accumulated and depreciated), in both cases entering into the production function. Furthermore, they solve the problem of the firm and provide simulation results for both types of management (design and capital). In all these empirical results, education of the employees sometimes enters into the explanatory set for output, performance, and productivity measures, as a control to management. This is crucial as productivity is clearly dependent on the skill intensity of the employees.

However, firms demand human capital and this demand would depend on output measures and management. This would be a human capital demand approach that has not yet been taken to data. Additionally, it can be conjectured that the management technology also depends on the human capital employed in the firm, not only due to direct participation of employees in some management decisions in modern companies, but also because firms that demand more skilled labor also demand more skilled managers.

We take this alternative avenue to highlight the effect that management has in the skill intensity (or demand) of firms. The contribution closest to ours is Bender et al. (2018), who use a German firms database and find that better-managed firms recruit and retain workers with higher average human capital. The conceptual point of departure is that the relationship between management and productivity is intermediated by the talent of the CEO. This *talent of the CEO* concept can be enlarged to the culture of the firm, which is shaped by incentive packages offered to both managers and non-manager workers in the firm.

In our paper, rather than estimating TFP regressions we estimate human capital (skills) demand regressions. To our knowledge this is the first time this is reported in this literature. Apparently, this only consists of solving the firm's problem in order to the human capital demanded. However, due to the controls in the right-hand-side of the regressions, this yields structurally different results. We also analyze the influence of specific components of management on the demand for skills, which we also consider to be a novelty in the literature that relates management quality to measures of firm behavior or performance.

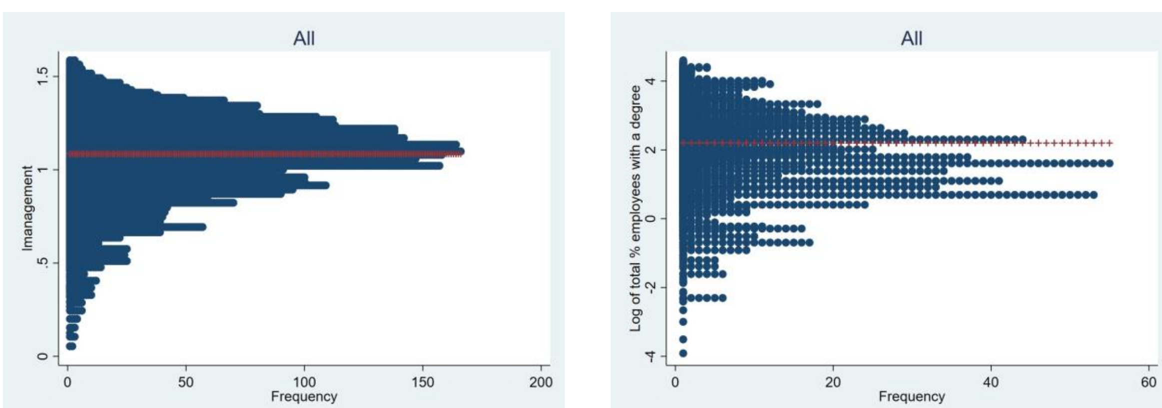
In Section 2 we present descriptive statistics and some empirical evidence of the relationship between human capital (or skills) employed in firms and management practices followed in the same firms. In Section 3 we devise the model building on Bloom et al. (2017) and obtain the human capital demand equations. and present a simple quantitative exercise. In Section 4 we show the regression results in which we estimate the derived theoretical relationship. We also present regressions including specific components of the management index. Finally, in Section 5 we conclude.

2 Descriptive Statistics and Empirical Motivation

In this Section we present descriptive statistics (Table 1) on the main variables used in the paper, including those for skills, management and physical capital. As sources we use the WMS data provided by Bloom and Van Reenen (2010), Bloom and Van Reenen (2007), and Bloom et al. (2012a). Figure 1 presents the distribution of both the *ln(% Employees with a degree)* and *ln(Management)*, the main variables for our analysis..

