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How important are management practices for the productivity of small and medium enterprises?

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Abstract: Is the lack of 'managerial capital', alongside human and financial capital, a constraint on the growth of firms in developing countries? The evidence on this is still mixed, especially among small and medium enterprises. This paper uses a panel of Vietnamese small and medium enterprises to investigate this question. We build a multidimensional measure of managerial capital, combining both practices and attitudes, and link it with consistent estimates of firm-level productivity and mark-up. Even though bias may still affect the estimation of the overall influence of managerial capital on productivity, we show that there is a positive and significant association. Changes in management practices allow firms to be more efficient. Furthermore, we compare this association by firm size, and show that managerial capital is arguably as important for micro and small firms as it is for medium firms. Finally, it appears that the indicators related to 'entrepreneurial attitudes' play a more important role than elementary business skills.

Keywords: entrepreneurship, informal economy, informal sector, economic development
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Neither husband nor wife knew how to read—a slight defect of education, which did not prevent them from ciphering admirably and doing a most flourishing business. […] To relieve himself of the necessity of keeping books and accounts, he bought and sold for cash only.

Balzac, *Le Curé de Village, 1841*

1 Introduction

Few will question the relevance of a multinational manufacturing corporation's expenditure on advertising. However, eyebrows may be raised if the same question is asked about a single, informal worker producing rubber sandals. The purpose of this paper is to ask, in a comparative manner, the question: does managerial capital (MC) have the same effect on productivity among micro, small, and medium firms? While past and ongoing research in management studies and economics has proved the relevance of MC for large or medium enterprises, the population of micro and small enterprises has largely been ignored.

Given the weight of micro, small, and medium enterprises (MSMEs) in total employment, and because the long-awaited development process is occurring through productivity gains, there is value in understanding the mechanisms that foster (or limit) their expansion. Several types of constraints to expansion have already been put forward, with access to savings (Dupas and Robinson 2013), access to finance (de Mel et al. 2008), and human capital (Hsieh and Klenow 2009) being among the more documented ones. The lack of MC, by contrast, has only recently emerged as a constraint (Bruhn et al. 2010).

In the developing world MSMEs rarely use what are considered to be elementary business practices in industrialized countries. The majority do not keep basic written accounts, and they compete mostly with other local household businesses. Yet, micro entrepreneurs themselves mention factors such as 'keeping and interpreting financial records' or 'promoting products' as being important for business success (Bradford 2007). However, some enterprises do display high organizational and managerial abilities. This heterogeneity in MC endowment can enter the production function as an additional efficiency factor; it could be argued that even among micro firms, managerial inputs can improve the productivity of other inputs. Competing more aggressively, advertising products, incentivizing wage determination or innovating could lead to higher value added.

Proving a causal relationship between productivity and MC is challenging, as the latter does not offer exogenous variations. It is, rather, part of the often-blamed (and always unobserved) 'ability' of the firm's operator, and any relation found to productivity can be attributed to some other unobserved factor. This paper's approach is therefore not to argue that the results are fully causal, which observational data would struggle to back up. Instead, it measures the effect of changes in firms' MC on productivity and mark-up and compares this relationship by firm size. To do this, we use a synthetic indicator of MC and consistent productivity and mark-up estimates. We aim to show that MC matters for micro and small firms, and to identify which dimension of MC is the most influential.

We rely on a panel of Vietnamese MSMEs which includes proxies for several aspects of MC. We start by estimating the productivity and mark-up of firms, controlling for simultaneity and input price bias. We propose a multidimensional measure of MC based on five axes used to compute a weighted score. We then investigate the effect of MC on firm-level productivity and mark-up, controlling for unvarying heterogeneity. We find that changes in MC are associated with large positive effects on productivity, but they do not enhance firms' market power. We also test for heterogeneity of the effect by firm size category. While larger firms are found to be more productive than smaller ones, on average, we find that the effect of MC is still significant—and of comparable magnitude—among the smallest firms. Micro and small firms that have higher levels of managerial ability are indeed more efficient than others—and they are *as much* more efficient as medium-size firms. We further investigate the separated effect of the MC indicators and find the effect to be mainly driven by firms' ability to advertise and compete aggressively.

Section 2 of the paper reviews the literature, Section 3 presents the data, and Section 4 provides the empirical measures of productivity and MC. Section 5 presents the estimation results of the link between MC and productivity and Section 6 presents the robustness test. Section 7 concludes.

2 Literature review: what do we know about the managerial capital of micro and small enterprises?

What exactly constitutes managerial capital (MC)? The notion has no widely accepted definition and borrows from several fields of studies, which have complementary definitions. As Syverson puts it (2011), 'Managers are conductors of an input orchestra'. Defining MC then amounts to measuring the length of the conductor's baton, but it could also relate to the conductor's attitude and psychological traits. In the related development economics literature that has recently surged, MC is persistently proxied by business practices (and among micro and small firms, by elementary business skills). Management studies, in which the focus has long been on the influence of managers, additional features of MC relate to the entrepreneurial spirit. Taken broadly, MC thus refers to all *practices* and *traits* of an enterprise operator that potentially have an influence on the firm's efficiency. This can include formal book-keeping, inventory management, financial or strategic planning, and pricing strategy, as well as innovativeness or self-confidence.

There is general consensus on what are considered to be 'good practices' for large enterprises and the effects of these practices on productivity are well known (Bloom, Mahajan et al. 2010; Syverson 2011; Bloom, Eifert et al. 2013; Bloom, Schankerman et al. 2013). The picture is fuzzier in the case of household micro and small firms. This section starts by reviewing the literature to determine which skills, practices, or characteristics can proxy managerial capital among micro and small firms, and to what extent their influence on performance is established. Evidence regarding business practices is found in the field of development economics, where a recent surge in the evaluation of business training programmes has provided insight into their relevance. Contributions are also found in the field of management and entrepreneurial studies, where the relevance of the notion of entrepreneurial orientation (EO) among micro firms in developing countries has received recent attention.

2.1 Business practices: mixed evidence from business training programmes

Numerous programmes have been launched around the developing world to improve the business skills of microenterprises, and this has led to a substantial body of literature evaluating the impact of these programmes. The content of these programmes gives insights into what economists consider to be important business skills for this population. They are often elementary, compared to those of larger firms, and frequently include book-keeping, separating household and business budgets, elaborating growth strategies, financial planning, pricing and cost calculation, marketing, inventory management, savings, and debt management.

These programmes differ in content and in terms of target population, scale, means, and implementation schemes, which makes it difficult to draw clear conclusions. However, two recent papers have presented their results. McKenzie and Woodruff (2014) reviewed 20 studies (including 16 randomized control trials), of which only two had sufficient statistical power to show significant impacts from these programmes. These two studies found that training had an impact on short-term profits and sales: Berge et al. (2014), by combining survey data and lab experiment, and De Mel et al. (2014), by evaluating a combination of training and grants. The other studies they reviewed lacked statistical power, and long-term profits were not significantly affected. This led McKenzie and Woodruff (2014) to conclude that 'there is little evidence to help guide policymakers as to whether any impacts found come from […] productivity improvements, and little evidence to guide the development of the provision of training'. In addition to this review, Cho and Honorati (2013) conducted a meta-analysis using 37 impact evaluation studies—with some overlap with the studies reviewed by McKenzie and Woodruff (2014). They obtained constrasting results showing little effect of training programmes on labour outcomes, although there was clearer evidence of improvement in business practices. More importantly perhaps, they suggest that a combination of interventions is likely to yield better results than each intervention being applied separately.

2.2 Entrepreneurial orientation and the managerial performance of micro enterprises

The traits and attitudes of managers may matter as much as business practices. The analysis of attitudes and psychological factors is another topic covered by some business training, which, unsurprisingly, has been more popular in managerial studies than in economics.

Making business owners more proactive and perseverant seems to increase their performance (Glaub and Frese 2011). This finding echoes a second and complementary strand of literature on the link between management and the performance of microenterprises. The concept of entrepreneurial orientation (EO) is a potential proxy for unobserved managerial ability related to attitudes (Miller 1983; Covin and Slevin 1989). EO can be measured at the firm level along five dimensions: proactiveness, innovativeness, risk-taking, competitive aggressiveness, and autonomy of workers (Lumpkin and Dess 1996).

A recent set of papers aimed at providing empirical evidence on the link between EO and the performance of microenterprises found a positive association between EO and performance in the case of Mexico, Argentina, Malaysia, and the Philippines (Campos et al. 2013; Berrone et al. 2014; Lindsay et al. 2014; Munoz et al. 2015). While their results converge, these studies, however, share numerous and substantial methodological shortcomings. First, the samples are small, ranging from 151 to 735 observations (with a 46 per cent response rate for the latter) and generally non-random—with on-site or administrative identification of respondents, which likely results in sampling errors. Second, the questionnaires are often self-administered or mailed. Consequently, accurate measures of performance are beyond the reach of these surveys, and all of the cited papers rely on self-reported evaluations of performance, the consistency of which is highly questionable.[1] Further meta-analysis, as carried out by Rauch et al. (2009), is also problematic. Among the 53 samples used, the average sample size is just under 270 respondents and only seven papers use a dependent variable that is not 'perceived performance'.

Findings from the evaluation of training programmes aimed at improving business practices have shown few significant improvements in performance. Similarly, the empirical investigations into the role of EO (which approximates the part of managerial ability related to attitudes) among

[1] In general, relying on self-reported perception is problematic for comparison purposes. In some cases, the questions used are beyond the reporting capacity of many micro-entrepreneurs, e.g. 'return on capital employed' or 'growth of the company's value' (Campos et al. 2013; Munoz et al. 2015).

microenterprises suffer from too many methodological shortcomings to provide convincing evidence. There is thus room for a closer look at the link between MC (understood as practices and traits) and productivity and at the potential heterogeneity of this link across firm size. The only contribution in this regard is by McKenzie and Woodruff (2016), who looked at the influence on productivity of business practices in marketing, stock-keeping, record-keeping, and financial planning. Their results, which to some extent contradict the lack of impact of business training, show that these practices explain as much variation in outcomes in microenterprises as in large firms. Notwithstanding the importance of this contribution to the literature on the MC of microenterprises, their data do not allow consistent productivity levels to be estimated.

Against this backdrop, this paper relies on a rich panel data of MSMEs, covering mostly micro and small informal firms, and several indicators of both business practices and entrepreneurial attitudes. The estimation of consistent firm-level productivity is a necessary, and complex, first step, as unbiased estimation of production functions is an ongoing topic in empirical economics. Using an MC index, we then estimate its influence on productivity, removing fixed observed and unobserved heterogeneity and, more importantly, we test the heterogeneity of this influence by firm size.

3 Data

This paper relies on a panel of household firms with 8,864 observations of 2,901 unique firms carried out between 2007 and 2013. It is based on the panel data of manufacturing SMEs collected in a project involving the Vietnamese Central Institute for Economic Management (CIEM) of the Ministry of Planning and Investment of Viet Nam (MPI); the Institute of Labour Science and Social Affairs (ILSSA) of the Ministry of Labour, Invalids and Social Affairs (MoLISA); the Development Economics Research Group (DERG) of the University of Copenhagen; and the United Nations University World Institute for Development Economics Research (UNU-WIDER). The survey was initially funded by the Royal Embassy of Denmark in Viet Nam under the Business Sector Programme Support.[2] The panel data have been extensively used in academic research.

The SME survey has been conducted nine times, most recently in 2005, 2007, 2009, 2011, 2013, and 2015. As the proxy indicators of MC changed substantially in the 2005 and 2015 survey rounds, we restrict our sample to the 2007 to 2013 rounds. The resulting dataset thus combines four surveys, one carried out every two years. For each survey, outputs are available for years *n* and *n-1*. The sample size for each survey was initially around 2,500 firms, from which observations present in only one year were dropped. The resulting sample included 8,864 observations.

The surveys were conducted in ten provinces in Viet Nam. The stratification was initially based on type of ownership and aimed to reproduce the structure found in the General Statistics Office (GSO) figures and other pre-existing SME surveys in Viet Nam, such as Sakai and Takada (2000). A significant share of informal firms was included, using on-site identification. Further renewal of the sample involved selecting firms from both the new GSO listings and informal firms identified on-site. As a result, the SME surveys are not representative of the informal sector in Viet Nam, as they are biased towards larger firms, but they do provide a picture of the MSME segment. As the

[2] See UNU-WIDER (n.d.).

initial sampling in 2005 was based on an earlier survey from 1997, there is also 'a slight bias against young, newly established enterprises' (Rand 2004).

A notable feature is the stability of the questionnaire over time, which consists of three modules: (i) a main enterprise questionnaire; (ii) an 'employee module'; and (iii) an 'economic accounts module'. Information collected includes firm and owner/manager characteristics, as well as detailed records of production, sales, and inputs. The enterprise questionnaire also includes a rich set of MC indicators.

The sample is primarily made up of micro firms, consistently representing around 70 per cent of observations, depending on the year.[3] Informal household firms, defined as having no business registration certificate, represent 26 to 34 per cent of firms per year, which shows that the sampling methodology (and renewal procedure) performed well in including those units, even though no representativity is claimed. The average size in the sample is around 14 workers. Fewer than 35 per cent of firms operate in premises that are dedicated to production only, which means that the majority operate at home or in shared spaces.

4 Empirical strategy

If MC does have an influence on productivity, it should enable firms to reach a similar level of output with less inputs—or conversely to increase output while inputs are kept constant. This may reflect firms being more efficient in their production processes, but it may also signal increased market power. In order to evaluate this link and to further test its relevance by firm size, the necessary first step is to estimate firm-level productivity and mark-up. Sub-sections 4.1 and 4.2 provide details of these estimations, which have to overcome a number of endogeneity concerns. Sub-section 4.3 describes the proxy variables for managerial capital and the construction of the index, which is based on business practices (formal accounts, advertising, wage determination) and entrepreneurial traits (innovation, aggressive competition).

4.1 Estimating firm-level productivity

Empirical study of the link between MC and firm-level productivity can only be as good as the first-stage estimations of this productivity. The correct identification of the production functions, is among the oldest challenge in the empirical economic literature and is still evolving. Recent complementary methods are enabling significant progress towards overcoming the endogeneity challenges. Essentially, true productivity levels remain unobserved and so are productivity shocks to which firms may react differently. As long as input levels are chosen in relation to these unobserved determinants, ordinary least squares (OLS) estimations will be biased.