Table 1: Descriptive Statistics

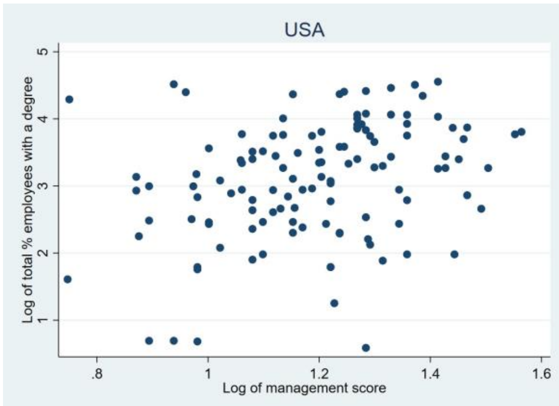
	Mean	SD	Min	Max
Data from Bloom and Van Reenen (2010)				
ln(% Employees with a degree)	0.066	0.449	0	4.554
ln(Management)	1.061	0.242	0	1.609
ln(Capital/employee)	1.406	1.859	-4.480	9.239
Data from Bloom et al. (2012a)				
ln(% Employees with a degree)	1.655	1.348	-3.912	4.605
ln(Management)	1.085	0.219	0.054	1.587
ln(Capital/employee)	3.617	1.176	-2.555	9.225
Data from Bloom and Van Reenen (2007)				
ln(% Employees with a degree)	2.754	0.855	0.598	4.554
ln(Management)	1.145	0.265	0.054	1.609
ln(Capital/employee)	3.382	0.802	0.261	6.025
Ln(Wages)	3.633	0.332	2.996	4.605



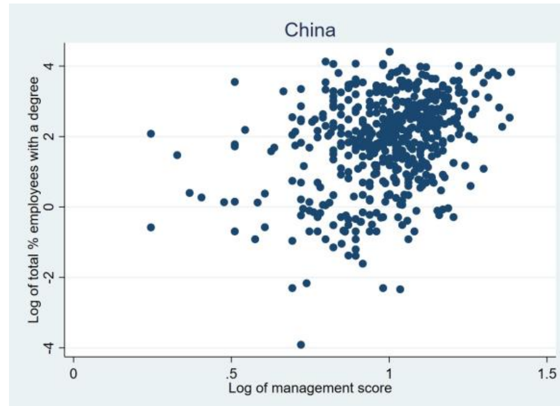
((a)) Management Score ((b)) Demand for Skills

Figure 1: Distribution of Management Score and Demand for Skills.

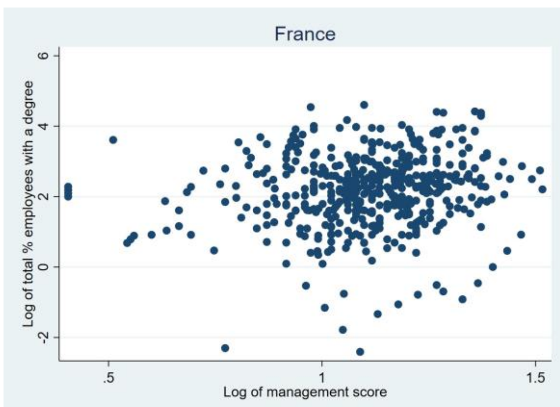
Figure 2 presents scatterplots of the two variables for specific countries. Simple correlations between both variables oscillate significantly from a lower positive correlation of 3% in Japan, to values around 15% for Germany, France and the UK and attains values nearly 31% for China and the USA.



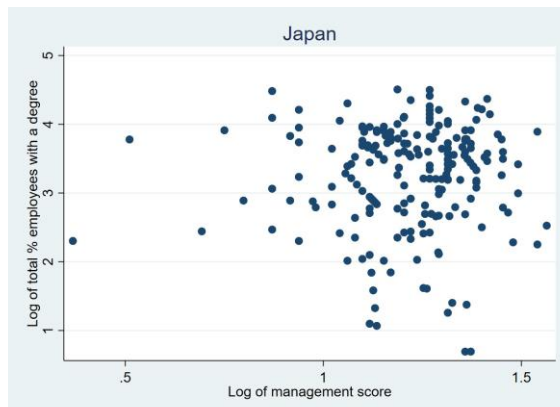
((a)) Management Score vs % of Employees with a degree – USA