Specifying a Cobb–Douglas value added function:

$$VA_{it} = \beta_0 + \beta_1 l_{it} + \beta_2 k_{it} + \omega_{it} + \varepsilon_{it} \tag{1}$$

Where VA_{it} is the value added of firm *i* at time *t*. *l* and *k*, are respectively the labour and capital inputs. All variables are transformed in natural logarithm. The error term has two components, ω_{it} and ε_{it}, the former being correlated with inputs. The size and direction of the bias of the OLS coefficient on capital will depend on the correlation between inputs and productivity shocks, and

[3] A detailed description of our sample and the variables used in the paper is presented in Appendix Table A1.

more crucially on whether this correlation varies with time. If it does not, the inclusion of firm-level fixed-effects will yield consistent coefficients. Provided firm exit is also determined by this unobserved but unvarying productivity, then fixed effects will also solve potential selection bias due to endogenous exits. The unvarying nature of the unobserved productivity could, however, be a rather strong hypothesis, especially when using long-term panels. Other approaches allow for inputs to be endogenous with respect to a time-varying unobservable. Three contributions largely frame the empirical literature in this regard: Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015) (henceforth OP, LP, and ACF respectively). The first two rely on the relationship between some intermediate input entering the production function and the unobserved productivity:

$$m_{it} = f_t(k_{it}, \omega_{it}) \tag{2}$$

This function can be inverted, assuming in particular a monotonic increase in ω_{it} so that the productivity is a function of two *observed* inputs:

$$\omega_{it} = g_t(k_{it}, m_{it}) \tag{3}$$

OP build on the idea that firms change investment (conditional on capital stock) in response to productivity shocks and provide a non-parametric representation of this inverse function to estimate production functions in two stages. However, investment may not react strongly to productivity shocks—or at least, not monotonically—and the adjustments may take place at other levels. LP suggest using, instead, a more varying intermediate input demand function such as material expenditure or energy costs. ACF highlight a functional dependence problem with the specifications of both OP and LP, whereby labour can be a deterministic function of the variables on which the first stage is conditioned. They propose an alternative (though quite related) estimation strategy, where inverted input demand functions are conditional on the choice of labour input. Wooldridge (2009) additionally proposes a stacked version of LP's moments, estimated by generalized method of moments (GMM) with efficiency gains, again based on unconditional input demands.[4] As well as being more efficient than the two-step estimators, this procedure can also correct for serial correlation (Van Beveren 2010).

All these estimation techniques rely on structural assumptions that, despite progressively gaining in generality, still largely condition their validity or failure. In practice, the specificities of the firms' populations and of the available information therefore weight equally or more than the overall performance of each technique in choosing the empirical approach. In the specific case of Vietnamese manufacturing SMEs, we use a combination of FE, LP, and Wooldridge's (2009) estimations of production function in addition to the benchmark OLS regressions.

OLS estimation of the firm-level value added function hence follows equation (1), including a time trend. Assuming that the unobserved productivity is mostly fixed in time, we estimate the same equation with firm-level fixed effects:

$$VA_{it} = \beta_0 + \beta_l l_{it} + \beta_k k_{it} + \omega_i + \varepsilon_{it} \tag{4}$$

[4] Comprehensive reviews of production function estimation techniques include Eberhardt and Helmers (2010) and Van Beveren (2010).

From both regressions, we can predict the productivity levels by taking:

$$\widehat{\omega} = (\varepsilon_{it} - \widehat{\beta_l} l_{it} - \widehat{\beta_k} k_{it}) \quad (5)$$

Further controlling for the simultaneity of inputs using LP, OP, or ACF requires additional hypothesis on the evolution of productivity and on the timing of firms' choices. As investment only concerns 45.5 per cent of firms across years (only 33.7 per cent among firms with one or two workers), it cannot be used as a proxy without introducing selection bias. Among the available non-parametric corrections, the LP procedure thus makes more sense and electricity costs are used as intermediate input proxy in the core of the paper. Productivity is then typically assumed to follow a first-order Markov process: $\omega_{it} = E(\omega_{it}|\omega_{it-1}) + \xi_{it}$ where ξ_{it} is uncorrelated with k_{it} but can depend on l_{it}. The LP procedure then assumes that given k_{it} the firm will decide on l_{it}, and then determine m_{it} accordingly. The rearrangement of equation (1) is thus:

$$VA_{it} = \beta_l l_{it} + \varphi_{it}(k_{it}, m_{it}) + \varepsilon_{it} \quad (6)$$

Where:

$$\varphi_{it}(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + g_t(k_{it}, m_{it}) \quad (7)$$

and

$$E(\varepsilon_{it}|\, l_{it}, k_{it}, m_{it}) = 0 \quad (8)$$

The ACF critique essentially states that l_t and m_t are instead chosen simultaneously, which plagues the identification of β_l in the first stage. Following Wooldridge (2009), the last and preferred specification of productivity estimation in this paper consists in estimating β_k and β_l directly by GMM.

Assuming:

$$E(\omega_{it}|\, l_{it}, k_{it}, m_{it}, l_{it-1}, k_{it-1}, m_{it-1}, \dots, l_{i1}, k_{i1}, m_{i1}) = 0 \quad (9)$$

and restricting the dynamics of productivity shocks:

$$E(\omega_{it}|\, k_{it}, l_{it-1}, k_{it-1}, m_{it-1}, \dots) = E(\omega_{it}|\, \omega_{it-1}) = j(\omega_{it-1}) = j(g(l_{it-1}, k_{it-1})) \quad (10)$$

We can write $\omega_{it} = j(\omega_{it-1}) + a_{it}$ with $E(a_{it}|\, k_{it}, l_{it-1}, k_{it-1}, m_{it-1}, \dots) = 0$. In other words, inputs l_{it} and m_{it} are correlated with productivity innovations a_{it}; whereas k_{it}, which is set at the previous period, is not. Neither are all past values of l_{it}, k_{it} and m_{it}. They provide a set of instruments to identify β_l and β_k.

We estimate the four models (OLS, FE, LP, and Wooldridge) of value added function from the unbalanced panel of firms.[5] We use the log of deflated value added as outcome, the log of total employment at year *n*, and the log of real capital value at the end of the previous year as inputs. The LP model further includes the log of real electricity expenditures from the last period as proxy.

[5] On implementing production function estimators in Stata, see Yasar et al. (2008), Petrin (n.d.) and Petrin et al. (2004).

Wooldridge's estimations of productivity rely on lagged values of l_i and exponential functions of log inputs and intermediate input.

Concerns about input prices bias, the endogenous exit of firms, and industry-specific effects may remain. Indeed, if firms face different input demand functions (and/or operate at different points of the curves), the correction introduced by the proxy intermediate input variable will further bias the results. Electricity costs are, however, arguably similar across firms, and should not introduce further differences. Material expenditures are used as robustness checks to estimate alternative productivity measures (available upon request). Next, to the extent less productive firms are more likely to exit the sample, it is still possible that the productivity estimations will suffer from endogenous exit. The only method that directly corrects for this is the OP estimation, and, in practice, the corrections for firm exit are very small.[6] Lastly, a common practice (challenged, among others, by Bernard et al. (2009)) consists in estimating production function separated by industry. Given the high concentration of our sample firms within a few sectors (See Appendix Table A1), industry-specific estimates would require grouping arbitrarily sectors where few observations exist, and would result in introducing additional noise rather than separating heterogeneous manufacturing firms. Productivity is thus estimated on the full sample of firms.

Table 1 presents the coefficient estimates of the firm-level production function on the whole population of firms, using the unbalanced panel. Column 1 corresponds to OLS estimation of equation (1) with an additional time trend, column 2 further introduces fixed effects to estimate equation (4), column 3 applies the LP procedure with electricity costs as intermediate input, and column 4 implements Wooldridge's GMM estimation. Values of inputs, output, and value added are all deflated using the regional price deflator for the 2005–15 periods. Past values of inputs are limited to one lag in order to prevent losing years of observations. Values of inputs in 2007 are only used as past values in the LP and Wooldrige specifications. The LP and Wooldrige results also use fewer observations due to missing information on intermediate input variables. Looking at excluded firms did not reveal any specific pattern. In particular, excluded firms were not concentrated among the smallest microenterprises, which could have been using proportionally less electricity.

Table 1: Production function estimations

	OLS	FE	LP	Wooldrige
Log of labour	0.967***	0.686***	0.892***	0.941***
	(0.011)	(0.020)	(0.013)	(0.020)
Log of capital	0.226***	0.150***	0.143***	0.154***
	(0.008)	(0.010)	(0.012)	(0.010)
year=2009	0.091***			
	(0.017)			
year=2011	0.234***			
	(0.019)			
year=2013	0.275***			
	(0.020)			
Constant	7.306***	9.239***		0.210
	(0.095)	(0.137)		(2.533)
Observations	8,759	8,759	5,822	5,797

Note: *** p<0.01, ** p<0.05, * p<0.1. Clustered standard errors. by firms in models 1, 2, and 4, bootstrapped with 250 replications for LP estimates. Source: Authors' calculations.

[6] Such is the case for Newman et al. (2015) using Vietnamese data on larger firms.

Compared to the benchmark and expectedly biased OLS estimations, all corrections consistently reduce the estimated returns to capital, which is consistent with the simultaneity bias (more productive firms choosing more capital). The reduction in the labour coefficient is less marked; heterogeneity in productivity levels may arguably allow employing more workers altogether, or producing the same output with less workers. Fixed effects estimations overcorrect the bias for both inputs and find lower returns (and overall decreasing returns to scale). Correcting for fixed and varying simultaneity, both models find returns to capital of nearly 15 per cent at the mean, and the preferred Wooldridge specification yields high average returns to labour, close to the OLS estimates. One explanation may lie in the proportion of micro firms in the sample for which more productive firms are those who can employ an additional worker.

4.2 Estimating mark-ups

Measuring the effect of MC on firm performance through productivity was not able to be completely satisfied since productivity does not perfectly capture a firm's market power. Two key aspects of firm performance have been emphasized in the literature—technical efficiency in production and market power. If the market is perfectly competitive, price is equal to marginal cost and, then, product efficiency is a sufficient measure. However, perfect competition is hard to find and justify. A firm that takes advantage of the price–cost margin, may earn higher profits but not necessarily improve its physical efficiency. Thus, in addition to firm productivity, we estimate mark-ups as another measure of firm performance to distinguish different channels by which MC may have any effect on firm performance.

The literature on mark-up estimation is quite extensive, starting with Hall's (1986, 1988, 1990) approach, and then Klette (1999), who addresses the limitations of Hall's approach. Central to their approaches is the idea that under imperfect competition, the association between inputs and output growth is disproportional, and this difference is measured by a relevant mark-up. However, since their methods generate estimated mark-ups at the industry level, we focus on another empirical framework developed by De Loecker and Warzynski (2012) (hereafter DLW) to estimate firm-specific mark-ups. Their empirical model is based on an assumption that a firm minimizes its cost for a variable input that can be adjusted freely. The thinking behind this approach is that, holding other inputs constant, a competitive firm will expand its use of one input (material in our case) until the revenue share of materials equals the output elasticity, which reduces as materials input increases. However, a firm may choose not to increase this input to the equality point, but to produce a lower quantity and raise the output price instead. In this case, it indicates that the firm is able to exercise market power by charging a price above marginal cost. The mark-ups expression is given by:

$$\mu_{it} = \theta_{it}^{X}(\alpha_{it}^{X})^{-1} \tag{11}$$

where μ_{it} is the mark-up or price-marginal cost fraction of firm *i* at time t; θ_{it}^{X} is the output elasticity of an input X; and α_{it}^{X} is the expenditure share of the input X in the total sales. This variable input could be either labour or intermediate materials. However, in our data, many firms are household businesses that do not pay wages (approximately 1,600 observation), making us unable to calculate the expenditure share of labour in the total shares. Thus, we estimate mark-ups using materials as our variable input. It can be seen that while the revenue share of materials can be directly obtained from the data, the estimation of output elasticity is more challenging. Indeed, we need to estimate the gross output production function in order to find output elasticity of materials.[7] The gross output translog production function is given by:

$$Output_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_i + \varepsilon_{it} \tag{12}$$

The output elasticity for an input free of adjustment cost (materials) is then estimated as:

$$\hat{\theta}_{it}^{M} = \hat{\beta}_m + 2\hat{\beta}_{mm} m_{it} + \hat{\beta}_{ml} l_{it} + \hat{\beta}_{mk} k_{it} + \hat{\beta}_{lmk} l_{it} k_{it} \tag{13}$$

After estimating the output elasticity of materials (and the share of materials in the total output), we can calculate the firm's mark-ups. It should be noted that this estimation is based on a non-Cobb–Douglas production function specification, but we can also estimate the firm's mark-up using the Cobb–Douglas function by similar procedures without adding polynomial function. Our estimated mark-ups based on the Cobb–Douglas production function is 1.92 at the mean and 1.30 for the median, while the estimation is 1.14 and 0.83, respectively, under a translog production function. Our estimated mark-ups under translog specifications are slightly lower than DLW's (2012) estimations for firms in Slovenia and mark-ups reported by Rand (2017) who use the same survey but at different periods of time. The gap would be due to the differences in the nature of the dataset between a survey and a census (Rand 2017) in the case of DLW (2012) and due to the differences in approach, between estimations based on output elasticity of labour and elasticity of materials. We will use the preferred translog specification in examining the link between MC and firm performance in Section 5.

4.3 A multidimensional measure of managerial capital

Managerial capital (MC), as shown in Section 2, relates to all the practices and traits of business operators that have the potential to influence firms' efficiency. A major advantage of the SME survey in this regard is that it not only provides indicators linked with business practices, but also proxies of entrepreneurial attitudes. In this study we use a multidimensional measure of MC, based on five proxy variables that are found (and are consistent) in all rounds of the survey. The incidence of each indicator by firm size is provided in Table 2.

First, book-keeping is indicated by whether the respondent does 'maintain a formal accounting book'. Thirty-eight per cent of firms across years do keep formal accounts, and the proportion strongly increases with firm size. It should be stressed that this variable captures the existence of a complete set of accounts; a negative answer may not indicate the total absence of books, as many microenterprises may keep simple records through personal notes. The difference that is captured is that between keeping no or elementary books and using a complete accounting system. Second, a binary indication of marketing efforts is based on a positive answer to the question 'do you advertise your products?', and includes all practices from door-to-door information to radio or TV spots. Advertising is almost inexistent among micro firms (4 per cent), but is less rare among medium firms (26 per cent). A third indication of business practices is the method of wage determination, indicating whether wages are determined by following other sectors' rates, following local competitors' rates, by individual negotiations, by the paying capacity of the firm, or by none of these methods (which is the case for almost 15 per cent of firms that have no employees). The most common method for determining wages in all firms is individual negotiations, while micro firms, even among those paying wages, predominantly report no fixed method for determining wages (29 per cent). The last two indicators proxy dimensions of firms'

[7] See DLW (2012) for the GMM procedures to identify the output elasticity of materials followed in this paper.

entrepreneurial orientation. Innovation is used as the third axis, and covers all forms of innovation from 'introducing new products' or 'new processes or technologies', to the 'improvement of existing products'. On average, more than 55 per cent of MSMEs in Viet Nam have at least one kind of innovation—the bigger they are, the higher their level of innovation.