((b)) Management Score vs % of Employees with a degree – China



((c)) Management Score vs % of Employees with a degree – France



((d)) Management Score vs % of Employees with a degree – Japan

Figure 2: Examples of Scatterplots between Management and Demand for Skills for a set of countries

Small changes in specifications and data lead to quite different coefficients for management in regressions for human capital (or skills intensity).[1] This calls for the need for some theoretical guidance on the specification of the equation for skills to be estimated. The model in Section 3 provides such guidance.

3 The Model

The model builds on Bloom et al. (2017) but is modified to include human capital (or skills) and efficiency wages.

[1] Results of alternative regressions are available upon request.

3.1 Setup

The final good technology in each firm is

$$Y_i = F(A_i,H_i,K_i,M_i) \quad (1)$$

where A is technology or Total Factor Productivity (TFP), H is human capital, K is physical capital, and M is Management. The *Management as Technology* perspective assumes that some types of *best practices* of management (e.g. not promoting incompetent employees to senior positions, or collecting some information before making decisions, Taylor's Scientific Management; Lean Manufacturing; Deming's Total Quality Management, incentive pay etc.) increases efficiency. It is obvious that some of these practices are directly linked with the intensity of skills employed and so we can expect that management practices increase the intensity of skills. On the contrary, the *Management as Design* perspective assumes that differences in practices are simply styles optimized to a firm's environment. This means that some practices could increase (or decrease) efficiency depending on this environment. A particular example is purely tenured-based which can lead to a reduction of influence activities but otherwise (or in other firms) reduce output.

Without loss of generality we assume that output Y_i is a real quantity and thus following the *Management as Technology* perspective we use a Cobb-Douglas technology as in Bloom et al. (2017), extended to allow for human capital and individual effort determining efficiency:[2]

$$Y_i = A_i H_i^a K_i^b M_i^c \quad (2)$$

with $0 < a,b,c < 1$, $A_i = A_0 e(w_i,w_a)$ denoting that productivity is determined by efficiency in work. This means that the efficiency of work (or effort e) is determined by industry-specific labor market conditions χ, which can be further specified including unemployment rates, u wages in firms that compete for the same skills, w_a and the own wage w. We specify effort as:

$$\begin{cases} \left(\frac{w_i-\chi}{\chi}\right)^{\beta} if w > w_a \\ 0 \ otherwise \end{cases} \quad (3)$$

where β measures the concavity of the effort function. While human capital is accumulated outside the firm (by households), physical capital and management are accumulated by the firm, such as:

$$K_{it} = (1 - \delta_k)K_{it-1} + I_{k,it}, \quad (4)$$

$$M_{it} = (1 - \delta_m)M_{it-1} + I_{m,it}, \quad (5)$$

[2] As in that paper, we also assume that since firms in our data are typically small in relation to their input and output markets, for tractability we ignore any general equilibrium effects, taking all input prices (for capital, labor, and management) as constant.

where δ_k and δ_m are depreciation rates of physical capital and management and $I_{k,it}$ and $I_{m,it}$ are investment in both types of capital, with the additional restriction that management capital cannot be sold and so $I_{m,it} \geq 0$.

Finally, the firm demand for skills or human capital and wage come from the firms' maximization problem using equation (1) in order to human capital and wage:

$$H_i = \frac{aY_i}{w_i} = \frac{aA_0 H_i^a K_i^b M_i^c}{w_i} = \frac{aA_0^{\frac{1}{1-a}} \left(\frac{w_i - \chi}{\chi}\right)^{\frac{\beta}{1-a}} K_i^{\frac{b}{1-a}} M_i^{\frac{c}{1-a}}}{w_i} = \frac{aA_0^{\frac{1}{1-a}} K_i^{\frac{b}{1-a}} M^{\frac{c}{1-a}}}{w_i \left(\frac{w_i}{\chi} - 1\right)^{\frac{\beta}{1-a}}} \tag{6}$$

$$w_i = \frac{\chi}{1-\beta} \tag{7}$$

where equation (6) comes from the equality of the wage and marginal productivity of skills and equation (7) comes from the so-called Solow Condition. This yields the following equation for the demand of skills:

$$H_i = \frac{aY_i}{w_i} = \frac{aA_0 H_i^a K_i^b M_i^c}{w_i} = \frac{aA_0^{\frac{1}{1-a}} \left(\frac{w_i - \chi}{\chi}\right)^{\frac{\beta}{1-a}} K_i^{\frac{b}{1-a}} M_i^{\frac{c}{1-a}}}{w_i} = \frac{aA_0^{\frac{1}{1-a}} K_i^{\frac{b}{1-a}} M^{\frac{c}{1-a}}}{\frac{\chi}{1-\beta} \left(\frac{\beta}{1-\beta}\right)^{\frac{\beta}{1-a}}} \tag{8}$$

Equation (8) will be the base for the quantitative assessment of the model as well as for the econometric estimation.

3.2 Calibration and a quantitative exercise

We want to infer some quantitative properties of the model and compare them with the econometric estimations we perform in the next section. To that end, we calibrated the model. For the parameters of the production function we assume constant returns to scale in equation (2), setting a = 0.4, b = 0.1 and c = 0.5.[3] The parameters of the efficiency wage setting are χ = 1 and β = 0.5, assuming a concave function in (3). Depreciation for physical capital and management (as a technology) are in line with the literature (5% for physical capital and 1% for management, assuming that management practices – or culture – depreciates less than physical capital). For the initial levels of physical capital, human capital, and management we use values from the data averages in Table 1. The initial value for output is calculated using equation (2) and assuming A_0=1. Finally, investment in physical capital assumes a flexible accelerator approach for which we need a real interest rate (assumed to be r = 0.1), and the value for accelerator, assumed to be 0.2.[4] In the baseline the investment in Management will be zero, and so, m_{acc} = 0. Most of the assumptions will be relaxed in some of the exercises.

[3] These values are in line with the estimated coefficients e.g. in Table 3. Note that small changes in these values, namely the assumption of decreasing returns to scale, do not change the nature of our quantitative results.

[4] In this case investment is given by $I_t = acc_k(\Delta Y/(r + \delta_k))$.

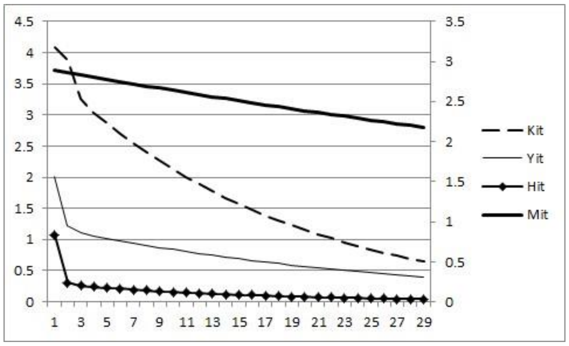
Table 2: Calibration

Calibrated values						
a	b	c	χ	β	δ_k	δ_m
0.4	0.1	0.5	1	0.5	0.05	0.01
Initial values and additional variables						
K_0	H_0	M_0	Y_0	r	k_{acc}	m_{acc}
4.080	1.068	2.889	2.009	0.1	0.2	0