Finally, we construct an indicator of competitive aggressiveness combining two variables: firms that report 'fixing prices lower than competitors', and firms that report 'bribes to gain new markets'. The latter is probably less consensual, but while bribes in general have a negative impact on many outcomes, firm-level corruption restricted to 'non-extortive' bribes can have a positive impact (Vial and Hanoteau 2010). Only 7 per cent of small and medium firms and 3 per cent of micro firms show some degree of aggressive competitive behaviour. The discriminating power of most of the MC proxies is high, with few firms reporting 'good' business practices or entrepreneurial behaviours.

Table 2: Proxies of managerial capital: incidence by firm size

	Formal accounts	Advertising	Innovation	Aggressive competition
Micro	0.20	0.04	0.47	0.03
Small	0.79	0.26	0.72	0.08
Medium	0.99	0.49	0.80	0.07
Total	0.38	0.12	0.55	0.05
	Workers' management (wage determination)			
	None	*Follow local private rates*	*Follow state enterprises*	*Set by authorities*
Micro	0.29	0.11	0.01	0.01
Small	0.00	0.19	0.03	0.04
Medium	0.01	0.23	0.22	0.08
Total	0.21	0.14	0.01	0.02
	Workers' management (wage determination)			
	Follow rates in agriculture	*Individual negotiations*	*Paying capacity*	*Other*
Micro	0.01	0.38	0.16	0.01
Small	0.01	0.43	0.27	0.02
Medium	0.01	0.35	0.28	0.02
Total	0.01	0.39	0.19	0.02

Source: Authors' calculations.

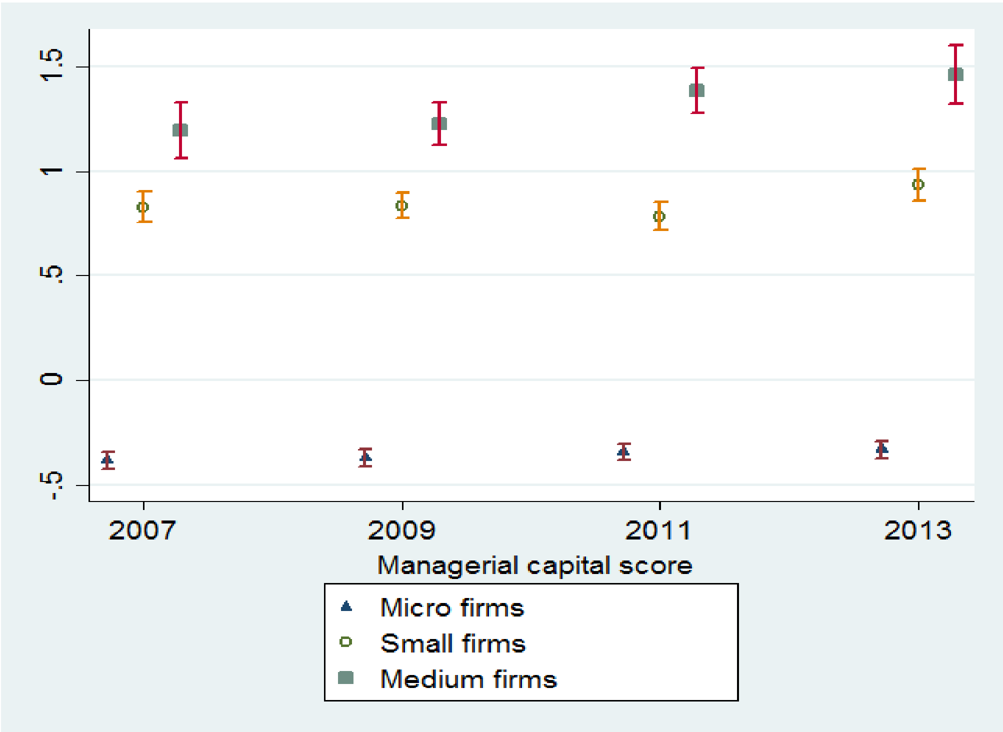
A synthetic indicator of MC is built using multiple correspondence analysis (MCA) for each year, and is used in estimating the effect of MC on productivity (before using each indicator separately). All variables except wage determination are binary. Wage determination is kept flexible in MCA as there is no indication of one method being a priori superior to the other. MCA builds a binary indicator matrix that shows the incidence of each axis by firm, which is used to obtain weights from the factorial axis. A firm's MC score is thus calculated by the weighted sum of its responses, and can be noted as:

$$MC_i = \sum_{j=1,..,5} D_{ij} W_j$$

where MC_i is the i-th observation's managerial capital score, D_{ij} the response of unit *i* to dimension *j*, and W_j the MCA weight for the first axis applied to category j. Descriptive statistics on the normalized score by year and firm size are provided in Table 1. Detailed results of the MCA are provided in Appendix Table A1.

The distribution of the MC normalized score by firm size is plotted in Figure 1 (MCA results are provided in Appendix Tables A2 and A3). The score values can be compared between firms, rather than directly interpreted in levels. Units with a higher score display a mix of more frequent business practices (keeping written accounts, advertising, fixing wages in line with the state authorities' rate or relatively to local competitors) and more entrepreneurial traits (competing aggressively, innovating through products or technologies). As expected, the smaller the firm, the lower the MC: micro firms are concentrated in the lowest score values, and almost none show high levels of MC score.

Figure 1: Managerial capital normalized score by year and firm size



Source: Authors' calculations.

5 Managerial capital and firm performance

The primary objective of this paper is to investigate the link between managerial capital (MC) and productivity, and to test whether this link depends on firm size. OLS regressions of MC on productivity are likely to be biased by the exclusion of variables positively associated with both MC and productivity, even when both variables are measured convincingly. As MC essentially aims at measuring owners' abilities, any proxy can only capture part of this. The strategy used in this paper is to get as close to causal inference as possible using the whole population of firms, and then to test whether these associations are similar across firm size. The assumption is that even though some varying heterogeneity could plague the estimation of the MC-productivity link, these potential biases can be constant by firm size, and comparing the significance and size of the effects is hence feasible.

In order to control for all fixed determinants of MC and productivity, whether observed or not, all estimates use firm-level fixed effects. The outcome variable is the total factor productivity estimated in Section 4. Specifically, we use the standardized productivity estimates of the preferred specification (Wooldridge 2009). The baseline specification is thus:

$$\Omega_{it} = \beta_0 + \beta_1 MC_{it} + \beta_2 S_{it} + \gamma C + \omega_i + \varepsilon_{it} \tag{14}$$

Where Ω_{it} represents firm-level productivity estimated by Wooldridge's (2009) GMM, MC_{it} is the managerial capital score of firm *i* at time *t*, S_{it} is the firm size category, and C is a vector of controls for trends. This set of control variables aims to remove potentially differentiated evolutions by years, sectors, or regions (and finally with time*regions). As neither the productivity levels nor the MC scores can be directly interpreted in levels, all results are provided as standardized variations. The results of this baseline estimation are provided in the first column of Table 3. We find that a standard deviation in MC score results in an 8 per cent increase in productivity, on average, among the MSME sample, significant at 1 per cent. This average effect is net of the influence of firm size.