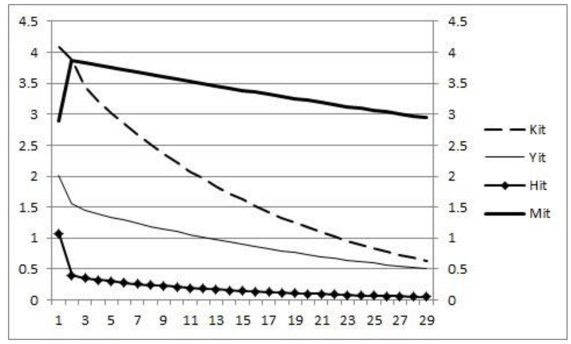
In the first exercise (Figure 1(a)) the main force in place is the depreciation rate for physical capital, which makes the series decrease following a higher initial value. In Figure 1(b) we observe the resulting evolution of the series after a one-off positive shock in Management (we introduce a nearly 1/3 increase of the initial value). Output, physical capital, and demand for human capital initially respond positively to the shock but decrease thereafter. Most interesting scenarios happen when we allow for a permanent shock in management allowing for a 20% increase in the score (of the previous period) per period (Figure 1(c)). In this exponential growth case, output and the demand for skills also grow exponentially. After 30 periods the demand for skills rises almost 100 times, at an average period growth rate of 4.6%. Finally in Figure 1(d), we assume a more modest permanent increase in management – 10% increase in the score (of the previous period) per period. Note that in any case the increase in management is always a force in opposition to that of the depreciation effects since there is no exogenous shock in management other than technology.[5] In this last case, this becomes especially visible since the evolution of physical capital is U-shaped. Only after a certain period does the positive effect of management offset and eventually surpass the negative effect of depreciations. This is also visible in the demand for skills, which is much flatter than before. At the end 0f the 30^{th} period the demand for skills is almost at the same level as the average value of the data, the departing point.

The effect of management in the demand for skills may be calculated as $\Delta H/\Delta M$. We do that for the first 30 periods. This yields an average value per period of 36.1% in the first (baseline) scenario, 34.7% in the second scenario, 37.9% in the third, and 3.11% in the last one.

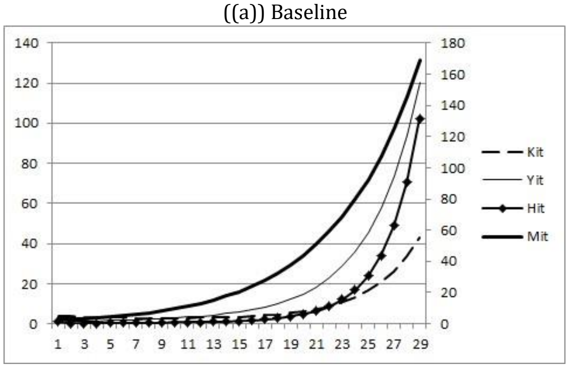
[5] The evolution of investment in physical capital is endogenous.



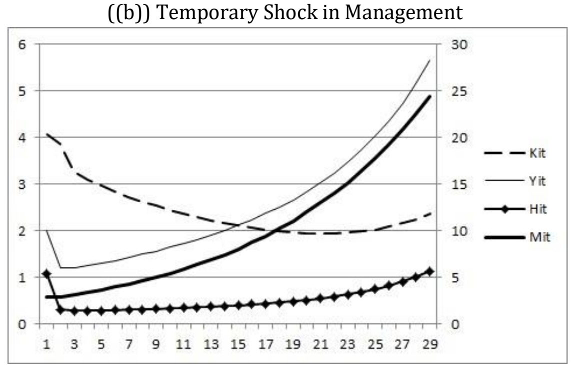
((a)) Baseline



((b)) Temporary Shock in Management



((c)) Permanent Shock in Management



((d)) Lower permanent investment in Management

Figure 3: Simulated Series for Capital, Human Capital, Output, and Management.
Note: right-hand scale is for Management

4 Estimation

We now estimate equation (8) in log form, using the percent of college degree to proxy H_i, capital per employee to proxy K_i, the management index M_i, and general and noise controls as in regressions of Section 2. Specifically, industry dummies proxy the possible effect of industry labor market conditions.

Table 3 shows high significance for coefficients on Management using a log-log specification uncovered by a simple model with efficiency wages, in spite of very different quantitative effects depending on the database used. A 1% increase of Management increases the percentage of college degrees employed from 1.9% to 129.5%. This means that if a firm has 20% of college degree holders in its workforce, a 1% increase in the quality of management index would imply that it will have nearly 24% to nearly 46%. These values are consistent with the almost 40% increase in the demand for skills for a 1% increase in management obtained in the simulation of the model we presented above. This leads us to believe that the simple model we devised to highlight the relationship between Management and the demand for skills is particularly useful in predicting realistic quantitative effects. We also learn that differences in estimates may derive from different investment patterns in management (both investment and depreciation rates) that may be present in different databases.