A further concern regarding bias arises from the limited indicators of managerial capital available in the data. As other practices and traits that could serve as additional proxies are not available in our data, part of the manager's ability remains unobserved by our MC score. We introduce a set of controls to proxy individual ability, which shows some variation across year (firm owner does change in some cases). Gender, education (higher secondary or more), and age are controlled for in the following model (included in the *X* vector). An additional set of time-varying firm characteristics is included: informality (being registered or not), type of premises, and access to infrastructures (road, in this case). We also add a set of social networks, measured by the number of contacts in the same business sector, different sector, banking officials, and politicians/civil officials. All can vary during the time period considered and may influence productivity. These additional controls have little influence on the MC coefficient, which tends to indicate that fixed-effects estimates removed most of the existing bias.

Looking at the description of MC score by size, we know that larger firms have both better business practices and more entrepreneurial attitudes. We also know from sub-section 4.1 estimates that productivity levels strongly and constantly increase with firm size. The results provided in Table 3 are net of this firm size effect, but the coefficient of MC score can nevertheless have different slopes depending on the size category if its influence on microenterprises is lower than in small and medium firms. A third model includes interactions between MC index and size categories:

$$\Omega_{it} = \beta_0 + \beta_1 MC_{it} + \beta_2 S_{it} + \gamma C + \delta X + \theta(MC_{it} * S_{it}) + \omega_i + \varepsilon_{it} \tag{15}$$

The vector θ of estimated coefficients by size is then used to test for a differentiated effect of MC depending on the category. In Table 3, we report a Wald test for joint significance of the interaction term.

Table 3: Managerial capital and productivity

	(1)	(2)	(3)	(4)	(5)	(6)
Standardized values of (MC)	0.083***	0.089***	0.115***	0.114***	0.117***	0.111***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)	(0.012)
Small size (11–50)	0.562***	0.545***	0.601***	0.600***	0.595***	0.516***
	(0.022)	(0.022)	(0.026)	(0.026)	(0.026)	(0.026)
Medium (51–300)	1.177***	1.144***	1.149***	1.147***	1.147***	1.025***
	(0.051)	(0.051)	(0.060)	(0.060)	(0.063)	(0.059)
(Small)*MC				-0.099***	-0.101***	-0.085***
				(0.019)	(0.019)	(0.018)
(Medium)*MC				-0.057*	-0.057	-0.043
				(0.035)	(0.035)	(0.033)
Log of mark-ups						0.338***
						(0.041)
Controls (ability)	No	Yes	Yes	Yes	Yes	Yes
Controls (social networks)	No	No	Yes	Yes	Yes	Yes
Time dummies	No	Yes	Yes	Yes	Yes	Yes
Sector dummies	No	Yes	Yes	Yes	Yes	Yes
Region dummies	No	Yes	Yes	Yes	No	No
Time*region interaction	No	Yes	Yes	Yes	No	No
District dummies	No	No	No	No	Yes	Yes
Time*District interactions	No	No	No	No	Yes	Yes
Constant	-0.179***	-0.308**	-0.289**	-0.359***	-0.244	-0.112
	(0.006)	(0.120)	(0.119)	(0.123)	(0.165)	(0.153)
Observations	5,893	5,893	5,893	5,893	5,893	5,843
R-squared	0.281	0.314	0.320	0.323	0.380	0.447
Number of id	2,782	2,782	2,782	2,782	2,782	2,767

Note: Testparm interactions (column 5): F (2, 2,781) = 11.55. Prob > F = 0.000. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations.

As much as MC and productivity depend on firm size, the effect of the former on the latter is as important among micro firms as among medium ones. The marginal effects depending on the size category and significance levels are reported in Appendix Table A4 and confirm this finding. The MC indicators, although more scarcely found among micro firms, discriminate equally or more in this population between productive firms and subsistence businesses. The effect of business practices and EO on productivity is thus as large as among larger enterprises.

We continue our analysis of the association between MC and mark-ups by re-running all the above estimations in which log of mark-ups is the outcome (Table 4). Firm size has a strong association with mark-ups but our variable of interest, MC, does not have a consistent significant effect on mark-ups. Since mark-ups reflect firms' market power, the insignificant results mean that the market could be highly competitive and higher MC would not play a role in increasing the firm's mark-ups. We then use log of mark-ups as a control for our estimation on MC and productivity. The results are shown in column 6 of Table 3. We find that mark-ups have a positive association with firms' productivity but our coefficient of MC on productivity does not change. This suggests that the role of MC lies mainly in technical efficiency.

Table 4: Managerial capital and firms' mark-ups

Log of mark-ups	(1)	(2)	(3)	(4)	(5)
Standardized values of (MC)	0.009	0.012	0.017	0.017	0.018*
	(0.009)	(0.009)	(0.011)	(0.011)	(0.011)
Small size (11-50)	0.191***	0.204***	0.213***	0.213***	0.223***
	(0.025)	(0.024)	(0.026)	(0.026)	(0.025)
Medium (51-300)	0.282***	0.307***	0.338***	0.339***	0.333***
	(0.037)	(0.037)	(0.048)	(0.048)	(0.057)
(Small)*MC			-0.015	-0.014	-0.019
			(0.022)	(0.022)	(0.021)
(Medium)*MC			-0.033	-0.032	-0.025
			(0.023)	(0.023)	(0.028)
Controls (ability)	No	Yes	Yes	Yes	Yes
Controls (social networks)	No	No	Yes	Yes	Yes
Time dummies	No	Yes	Yes	Yes	Yes
Sector dummies	No	Yes	Yes	Yes	Yes
Region dummies	No	Yes	Yes	Yes	No
Time*region interaction	No	Yes	Yes	Yes	No
District dummies	No	No	No	No	Yes
Time*District interactions	No	No	No	No	Yes
Constant	-0.177***	-0.212***	-0.211***	-0.186**	-0.319***
	(0.007)	(0.073)	(0.073)	(0.075)	(0.103)
Observations	5,901	5,901	5,901	5,901	5,901
R-squared	0.033	0.078	0.078	0.080	0.180
Number of id	2,773	2,773	2,773	2,773	2,773

Note: *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations.

These results provide a global picture of the relationship between MC and productivity by firm size. They show that when every other factor (except some possibly remaining time-varying heterogeneity) is controlled for, including the same levels of inputs, firms with a higher MC generate more output because they are technically more efficient. However, they say little about the relative importance of our indicators of MC. Different types of business practices or entrepreneurial attitudes have different types of impact. Formal written accounts or wage determination may influence the labour or capital productivity (as each additional worker or capital unit may be more effective). On the other hand, marketing, aggressive competition, or innovation might directly increase the value added for given levels of inputs. A first indication lies in the individual contributions of each variable to the MC score, where advertising, accounts, and competition seem to be the most discriminating factors. An alternative possibility is to regress all indicators separately on productivity.

Table 5 provides the coefficients of the separate indicators. As they conceptually represent different parts of a single variable, including all the indicators jointly could result in multi-collinearity. It is nevertheless possible to gain an insight into which has the largest influence. The wage determination variable is transformed into a binary indication: autonomy in wage setting if a firm determines wages based on local private rates, state-owned enterprises' (SOEs) or authority's rates (these three methods are found to be the most weighted in the MC score).