Table 3: Regressions for skills

Dependent variable: ln % Employees with College degree				
	(1)	(2)	(3)	(4)
$ln(Management)$	0.019***	0.627***	1.295***	0.929***
	(0.006)	(0.097)	(0.279)	(0.000)
$ln(Capital/employee)$	0.001	0.062***	0.016	-0.000***
	(0.001)	(0.022)	(0.036)	(0.000)
$Ln(Wages)$	–	–	–	0.000***
				(0.000)
Firms	5085	2927	523	313
Observations	27481	7094	4293	2218

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard-errors presented in parentheses are clustered by firm when there are several observations by firm and heteroscedasticity-robust otherwise. Constants and all controls are included in regressions but not shown in the table. Column (1) presents the results of a regression using data from Bloom and Van Reenen (2010). Column (2) presents the results of a regression using data from Bloom et al. (2012a). Column (3) presents the results of a regression using data from Bloom and Van Reenen (2007). Column (4) presents the results of a regression using data from Bloom and Van Reenen (2007), in which we also control for firms' own wages (which are not available in other databases).

4.1 The influence of sub-items of Management

The management score is divided into four main dimensions: lean, performance, target, and talent. The first is focused on production processes, the second focuses on how performance is measured and tackled. The third focuses on how the firm defines and interconnects goals between the short and the long run and between financial and nonfinancial goals. Finally, talent captures how the firm implements policies that reward, promote, and attract talents. Those four dimensions may have different effects in the demand for skills. Table 5 shows results in which each of these four dimensions are introduced. Looking at the results we can evaluate the quantitative effects of those four dimensions in the demand for skills. Interestingly, all sub-items help to increase the demand for skills. The most important quantitatively are the target and talent dimensions followed by performance and lean, respectively. It is interesting that a 1% increase in target leads to a 43% to 103% increase in the percentage of college degrees employed, a 1% increase in talent to an increase of nearly 70%, and a 1% increase in performance to an increase of between 30% and 70% increase in the percentage of college degrees employed. Finally, a 1% increase in lean would lead to, at best, a 20% increase in the percentage of college degrees employed.

Another issue that is interesting to be explored is the effect of each of those components maintaining the overall management score as constant. This could indicate to firm which dimension it might wish to act in so as to increase the employment of skills, and also to policy makers that are interested in increasing the skill intensity of the firms. Our results show that in that case increasing target and talent while decreasing performance for a given level of management will increase the demand for skills.[6]

Table 4: Regressions for skills - sub-items

Dependent variable: ln % Employees with College degree								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ln(Lean)$	0.184***	0.240	–	–	–	–	–	–
	(0.054)	(0.190)						
$ln(Performance)$	–	–	0.296***	0.693***	–	–	–	–
			(0.074)	(0.176)				
$Ln(Talent)$	–	–	–	–	0.681***	0.748***	–	–
					(0.090)	(0.273)		
$Ln(Target)$	–	–	–	–	–	–	0.429***	1.035***
							(0.077)	(0.183)
Firms	2924	523	2027	523	2927	523	2927	523
Observations	7088	4293	7090	4293	7094	4293	7094	4293

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard-errors presented in parentheses are clustered by firm when there are several observations by firm and heteroscedasticity-robust otherwise. Constants and all controls (including *ln(Capital/employee)*) are included in regressions but not shown in the table. Odd Columns present the results of a regression using data from Bloom et al. (2012a). Even Columns present the results of a regression using data from Bloom and Van Reenen (2007). The first database used for regressions in Table 4 does not have information for the sub-items.

5 Conclusion

Research on the influence of management in firms' performance has been focused on productivity measures. Alternatively, our focus is on the influence of management in the demand for skills. We devise a simple firms' model highlighting that investment in management as a technology as well as its depreciation may be at the center of the explanation of such a linkage. Thus our contribution relies on studying the influence of Management and its components in the firms' demand for skills, an overlooked relationship in the literature.

Empirical estimations show high significance for coefficients on Management using a log-log specification. A 1% increase of Management increases the percentage of college degrees employed from 1.9% to 129.5%. This means that if a firm has 20% of college degree holders in its workforce, a 1% increase in the quality of management index would imply that it will have nearly 24% to nearly 46% of college degree holders after the shock. These values are consistent with the almost 40% increase in the demand for skills for a 1% increase in management obtained in the simulation of the model we presented above. We also present evidence of the

[6] Results are available upon request. This means that we obtain significant and positive coefficients for target and talent in regressions in which the (total) management score also enters as covariate, and negative and significant coefficients for performance are obtained in those regressions. Lean becomes nonsignificant in regressions in which the (total) management score also enters as covariate.

influence of the sub-items of Management on skills' demand and discovered that, besides the talent component of Management, target and performance components greatly influence the demand for skills.

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Appendix A Estimations in Selected Databases

In this appendix, we present regressions based on panel data from Bloom and Van Reenen (2010) and Bloom et al. (2012a).

Table A.1: Regressions for skills with data from Bloom and Van Reenen (2010)

	Dependent variable: ln % Employees with College degree				
	(1)	(2)	(3)	(4)	(5)
Management	0.099***	0.073***	0.021***	0.024***	0.036***
	(0.014)	(0.016)	(0.007)	(0.008)	(0.008)

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard-errors presented in parentheses are clustered by firm when there are several observations by firm and heteroscedasticity-robust otherwise. Data from Bloom and Van Reenen (2010). Why Do Management Practices Differ across Firms and Countries? *Journal of Economic Perspectives*, Vol. 24, No. 1. First column includes Ln(Sales/Employee) as covariate, 4399 firms and 13611 observations. Second column includes Ln(Sales/Employee), country&industry dummies, 3657 firms and 10392 observations. Column (3) adds general controls and noise controls and Ln(Capital/Employee), 3391 firms and 9696 observations. Column (4) drops Ln(Sales/Employee) and Ln(Capital/Employee) but includes Profitability (ROCE), and the three types of controls, 2491 firms and 8650 observations. Column (5) includes all previous controls simultaneously and 1542 firms, and 5283 observations. General controls include firm-level controls for ln(average hours worked) and ln(firm age) and noise controls include 78 interviewer dummies, the seniority and tenure of the manager who responded, the day of the week the interview was conducted, the time of day the interview was conducted, the duration of the interviews, and an indicator of the reliability of the information as coded by the interviewer.

Table A.2: Regressions for skills with data from Bloom et al. (2012a)

	Dependent variable: ln % Employees with College degree								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Management	0.292***	0.270***	0.191***	0.197***	0.322***	0.270***	0.212***	0.234***	0.234***
	(0.024)	(0.025)	(0.015)	(0.015)	(0.036)	(0.035)	(0.036)	(0.035)	(0.035)

Notes: * p<0.10, ** p<0.05, *** p<0.01. Standard-errors presented in parentheses are clustered by firm when there are several observations by firm and heteroscedasticity-robust otherwise. Data from Bloom et al. (2012a). *Academy of Management Perspectives*, Vol. 26, No. 1. Columns (1) and (2) are for nonmanagers and use 5407 observations. Columns (3) and (4) are for managers and use 7559 observations. Column (5) includes Ln(Sales/Employee) as covariate, 2927 firms and 7094 observations. Column (6) includes Ln(Sales/Employee), country&industry dummies, 2927 firms and 7094 observations. Column (7) adds general controls – without firm age – and noise controls and Ln(Capital/Employee), 2901 firms and 7000 observations. Column (8) drop Ln(Sales/Employee) and Ln(Capital/Employee) but includes Profitability (ROCE), and the three types of controls, 2901 firms and 7000 observations. Column (9) includes the three types of controls and sales growth using 2901 firms, and 7000 observations.