Table 5: Managerial capital indicators and productivity

	(1)	(2)	(3)	(4)
Advertising	0.049**	0.024	0.027	0.032*
	(0.024)	(0.018)	(0.018)	(0.018)
Innovation	0.052***	0.035***	0.029***	0.027**
	(0.012)	(0.010)	(0.011)	(0.011)
Competition	0.047*	0.018	0.023	0.031
	(0.029)	(0.024)	(0.025)	(0.025)
Accounts	0.051*	0.026	0.023	0.035
	(0.026)	(0.022)	(0.022)	(0.022)
Wage determination	0.026	0.026**	0.025*	0.021
	(0.016)	(0.013)	(0.013)	(0.013)
Size categories	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Time and regions dummies	No	No	Yes	No
Time and district dummies	No	No	No	Yes
Constant	-0.058***	-0.219***	-0.401***	-0.266
	(0.012)	(0.012)	(0.127)	(0.169)
Observations				
R-squared	5,893	5,893	5,893	5,893
Number of id	0.011	0.267	0.300	0.358

Note: Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations.

Column 1 provides fixed effects estimated with no controls and no time trends. Column 2 adds size categories, and columns 3 and 4 include all additional varying controls and trends. Entrepreneurial orientation, measured by innovation, and business practices, measured by autonomy in wage determination aggressiveness, turn out to be the most influential factors in all models. The absence of significant effects of other dimensions should not lead to the conclusion that they are irrelevant dimensions of MC; the joint influence of all factors is proven above; it is rather the intensity of each variable that is jointly evaluated here.

6 Robustness

Most of the previous analysis relies on the firm-level productivity estimated in the first stage. A remaining bias in these estimates would cast doubt on the results of the second stage, in particular if the bias is somehow also correlated with MC. The results were re-obtained using an alternative estimation of productivity, based on a different correction for simultaneity using material expenditures. The results of the production function estimations are provided in Table 6, using the same specifications as in sub-section 4.1.

Table 6: Production function estimates using log material expenditures

	OLS	FE	LP	Wooldridge
Log of labour	0.967***	0.686***	0.845***	0.856***
	(0.011)	(0.020)	(0.013)	(0.019)
Log of capital	0.226***	0.150***	0.147***	0.164***
	(0.008)	(0.010)	(0.012)	(0.010)
year=2009	0.091***			
	(0.017)			
year=2011	0.234***			
	(0.019)			
year=2013	0.275***			
	(0.020)			
Constant	7.306***	9.239***		-4.503
	(0.095)	(0.137)		(3.016)
Observations	8,759	8,759	5,826	5,817

Note: Clustered standard errors. by firms in models 1,2, and 4, bootstrapped with 250 replications for LP estimates. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations.

Returns to capital and labour go through overall comparable corrections when using this alternative proxy of material expenditures, although the coefficients of capital of the LP and Wooldridge estimators are higher (and the returns to labour are lower). Firm-level productivity is then used as outcome variable and the results of similar regressions to those in Section 5 are provided in Table 7. The effect of MC is consistent and still yields a 10 per cent increase in productivity per standard deviation. The heterogeneity of the coefficient by firm size is, again, impossible to back up: MC does matter among small firms, at least as much as it does for medium-size ones. Finally, productivity estimates using corrections other than the preferred Wooldridge specification (fixed effects and LP) were used with similar results.

Table 7: Managerial capital and alternative measures of productivity

	(1)	(2)	(3)	(4)	(5)
Standardized values of (MC)	0.071***	0.079***	0.101***	0.100***	0.100***
	(0.010)	(0.010)	(0.012)	(0.012)	(0.012)
Small size (11–50)	0.528***	0.507***	0.554***	0.554***	0.551***
	(0.022)	(0.021)	(0.025)	(0.025)	(0.024)
Medium (51–300)	1.090***	1.052***	1.056***	1.056***	1.050***
	(0.052)	(0.051)	(0.058)	(0.059)	(0.061)
(Small)*MC				-0.083***	-0.084***
				(0.019)	(0.019)
(Medium)*MC				-0.048	-0.048
				(0.035)	(0.035)
Log of mark-ups					
Controls (ability)	No	Yes	Yes	Yes	Yes
Controls (social networks)	No	No	Yes	Yes	Yes
Time dummies	No	Yes	Yes	Yes	Yes
Sector dummies	No	Yes	Yes	Yes	Yes
Region dummies	No	Yes	Yes	Yes	No
Time*region interaction	No	Yes	Yes	Yes	No
District dummies	No	No	No	No	Yes
Time*District interactions	No	No	No	No	Yes
Constant	-0.167***	-0.259**	-0.244*	-0.313**	-0.216
	(0.006)	(0.127)	(0.125)	(0.130)	(0.172)
Observations	5,913	5,913	5,913	5,913	5,913
R-squared	0.253	0.300	0.305	0.308	0.364
Number of id	2,775	2,775	2,775	2,775	2,775

Note: Testparm interactions (column 5): F (2, 2,774) = 9.4. Prob > F = 0.000. p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations.

7 Conclusion and discussion

This paper provides a straightforward answer to an open question of growing importance. It uses rich panel data consisting of 8,864 observations of 2,901 unique firms surveyed between 2007 and 2013, in which a set of MC indicators is available and consistent across years. One original feature is that these indicators enable combining standard indicators of business practices and less frequent indicators of firms' EO into a single score of MC. The results of consistent firm-level productivity and mark-up estimates are regressed on this score. A variation of one standard deviation in the MC score is associated with an 8 to 11 per cent significant increase in productivity. The interaction terms with firm size category are significant, as confirmed by further marginal results. However, we do not find a significant association with firms' market power. No clear causal statement is made on the relation between our measure of MC and productivity.

Even though a large number of biases are technically controlled for, variations in MC remain unexplained. Rather, the statement is that MC does matter among micro and small firms, at least as much as it matters among medium ones. The results of low estimated mark-ups and insignificant association between mark-ups and MC can be interpreted as follows: in highly competitive markets (concentrated in some specific sectors such as food and beverages, fabricated metal production, etc.), MC is important for firms to gain technical efficiency rather than to acquire greater market power. It is further shown that the part of MC score related to entrepreneurial attitude (innovation) is the more significant factor when considering all indicators separately rather than when combined.

The implications of these results are, however, not straightforward. By using observational data we are able to employ a more complex measure of MC, including elements that one cannot exogenously change with a training programme. However, this does not provide directly usable tools for enhancing micro-firm productivity. Recommending the enhancement of aggressive competition behaviours (including payment of bribes to access new markets) would hopefully provoke some opposition. Even if the results were more consensual, a key preliminary question would be to determine whether MC, and in particular its EO component, is teachable at all. If the observed variations find no explanation, one would be left with the frustrating justification of unobserved individual talent (as Balzac attributes to *Monsieur Graslin*, whose education level plays no part in explaining entrepreneurial talent). A rough indication is given in Appendix Table A5, which regresses MC scores on the set of available individual characteristics with OLS to provide some insights into its variation. Around 30 per cent of the variance of the MC score is explained by the (limited number of) individual characteristics. Yet, besides younger individuals having higher MC scores, education has by far the largest influence. The little variance explained can be interpreted as proof of the relevance of the MC index—which indicates more than the differences in education.

A useful comparison for challenging the validity of these results is the paper of McKenzie and Woodruff (2016) in which they evaluate the link between business practices and small firms' survival and profits. As well as using multiple countries, a further advantage of their paper is to include a larger set of business practices. However, they do not estimate unbiased firm-level productivity, and they focus only on business practices, with no indication of EO or attitudes. Their message is similar overall: MC (or more narrowly business practices) also matters for small firms in developing countries. The effect of the variation of the MC score is strictly comparable among size groups. The main difference lies in the size of the effects. McKenzie and Woodruff's (2016) effect of MC on profits is large (22 per cent at the mean for a one standard deviation in MC), which, they argue, echoes the findings of Bloom and Van Reenen (2007). The effect found in this paper, although significant, is lower (around 10 per cent). A likely explanation lies in the remaining bias that plagues the estimations and in the sharper productivity measures of this paper. The magnitude of effects found in the present study is easier to reconcile with the mixed results found in the evaluation of training programmes. It is nevertheless likely that the additional indicators included in their MC index do capture, at least partly, more variation in practices that influence small business productivity.

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Appendix

Table A1: Sample description

	2007		2009		2011		2013	
Observations	2,093		2,442		2,332		1,997	
	mean	sd	mean	sd	mean	sd	mean	sd
Micro firm (1–10)	0.70	0.46	0.71	0.45	0.73	0.45	0.76	0.43
Small firm (11–50)	0.24	0.43	0.23	0.42	0.22	0.41	0.19	0.40
Medium firm (51–300)	0.06	0.24	0.06	0.24	0.06	0.23	0.05	0.21
Average size	15.21	28.44	14.23	26.29	13.87	26.91	12.31	24.05
Real value added	1,061	3,017	1,217	3,762	1,480	7,965	1,134	3,871
Real capital	5,500	16,903	49,97	12,723	6,248	19,730	4,356	11,400
Informal (business registration)	0.30	0.46	0.34	0.47	0.28	0.45	0.26	0.44
Premises: residential	0.27	0.44	0.25	0.43	0.22	0.41	0.16	0.36
Premises: production	0.41	0.49	0.45	0.50	0.46	0.50	0.50	0.50
Premises: only production	0.32	0.47	0.30	0.46	0.32	0.47	0.35	0.48
Road access	0.76	0.43	0.78	0.41	0.78	0.42	0.84	0.37
Manager: male	0.67	0.47	0.66	0.47	0.63	0.48	0.62	0.49
Higher secondary education or more	0.55	0.50	0.58	0.49	0.62	0.49	0.69	0.46
Sector								
Food and beverages	0.29	0.45	0.29	0.46	0.31	0.46	0.31	0.46
Fabricated metal products	0.17	0.38	0.17	0.38	0.18	0.38	0.18	0.38
Wood	0.11	0.31	0.12	0.32	0.10	0.29	0.10	0.30
Furniture. jewellery. music equipment	0.08	0.27	0.07	0.25	0.08	0.28	0.09	0.28
Non-metallic mineral products	0.06	0.23	0.05	0.23	0.05	0.21	0.04	0.20
Textile	0.05	0.21	0.05	0.22	0.04	0.20	0.04	0.21
Apparel, leather	0.06	0.24	0.06	0.23	0.07	0.25	0.06	0.25
Other	0.19	0.39	0.19	0.39	0.17	0.38	0.17	0.38
Social network (Business people in the same sector)								
0–4 persons	0.58	0.49	0.50	0.50	0.58	0.49	0.51	0.50
5–9 persons	0.20	0.40	0.23	0.42	0.25	0.43	0.26	0.44
10–19 persons	0.13	0.34	0.16	0.37	0.12	0.32	0.16	0.37
20 and above	0.09	0.28	0.11	0.31	0.05	0.21	0.07	0.26
Social network (People in different sector)								
0–4 persons	0.22	0.42	0.24	0.42	0.11	0.31	0.09	0.29
5–9 persons	0.18	0.38	0.13	0.34	0.23	0.42	0.16	0.37
10–19 persons	0.26	0.44	0.29	0.45	0.30	0.46	0.32	0.47
20 and above	0.34	0.47	0.35	0.48	0.36	0.48	0.43	0.50
Banking officials								
No contact	0.54	0.50	0.42	0.49	0.54	0.50	0.47	0.50
1 contact	0.19	0.40	0.23	0.42	0.19	0.39	0.20	0.40
2 contacts	0.16	0.36	0.18	0.38	0.15	0.36	0.15	0.36
3 and more	0.11	0.31	0.17	0.37	0.12	0.32	0.17	0.38
Politicians and civil servants								
No contact	0.45	0.50	0.36	0.48	0.45	0.50	0.33	0.47
1 contact	0.21	0.40	0.20	0.40	0.23	0.42	0.28	0.45
2 contacts	0.18	0.38	0.20	0.40	0.20	0.40	0.21	0.41
3 and more	0.17	0.37	0.24	0.43	0.12	0.33	0.18	0.39

Source: Authors' calculations.

Table A2: Multiple correspondence analysis results—contribution to the first dimension and adjusted inertia

Variable	Value	Dimension1 coordinates	Variable	Value	Dimension1 coordinates
Advertising	0	0.354	Wages	None	2.156
	1	-2.719		Local private	-0.926
Innovation	0	1.007		Local SOEs	-1.355
	1	-0.839		Authorities	-2.613
Competition	0	0.102		Agricul. rate	0.509
	1	-2.117		Negotiation	-0.257
Accounts	0	0.976		Paying capcity	-0.782
	1	-1.614		Other	-0.201

	2007	2009	2011	2013
Number of obs.	2,093	2,442	2,332	1,997
Dimension				
Dimension 1	87.78	84.97	87.46	85.54
Dimension 2	0.68	1.02	0.25	0.68
Dimension 3	0.05	0.41	0.10	0.08

Note: Method: Burt/adjusted inertias.

Source: Authors' calculations.

Table A3: Managerial capital normalized score by year and firm size

	2007		2009		2011		2013	
	mean	sd	mean	sd	mean	sd	mean	sd
Micro	-0,382	0,809	-0,371	0,849	-0,342	0,842	-0,332	0,815
Small	0,830	0,811	0,837	0,712	0,785	0,787	0,934	0,781
Medium	1,196	0,752	1,227	0,636	1,389	0,643	1,463	0,689
Total	0.000	1.000	0.000	1.000	0.000	1.000	0.000	1.000

Source: Authors' calculations.

Table A4: Marginal effects of managerial capital on productivity by size category

Delta-method						
	dy/dx	Std. err.	z	P>z	[95% confidence	Interval]
Micro (1–10)	0.117	0.012	9.43	0.000	0.092	0.141
Small (11-50)	0.025	0.016	1.56	0.120	-0.006	0.056
Medium (51–300)	0.061	0.032	1.95	0.051	-0.00	0.124

Source: Authors' calculations.

Table A5: Explaining managerial capital

Male	-0.008
	(0.024)
Finished lower secondary education	0.150***
	(0.031)
Finished upper secondary education	0.709***
	(0.035)
Age 30–45	-0.267***
	(0.051)
Age 46–60	-0.366***
	(0.052)
Age >60	-0.333***
	(0.064)
Household size 3–5	0.012
	(0.029)
Household size>6	0.010
	(0.034)
Constant	0.121
	(0.118)
Time dummies	Yes
District dummies	Yes
Observations	8,864
R-squared	0.346

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculations.