Management practices and firm performance during the Great Recession*

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Abstract

This paper empirically examines how management practices affect firm productivity over the business cycle. Using plant-level high-dimensional human resource policies survey data collected in Spain in 2006, we employ *unsupervised machine learning* to describe clusters of management practices ("management styles"). We establish a positive correlation between a management style associated with structured management and performance prior to the 2008 financial crisis. Interestingly, this correlation turns negative during the financial crisis and positive again in the economic recovery post-2013. Our evidence suggests firms with more structured management are more likely to have practices fostering culture and intangible investments such that they focus in long-run profitability, prioritizing innovation over cost reduction, while having higher adjustment costs in the short-run through higher share of fixed assets and lower employee turnover.

JEL codes: M12, D22, C38

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1 Introduction

The study of management and its impact on economic performance is a central part of Economics research. As early as Adam Smith in his books *The Wealth of Nations* and *The Theory of Moral Sentiments*, economic thought has established the importance of management practices such as the division of labor, wage setting, employee incentives, and interpersonal authority. Yet, rigorous empirical economic research documenting the impact of different management practices on performance has only recently become the focus of a growing literature (Ichniowski et al., 1997; Ann et al., 2004; Helper and Henderson, 2014; Bloom et al., 2014, 2019). This literature has shown that management quality and structure as inputs of production vary profoundly across countries, across firms within a country, and even across plants within the same firm (Bloom et al., 2019). Understanding the causes and consequences of these differences in management as well as how they explain persistent productivity differences (Bloom and van Reenen, 2007) have clear implications for policies regarding productivity, growth, and income inequality. In this paper, we aim to contribute to the existing literature studying the effects of management on economic performance by shedding further light on the question of how and when management practices affect firm productivity.

A challenge for empirical studies of management practices has been that, arguably, there exist complementarities between individual practices, leading to sets of practices being adopted jointly by firms (Milgrom and Roberts, 1990, 1995; Ichniowski et al., 1997) and, consequently, complicating the identification of effects of specific management practices. In this paper, our approach to measure the impact of management practices embraces this complementarity. We leverage *unsupervised machine learning*, in particular *Latent Dirichlet Allocations* (LDA), to retrieve low-dimensional latent objects, which we term *management styles*, from highly dimensional survey data of Spanish manufacturing plants collected in 2006 (Blei et al., 2003; Erosheva et al., 2007)). Intuitively, the algorithm identifies groups of practices that tend to appear together across firms but whose presence also distinguishes firms from one another. This approach of applying unsupervised machine learning to management data is inspired by the work of Bandiera et al. (2020), who classify managers according to how they use their time.

Although our main data source in this paper is survey data of Spanish manufacturing plants, we focus on the sample of single-plant firms therein because there is an immediate match between the entity that decides on the adoption of management practices and its performance. This data set was collected in 2006 and provides extensive information on the manufacturing plants' human resource policies. In a first step of our analysis, we estimate and define two "pure" styles and describe every firm as a linear combination of these two pure styles. Note that the estimated styles do neither carry natural labels, nor are they ordinal. In order to work towards an interpretation of these abstract styles estimated by LDA, we compare single-plant to multi-plant firms. The latter have been shown to generally exhibit a more structured style of management which provides us with a benchmark (Bloom et al., 2012a,b). We document that single-plant firms whose management loads more heavily on what we call abstract Style 2 are similar to multi-plant firms in terms of management practices they employ. Hence, while subjective, we label management Style 2 as "structured" management style. This classification is also consistent with practices that are typical for this style in the management style distribution.

In a second step, we assess the interplay between management styles (as defined in our first step) and firm performance before, during and after the Great Recession. By doing so, we also speak to whether the effect of management is invariate to changing economic environments. In order to address these questions, we match our manufacturing plant survey data collected in 2006 with a panel of balance sheet data from *Bureau van Dijk* to obtain measures of productivity and firm performance. The firm survey data was collected in 2006—just before the Great Financial Crisis —and allows us to study the relationship of management with performance during the expansionary period before 2006 as well as during and after the ensuing *Great Recession*. We report three key results. First, we find a systematic and significant positive correlation of a structured management style with firm productivity prior to the Great Recession in 2006. Second, this correlation turns statistically significantly negative for firms' performance during the Great Recession, that is, between 2008 and 2012. Third and finally, we see reversal of the relationship during and bounce-back after the crisis post-2013.

These findings are consistent with a nuanced role for structured management practices. While structured approaches to management appear advantageous in stable and prosperous economies, management practices characterized by flexible and informal structures may offer a competitive edge during crises by facilitating rapid adjustments. Compellingly, we find that firms with more structured management in 2006 demonstrated higher productivity levels after the financial crisis (2013-2016). This finding suggests that firms that prioritize structured management may inherently favor long-term growth over those with less formalized practices. Our findings are (qualitatively) robust to alternative sample periods, alternative estimation procedures for management styles and TFP as well as different regression specifications.

Finally, we aim to uncover the mechanisms that would allow firms with more structured management thrive through benevolent economic times and in the long run, while they lag behind relative to firms with less structured management practices during the Great Recession. We show that firms with more structured management prioritize quality and innovation (over cost reductions), hold a higher share of fixed assets, do not reduce investments and are more likely to hire during the crisis (relative to less structured management firms), explicitly stating employment policies that keep workers when facing adverse economic shocks. Overall, their policies and behavior are practices aiming to foster "culture" that is more resilient in the long run despite its obvious rigidities and higher (endogenous) adjustment costs in the short run. These findings are consistent with the view that structured management practices are complementary and, thus, work better with a stable workforce that embraces and strengthens their internal organization and culture. In a nutshell, structured management appears to be complementary to non-tangible investments such as work culture, training and consumer relationships (Blader et al., 2020; Graham et al., 2022a,b). It is the combination of these tangible and non-tangible assets that is responsible for higher productivity levels in the long run despite occasional episodes of adverse shocks.

Our paper contributes to various streams of literature. These are extensive literatures and, therefore, in this section we focus on those papers that appear to be, to the best of our knowledge, most closely connected to our contribution. First and foremost, our paper contributes to the literature investigating what management practices work best. Bloom and van Reenen (2007), and all other papers derived from their original work related to the World Management Survey (WMS hereafter), collect information on management practices across firms in a systematic way, document differences across firms, industries and countries, and examine their relationship with outcomes. Culture and relational contracting within a firm's stakeholders should also factor into management style, and those are dimensions even harder to measure and quantify without a systematic approach to data collection. Their work studies management practices in manufacturing, the service industry, and even health care to name a few. This stream of work has been highly influential because it has shaped a modern view of "management practices" as being ordered along a uni-dimensional score ("good management"). Bloom et al. (2014) show robust empirical associations detailing the role and impact of the WMS measures of management that validates our findings. In particular, the management score employed in Bloom et al. (2014) captures a more structured approach to management and they document higher scores of management practices in multi-plant firms and multinational companies and their subsidiaries.

Methodologically speaking, we also contribute to the literature using unsupervised machine learning to retrieve meaningful information from highly dimensional data in the spirit of Bandiera et al. (2020). Extant data on firm policies come in the form of highly dimensional surveys with no obvious way of aggregation into a single score. We show that machine learning can be effective in identifying patterns and clusters of management policies across a large number of establishments and firms. Most importantly, the use of machine learning to study management styles allows economists to tackle and advance their knowledge of an old question in economics, that is, the role of complementarities within organizations. There exists evidence of such complementarities within organizations (Ann et al., 2004; Ichniowski et al., 1997). Yet, Brynjolfsson and Milgrom (2013) describe challenges in the empirical assessment of interdependencies between organizational practices, stating that the opportunities to run designed experiments in firms are "underexploited" in this respect. Unsupervised machine learning allows for complementarities of a large number of management policies, summarizing all information in a low-dimensional space which facilitates the analysis of the impact of management style on firm outcomes. It is part of our contribution to show that automated methods applied to firm surveys can be useful in capturing management styles. We leverage existing survey data and combine it with (now) standard machine learning techniques that allow us to cost-effectively address open questions before starting new and costly data collection initiatives.

Because the use of machine learning to classify management styles is part of our contribution, it warrants further discussion earlier in the paper and before we dive deeper into this methodology. Employing LDA, i.e., unsupervised machine learning, enables us to utilize all available dimensions of the survey data without prior conceptions on what constitutes *good* management while allowing us to retrieve a simple measure of management style that can be related to performance during times of economic expansion or crisis.

Even though data science methods are increasingly used in economics (Currie et al., 2020), many economists are still uncomfortable with the application of (unsupervised) machine learning tools. This is possibly due to the fact that, at times, it can be considered atheoretical, and many applications focus on short-term predictions without much economic intuition. Moreover, there is an obvious risk of ex-post rationalization of findings through data and story mining. We are acutely aware of this, but still believe that settings such as ours lend themselves well to the application of these techniques. Applying the algorithm allows us to leverage all available data without pre-imposing structure on its components. Furthermore, our results pass key sanity checks in that the retrieved management styles are meaningful, interpretable, not trivially explained by observable firm characteristics, and even, in line with existing literature, correlate significantly with firm productivity.

Finally, our paper also contributes to work on the impact of the 2008 Great Financial Crisis on firm's management and their performance.[1] Almunia et al. (2021) use firm-level Spanish data to investigate changes in export policies of Spanish firms before and after the crisis. They find that those firms hit the hardest in their domestic sales are also the firms that increase their exports the most after the crisis. Aghion et al. (2021) is close to our paper in that they investigate the optimal organizational form during "bad times". They find that firms that delegated more power from central headquarters to local plant managers prior to the Great Recession out-performed their centralized counterparts in sectors that were hit hardest by the subsequent crisis. Also close to our findings, Yang et al. (2025) find that CEOs use a wide range of markedly different processes to make strategic decisions; some follow highly formalized, rigorous, and deliberate processes while others rely heavily on instinct and habit. In their analysis, more structured strategy processes are associated with larger firm-size and faster employment growth. Our findings align with results in these two papers in that we find that those firms with a more structured management style outperformed

[1] Lamorgese et al. (2024) study another recent prominent crisis, the COVID19 pandemic, between 2020 and 2022. They show a positive effect of structured practices on productivity during this crisis. However, we would argue this relates to the specific nature of the pandemic. Firms with structured practices in place also had IT systems and objectives measurement in place. Thus, their transition to working from home worked more efficiently.

those firms with less structure prior to the crisis and in the long run, but this was no longer true during the crisis.

The paper is structured as follows. Section 2 describes our data. In Section 3 we describe our methodology when estimating latent management styles. Section 4 estimates total factor productivity (TFP hereafter) and examine the relationship between management styles and firm-level productivity before, during and after the Great Recession. In Section 5, we explore mechanisms behind our findings and provide additional results and robustness checks. Section 6 concludes.

2 Data

In this paper, we use two distinct sources of data. On the one hand, we measure management policies through a survey administered in 2006 to a sample of 1003 manufacturing plants in Spain. On the other hand, we use independently collected accounting data from *SABI* from 2001 to 2016 to measure plant and firm performance.[2] In what follows, we describe the survey and its matching with the SABI data.

2.1 The management survey

We estimate the latent structure of management styles using firm survey data collected in Spain in 2006. This survey on human resource (HR hereafter) practices was administered to a sample of Spanish manufacturing plants. The sample is representative of the population of manufacturing plants in Spain with 50 or more employees. In Table 1, we report the sample composition in terms of number of employees and industrial sector, and show that it mirrors the population composition. The survey was run at the establishment level, and collected through computer-assisted personal interviews with the general managers of those plants.[3] The responses from this survey have been used in earlier work although with a focus on individual policies and by employing methods not accounting for complementarities in those

[2] SABI stands for "Sistema de Análisis de Balances Ibéricos". A quick translation into English would be "System of Iberian Balance Sheet Analysis."

[3] Throughout the paper we use the terms *plant* and *establishment* interchangeably. Single-plant firms are the same as firms that only have one establishment. A multi-plant firm consists of multiple plants or establishments.

(Bayo-Moriones et al., 2013, 2017, 2025).[4]

The entire survey contains 1003 observations; 534 single-plant firms (SPFs) and 469 plants that belong to a superior organization. We refer to the latter group as *multi-plant firms* (MPFs). We restrict our analysis in this paper to the sample of single-plant firms. In single-plant firms, the link between management practices and firm performance is *direct* in the sense that no superior entity can interfere with decisions in a potentially unobserved manner. Thus, the unit of analysis is the firm or the establishment which is equivalent under the sample restrictions.

The survey asks the plants to provide information on a host of administrative information and HR practices for both blue-collar and white-collar workers. It can be broadly divided into eight sections: (i) administrative information (plant and firm characteristics, such as number of employees, and multinational and multi-plant status); (ii) HR's policies for blue-collar workers (demographic information, hiring and promotion processes, on-the-job training, etc.); (iii) compensation policies for blue-collar workers (incentive provision, evaluation criteria, etc.); (iv) workplace organization (hierarchical levels and supervisors' roles); (v) labor conflict and cooperation among blue-collar workers; (vi) governance and authority in the implementation of human resource strategies; (vii) profile of white-collar workers and other occupations in the plant; and (viii) plant manager characteristics (education, demographics, skill set, etc.).

Appendix Table A.1a provides summary statistics for those variables that we study in this analysis. The average firm has 116 employees although the distribution is highly skewed to the right (skewness ≈ 5). Further, the average firm has sales of about €28,639,000 worth of goods and services (also skewed to the right; skewness ≈ 7). The modal firm produces a consumer good, while the remaining firms are equally split between intermediate and capital goods. Two thirds of firms are in shared ownership, while a quarter are limited liability companies.

[4] Bayo-Moriones et al. (2017) discuss sample selection and sampling in more detail; Appendix 1 of said reference details the full questionnaire.

Sector (1)	% in sample (2)	% in population (3)
Food, beverages and tobacco	15.5	15.9
Textile industry, wearing apparel, leather and footwear	6.9	8.6
Wood and cork	3.4	2.6
Paper, editing and graphic design	7.0	8.1
Chemical industry	8.0	7.2
Rubber and plastic products	6.7	6.0
Non-metallic mineral products	10.8	9.7
Metallurgy and fabricated mechanical products	15.4	15,4
Machinery and mechanical equipment	7.5	8.0
Electrical, electronic and optical products and equipment	7.1	6.3
Transport equipment	6.0	6.5
Other manufacturing industries	5.7	5.5
Total	100	100

(a) Percentage of firms by sector of activity.

	$50 \leq$ workers < 100 (1)	$100 \leq$ workers < 500 (2)	≥ 500 workers (3)	**Total** (4)
% in sample	48.4	46.4	5.3	100
% in population	54.2	40.7	5.1	100

(b) Percentage of firms by size.

Table 1: Sample composition.
Notes: These tables report the sample composition in terms of sector of activity—Panel (a)—and number of employees—Panel (b).

2.2 Firm performance data

SABI is a database collected by Informa D&B in collaboration with Bureau Van Dijk. The database contains yearly balance sheet information for more than 2 million Spanish firms across all sectors in the Spanish economy.

We searched this extensive set of firms and aimed to link an entry to all 1003 manufacturing plants from our survey. We matched our manufacturing plants by firm name, tax ID (*CIF* in Spain), industry and location. We collected annual financial performance data at the firm level from 2001 to 2016. Out of the 534 SPF plants in the survey, we are able to match 456 (85%). When examining differences between matched and unmatched plants, we only find differences in the number of employees of the plant as self-reported in the survey. Interestingly, unmatched plants report a higher average number of employees than matched plants.[5]

This exercise resulted in an unbalanced panel across establishments and years as balance sheet records are not complete. It is important to note that the SABI database does not contain administrative tax data, and therefore not all firms in our sample report their accounting data every year. Furthermore, SABI collects balance sheet data at the *firm-level*, and it would be impossible to assign inputs and outputs to different establishments of a multi-plant firm. This constitutes another reason for why we restrict the sample to single-plant firms.[6]

From the SABI data, we primarily employ information on revenue, labor force, and assets to construct productivity.[7] We detail the procedure used to construct a measure of firm productivity in Section 4.1. In particular, we measure output using sales; capital input using total assets; and labor input using the number of employees. Appendix Table A.1b provides summary statistics for the variables used as inputs in the Total Factor Productivity (TFP) estimation for the three periods we consider in the analysis.

3 Estimating latent management styles

This section describes our use of unsupervised machine learning to estimate latent management styles using the survey data described in Section 2.1. We proceed by first providing details on how we construct the inputs for the unsupervised learning algorithm. Then we outline the algorithm we use to that effect. Next, we describe the results and analyze correlates of those results.

[5]See Table A.2 for a description of differences between matched and unmatched plants in our survey to SABI data.

[6]Appendix Table A.3 shows the number of firms in our final sample reporting their financial data year by year in SABI.

[7]The number of employees is also elicited in the firm survey. The correlation between both accounts of employment across data sets is 70%.

3.1 Measuring management practices

The unsupervised algorithm we employ to construct a low-dimensional measure of management style requires categorical data. While the majority of the survey's questions are indeed categorical, the answers' scales differ across questions. For instance, some question elicit agreement on five-point Likert scales, while other use ten-point scales; some questions are simple binary questions; and again others offer (non)-exclusive categorical answers. To construct the input matrix for the algorithm, we thus transform all questions into binary measurements which can be thought as the "smallest common denominator".

Even though the survey contains information on management policies and plant-level outcomes, in our exercise of measuring management practices, we only use variables detailing management policies. In total, we obtain 272 binary variables. We convert all types of agreement scales (three-point, five-point, seven-point) into three binary variables: i) an indicator for being to the "left" of the neutral mid-point, ii) an indicator for being at the neutral mid-point, and iii) an indicator for being to the right of the mid-point.[8] Categorical questions are transformed into binaries by generating an indicator for each answer possibility. For instance, a question asks for the number one management priority and offers *cost*, *flexibility*, *innovation*, and *quality* as answers. Our procedure generates four indicator variables which are equal to one if the plant reports the respective number one priority. Finally, there is a set of questions that require the surveyee to report a percentage between zero and 100. We convert the answer into three indicator variables: i) an indicator for the answer being 0 percent; ii) an indicator for the answer being greater than zero and no more than 50 percent; iii) an indicator for the answer being larger than 50 percent.

We refer to these 272 binary measurements as the management practices in our survey. Appendix Table B.1 details all the indicators along with the questions they originated from, and their sample means.

The algorithm requires the input matrix of management practices to only contain complete cases, that is, there cannot be management practices missing in the data. Owing to that restriction, we have to drop 71 plants from the sample. Appendix Table A.4 assesses whether the independently collected firm performance "SABI" data can predict whether some firms

[8] For example, consider a standard five-point Likert-scale going from strongly disagree, disagree, neither disagree nor agree, agree to strongly agree. "Neiter disagree nor agree" forms the neutral mid-point.

furnish incomplete records. While all point estimates weakly suggest that larger firms are less likely to exhibit missing records, none of the predictors is statistically significant even at 10%. Importantly, we also fail to reject that all coefficients in Column 6 of Appendix Table A.4 are *jointly* equal to zero.[9]

Thus, the final sample of plants used to estimate management style contains 463 firms out of the original sample of single-plant firms in the survey data.

3.2 Latent Dirichlet Allocation

We first briefly describe the algorithm, and the estimation specifications we employ to generate the low-dimensional measure of management style. We then turn to describing the results.

3.2.1 Estimation setup

The goal of our first empirical analysis is to retrieve a low-dimensional representation of management practices from the high-dimensional survey data. We argue that there are underlying management *styles* which generate differences in observed management *practices* across firms. In order to construct (estimate econometrically) these unobserved latent styles from firms' observed behavior, we employ *Latent Dirichlet Allocation* (LDA), an unsupervised learning algorithm which was originally conceived to find *topics* in text data (Blei et al., 2003; Erosheva et al., 2007). Yet, it lends itself to the analysis of categorical data more generally. The seminal analysis of CEO's time allocation by Bandiera et al. (2020) and on central bank communication by Hansen et al. (2018) introduced this type of analysis to a broader audience in economics.

LDA is a Bayesian hierarchical factor model and the intuition is most easily explained by using the analogy to text data. Each observation is a snippet of text (in our case, a firm with observed practices). This means that each snippet of text is a mixture of different

[9] A model with only region and sector fixed effects exhibits an adjusted R^2 of less than 0.01, thus suggesting that these time-invariant characteristics do not predict records being complete either. The model's explanatory power does not change if we include SABI predictors and region and sector fixed effects at the same time. Crucially, we still fail to reject that all SABI predictors are *jointly* equal to zero. The conclusions remain qualitatively unchanged if we estimate logit models rather than linear probability models which specifically take into account the binary nature of the dependent variable.

topics (analogously, each firm's management is a mixture of styles). In turn, each topic is a mixture distribution of all *words* that appear in the entirety of observed text. Put differently, each topic is a probability distribution across all words, where words that are strongly associated with a topic carry a higher loading. The analogue in the present situation is that a management style is a probability distribution across all observed practices. Thus, we apply LDA to model latent management styles as distributions over all observed practices, and to model firms' observed configurations of management practices as a mixture of these styles.[10]

The crucial input in the analysis is the number of latent styles to be estimated which is to be set by the researcher. We specify two latent styles of management based on the following three reasons. First, unlike traditional cluster analysis, e.g., k-means, LDA does not deterministically assign observations to clusters. Thus, a specification with two "pure" styles is able to capture heterogeneity beyond assigning membership to exactly one cluster by assigning every firm a linear weight of the two pure styles. Second, two latent factors simplify interpretability. As Blei (2012) points out, the ease of interpretation should be taken into account when choosing the parameters of unsupervised learning.[11]

LDA is a Bayesian technique and requires priors on both of the Dirichlet distributions. We follow Bandiera et al. (2020) in setting both priors. We place a neutral, uniform prior on the firm-over-style distribution (prior = 1) which would place firms' initial mixture of styles at 50:50. The prior on the style-over-practice distribution promotes sparsity (prior = 0.1). This reflects our conception that styles load heavily on a few rather than a lot of practices since there are likely to be few emblematic practices for each style.

Setting a non-zero prior ensures a non-zero posterior. Thus, the probability distributions we estimate have strictly positive loadings for each element. By virtue of being *probability* distributions, the loadings have to sum to one. This assumption results in all weights being strictly smaller than one.

[10]From a technical perspective, we estimate the models using Gibbs sampling, a Markov chain Monte Carlo algorithm (Griffiths and Steyvers, 2004). For the Gibbs sampler we specify a *burn in* period of 5,000 iterations; we then implement 10,000 iterations with a thinning parameter of 2,000.

[11]While not shown here, a cross-validation exercise suggests that model fit does not improve markedly when we estimate more latent styles. The at best marginal increase in model fit we obtain through more clusters is outweighed by the loss of interpretability.

Finally, note that LDA is an *unsupervised* learning algorithm and the estimation procedure does not force the resulting clusters to explain firm performance in any way. In contrast, supervised methods, such as classification trees, regularized regression or neural networks, are usually employed with the goal of using a set of variables to predict the values of a response variable. However, we would like to first understand what groups of management practices firms choose by finding a low-dimensional representation of these practices. We now turn to describing our estimated distributions of interest.

3.2.2 Estimation results

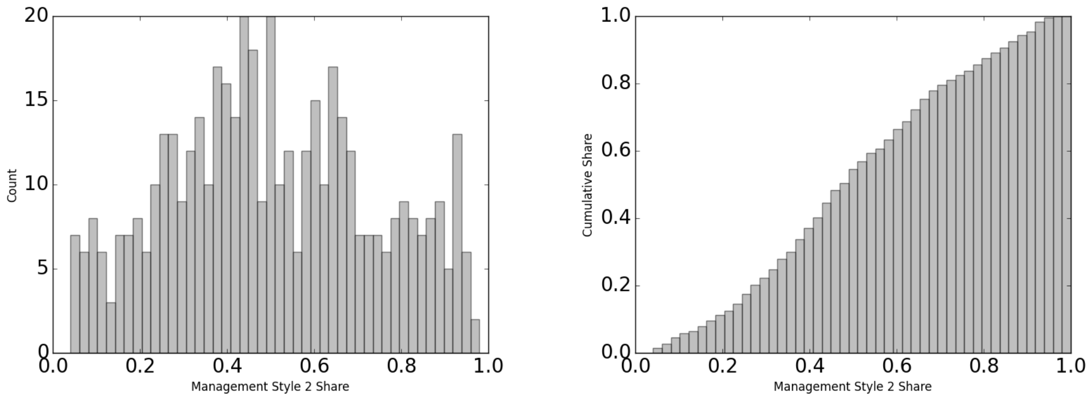
First, we obtain a distribution over all practices for both styles. In Figure 1 we summarize these distributions but explicitly abstain from attaching any labels to the output as styles are non-ordinal; hence, for now, we refer to the styles neutrally as *Style 1* and *Style 2*. Recall that the two style's weights are positive and sum to one; therefore, a firm's style distribution is fully characterized by either style share. We focus on the share of Style 2, which we also refer to as Style 2 intensity. Panel (a) of Figure 1 plots the count of firms across the Style 2 continuum. The distribution of styles across firms indicates substantial heterogeneity in how firms allocate their management practices. In the analysis, we provide results based on a continuous measure of Style 2 intensity as well as based on indicator variables for terciles.

For context, Appendix Figure A.1 plots all practices' loadings ordered according to their Style 1 loading. The figure demonstrates that the procedure is indeed able to identify two distinct latent constructs. Practices with lower loadings in Style 1 (indicative of a lesser role in style 1) tend to load highly on style 2. There are also practices that carry high loadings in both styles. This suggests the presence of practices that are employed in conjunction with those practices that are emblematic of both styles.

3.3 Characterizing firms' management styles

As mentioned above, latent management styles are not ordinal and, hence, any labels we may want to attach to these styles are necessarily subjective. We pursue two approaches in order to understand what these latent constructs actually capture.

First, we analyze those practices that characterize each style, respectively. Table 2 reports the ten organizational practices with the highest predictive power for each style; i.e., the



(a) Probability density. (b) Cumulative density.

Figure 1: Firms' style 2 intensities.

Notes: This figure plots the observed Style 2 intensities for all single-plant firms. These intensities were estimated using the single-plant sample alone. Panel (a) presents a histogram in which the unit interval was binned into 50 equidistant intervals. Panel (b) plots the cumulative density across those same 50 intervals.

probability of a style conditional on adopting a specific practice. Style 2 exhibits practices that focus on evaluation and staff development and suggest a structured approach to HR management. While we would like to emphasize that any label is subjective, we still conclude that Style 2 captures a more *structured* approach to management. In contrast, Style 1 represents an approach characterized by little attention to staff development or training.

Second, we continue by comparing firms of a certain configuration to a separate set of firms

Rank	Probability Assignment Style 1	Probability Assignment Style 2
1	Monotone technical tasks	Worker evaluation affects firing decisions
2	Work climate unimportant for HR	Superior evaluates worker
3	White collar does not improve firm processes	Several worker evaluations per year
4	Workers do not improve firm processes	Personality evaluated for white collar recruitment
5	White collar has no information on firm financial status	Worker evaluation affects salary decisions
6	No worker rotation	HR and senior staff make hiring decisions
7	White collar does not get paid training	50% of workers improve firm processes
8	No representation of plant workers	Worker evaluations every quarter
9	No formal or informal evaluation system	Evaluations affect on-the-job training
10	External hires preferred over promotion	Team-Climate affects white collar recruitment

Table 2: Ten practices with highest discriminating power $Pr(topic_i|practice_j)$ in each style.

whose management we can characterize *a priori*, that is, without relying on LDA. To this effect, we consider firms with several establishments, that is, multi-plant firms, possibly across countries. These firms can benefit from economies of scale, and may be forced to delegate decision across subsidiaries, leading them to employ more structured management practices (Bloom et al., 2012a,b). Thus, we seek to describe the management styles of single-plant firms by comparing them to multi-plant firms based on Style 2 intensity. An additional advantage of this approach is that it does not require a subjective evaluation of the style-over-practice distribution.[12]

We operationalize this comparison by first pooling the surveys of single-plant and multi-plant firms, and then estimate management styles in this joint sample using the LDA procedure exactly as described above.[13] This estimation returns style shares for each firm in the pooled sample, and we plot the Style 2 intensity for three types of firms defined as follows: i) multi-plant firms (which do not appear in the single-plant sample), ii) single-plant firms whose observed intensity of Style 2 in the *single-plant sample estimation* is (weakly) smaller than 0.5, i.e., those that we would describe as rather Style 1 firms, and iii) single-plant firms with an observed intensity of above 0.5, i.e, those that we would describe as rather Style 2 firms.

Figure 2 plots the result of this exercise. We show the probability density of Style 2 intensity estimated in the *joint sample* for those three types. First, we note that the distribution of MPFs puts most mass above 0.5. Secondly, the distribution of SPFs with Style 2 intensity (from the single-plant sample) also puts most mass above 0.5 in the joint estimation. Finally, the distribution of SPFs with SPF-only sample Style 2 intensity below 0.5 behaves the opposite way. In a nutshell, MPFs are similar to Style 2 firms in terms of practices employed. In line with prior findings in the literature, this would suggest that Style 2 firms employ a more structured management style.

[12]The second approach to understanding the pure style is by evaluating the style-over-practice distributions. This is more prone to researchers' imposing their conceptions of what styles *ought* to mean. By comparing styles without attaching labels, we attempt to generate an unbiased understanding of what pure styles represent.

[13]In order to carry out this exercise, we drop 20 practice indicators from the multi-plant survey as they are about autonomy from the superior organization and hence only relevant for MPFs. There is no guarantee that the two resulting pure management styles are comparable to the results obtained from using only the single-plant firms. The estimation in the joint sample proceeds exactly as the one in the single-plant sample. We employ equivalent Dirichlet priors and the MCMC parameters are kept constant.

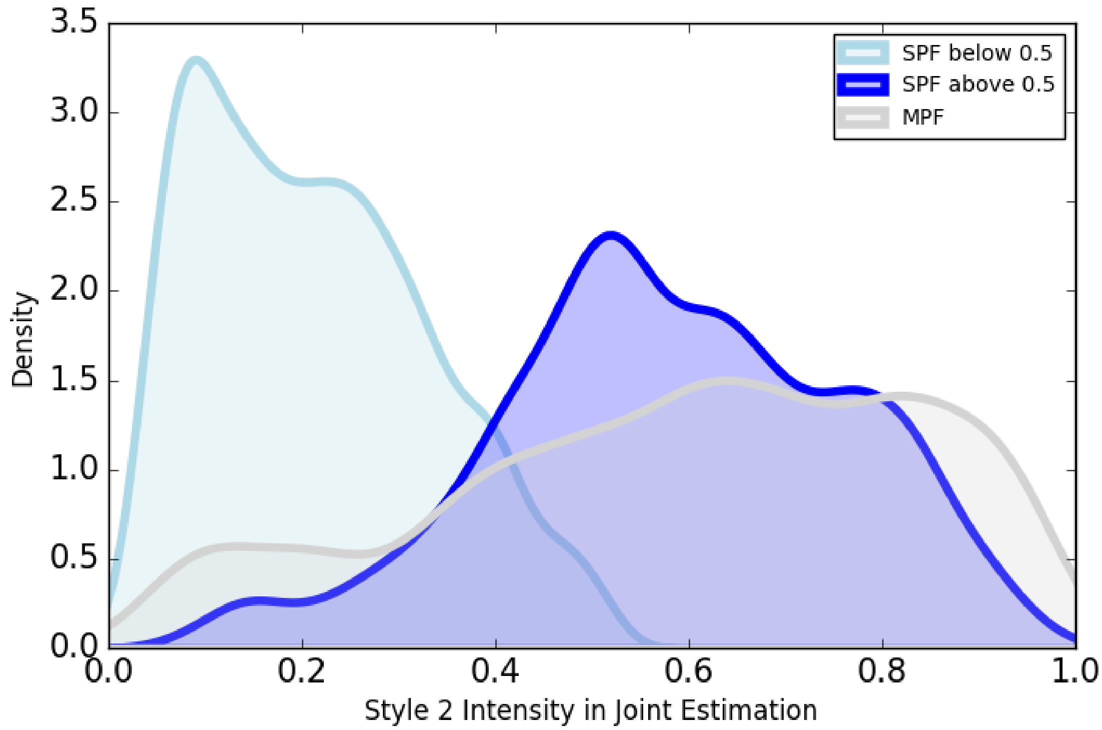


Figure 2: Understanding styles by comparing single- and multi-plant firms.

Notes: In this figure, we apply the LDA procedure described above to estimate management styles in a pooled sample of single- and multi-plant firms (n=871). We then plot the probability density of the corresponding Style 2 share separately for: i) those single-plant firms that exhibited a Style 2 intensity of (weakly) below 0.5 when styles are estimated in the *single-plant sample only*, ii) those single-plant firms with a corresponding intensity of above 0.5, and iii) all multi-plant firms.

3.4 Correlates of management styles

In this section, we explore how survey data correlates with our measure of Style 2 management and show that management styles are not trivially explained by observables. Recall from the previous discussion that firms with higher Style 2 intensities implement management practices that look more like those of multi-plant firms, stressing more structured forms of management. We denote firm i's Style 2 intensity by γ_i^2 and estimate:

$$\gamma_i^2 = \beta_0 + X_i\beta + \varepsilon_i \tag{1}$$

	Dependent variable: Style 2 intensity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log # employees	.17***						.2***	.17***
	(.017)						(.024)	(.017)
Log sales ['000 EUR]		.037***					-.01	
		(.01)					(.0088)	
Year plant opened			-.00055				.00075	.00038
			(.00047)				(.00051)	(.00046)
% for export				.0013**			.00077	.00057
				(.00045)			(.00044)	(.00038)
Produces consumer good					-.08**		-.049	-.088***
					(.025)		(.026)	(.024)
Produces intermediate good					-.03		.013	-.023
					(.031)		(.034)	(.031)
Shared ownership						-.0096	-.0061	-.028
						(.052)	(.057)	(.039)
Limited liability						-.077	-.043	-.052
						(.055)	(.056)	(.045)
Adj R-sq	.17	.04	.00064	.02	.013	.01	.22	.2
N. of cases	463	289	456	438	458	463	284	430

Table 3: Correlates of Style 2 intensity.

Notes: This table reports results from OLS regressions where the dependent variable is a firm's Style 2 intensity, a variable between zero and one. "Log" refers to the natural logarithm. "% for export" is a firm's self-reported share of output that is exported abroad. "Produces consumer/intermediate good" are indicator variables equal to one when the firm produces the respective output category, and zero otherwise. The omitted category for this class of indicators is producing a "capital" good. "Shared ownership" and "limited liability" are indicators equal to one when a firm is organized according to the respective ownership structure. The omitted category for this class of indicators is "other" ownership structures. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

where X_i captures firm characteristics, such as size, export dependency, or a firm's position along the value chain.[14] We provide both, results from univariate and multivariate specifications. The latter takes into account the correlation structure across firm characteristics. Inference is based on standard errors clustered at the three-digit industry level (at most 78 clusters).

[14] Almunia et al. (2021) document that firms at different positions in the value chain had different experiences (and margins of adjustment) during the Great Recession. Hence we control for this position in our analysis.

Table 3 reports results from OLS regressions where the dependent variable is a firm's Style 2 intensity and independent variables come from organization available in the 2006 plant-level survey. The results suggest that, while some correlates are significantly related to Style 2 in univariate regressions, they explain only a small fraction of the variation in Style 2. Once we include all independent variables in the regression, only number of employees and whether the plant produces consumer goods seem to be statistically significantly related to Style 2.[15]

In what follows, we produce graphical evidence of the relationship of management Style 2 with the number of employees, sales, year of plant opening, intensity of export dependency, value chain location and manufacturing sector within our sample. Figure A.2 zooms in on the (univariate) relationship between Style 2 intensity and firms' number of employees. A positive correlation is clearly visible. However, across the support of firms' number of employees, firm size does not explain variation in Style 2 intensity. We continue examining the relationship between Style 2 and sales in Figure A.3. Consistently with our description of Figure A.2, we find a positive relationship between Style 2 and sales but this relationship cannot explain much of the existing variation in sales across firms within our sample. We continue by exploring the relationship between Style 2 and year of plant opening in Figure A.4. There appears to be a mild negative relationship, but overall no significant positive or negative slope in the fitting line. We reach a similar conclusion when showing a positive association of Style 2 intensity and export dependency in Figure A.5, however, we show the latter is not substantively explained by the former. Finally, Figure A.6 shows a mildly positive relationship between Style 2 intensity and capital intensity, that is, value of assets over sales. Yet, this relationship is mainly driven by a few outliers in the right-hand side of the distribution.

We also examine whether Style 2 intensity is associated with different parts of the value chain or different manufacturing sectors within our sample. In Table 3, we found that firms that produce consumer goods tend to have lower Style 2 intensity, even after controlling for firm size. On average, a firm producing consumer goods has about eight to nine percentage points lower Style 2 intensity. Figure A.7 zooms in on this aspect, and graphically displays

[15]Table A.5 investigates whether firms' performance correlates with Style 2 intensity using SABI data. Specifically, we show positive correlations of Style 2 with firms' number of employees, sales or profit, and assets or equity. These correlations tend to be significant and confirm the notion that, on average, Style 2 intensity correlates with firm size. Individual effects are not statistically significant once we jointly include them in a multivariate regression.

lower Style 2 intensity in the consumption good sector. While medians differ across plants producing capital goods, intermediate goods and consumption goods, there is ample common support across different locations in the value chain. Finally, Figure A.8 examines the relationship between economic sector and Style 2 intensity. While office supplies, textiles and wood manufacturing seem to be associated with lower average intensities of Style 2, the support of the distribution of Style 2 overlaps across sectors and, therefore, we cannot claim that Style 2 intensity is associated with a particular manufacturing sector in our sample.

Thus, in summary, overall firm characteristics as elicited in the survey can explain only about one fifth of variation in Style 2 intensity. We note a significant positive association between firm size and location in the value chain (employees, whether the plant produces consumer goods) and Style 2 intensity. Yet, these characteristics only explain a minor part of the variation in Style 2 intensity.

4 Management style and firm performance

This section investigates how and when the management styles we estimated above correlate with firms' performance in our sample. We first construct measures of firm performance from the SABI data we describe in Section 2.2 which was collected independently of the firm survey data. This mimics the approach by Bloom and van Reenen (2007) who refer to this as the *two-step procedure* because it first estimates firm-level Total Factor Productivity (TFP), and then projects it into the space of management styles. By doing so, we make sure the information used in the estimation of TFP and the information used in the estimation of management styles are independent and, thus, any empirical relationship is not mechanical. Then, we proceed to test whether the correlation between management style and TFP differs during our period sample. In particular, we take advantage of the fact that our sample period (2001-2016) encompasses a period of economic growth prior to the Great Recession (2001-2006), the Great Recession itself (2008-2012) and a period of economic recovery after the Great Recession (2014-2016).[16] We show our findings below.

[16]Because 2007 is a year where growth slowed down but it remained on the positive side, we leave 2007 out of the crisis period and focus on years between 2008 and 2012, both included. Similarly, turning attention to the end of the crisis, we leave 2013 out of the recovery period because growth rates were still negative despite the positive trend. In the end, thus, for our main analysis we exclude 2007 and 2013 to define 2001-2006 as pre-crisis period and 2008-2012 as crisis period.

4.1 TFP and management style

In this paper, we use TFP as a measure of firms' performance. TFP can be interpreted as a firm's specific technology to combine labor and capital into output. First, we postulate that firms produce output Y using labor (L), capital (K), and a production technology α according to $Y = \alpha L^{\beta_1} K^{\beta_2}$. The βs denote the production elasticities with respect to labor and capital. By taking the natural logarithm we obtain the following equation where i indexes firms and t indexes years:

$$y_{it} = \alpha_i + \beta_1 L_{it} + \beta_2 K_{it} + \varepsilon_{it} \tag{2}$$

We use sales in Euros to proxy output, total assets to measure capital input, and the number of employees to measure labor input. Then, we estimate Equation (2) using OLS. The underlying, *unbalanced*, panel covers the period between 2001 and 2016.[17] We obtain a firm's TFP by taking the predicted value of α_i from Equation (2).[18]

Once TFP is estimated, we investigate whether and how the management style we estimated using firm survey data correlates with firms' TFP. To this effect, we estimate

$$\widehat{\alpha_{i,s,r}} = \beta_0 + \beta_1 \gamma^2_{i,s,r} + X_{i,s,r}\beta + \omega_r + \omega_s + \varepsilon_{i,s,r} \tag{3}$$

where i indexes a firm active in sector s and located in region r. The variable $\gamma^2_{i,r,s}$ denotes a firm's management Style 2 intensity, which is a value between 0 and 1. Higher values indicate a stronger Style 2 intensity, i.e. a more structured management approach. In $X_{i,r,s}$, we control for whether the firm exports its product and the firm's location along the value chain by including indicators for producing consumer goods or equipment leaving the firms producing capital goods as the omitted category. The ω_r and ω_s absorb time-invariant variation induced by regions and sectors, respectively. We cluster standard errors at the

[17] A total of 446 firms enter the productivity estimation, and the average firm appears 5.5 out of 6 times. While 11 firms only appear once, the average year has information for 331 firms. We estimate output elasticities of labor and capital to be 0.3 and 0.49, respectively. When only using firms for which we observe the complete panel structure, we estimate elasticities of 0.46 and 0.44, respectively.

[18] Appendix Figure A.9 shows the distribution of the estimated $\hat{\alpha}_i$ in the period 2001-2006, which is slightly skewed to the right. More importantly, we observe several extreme values indicating relatively (un)productive firms. While not shown in the paper, we run the same specifications winsorizing at 95% the TFP outlier values (see vertical lines in the figure). These results are available upon request.

Figure 3: Spanish growth and its manufacturing sector between 2001 and 2016.

three-digit industry level.

As anticipated above, we separate our empirical analysis into three periods between 2001 and 2016. This is motivated by the experience of the Spanish economy before, during and after the Great Recession. Figure 3 shows the evolution of overall GDP growth as well as the growth of the Spanish manufacturing sector. Note the economy grew at healthy rates between 2001 and 2006 with a sudden drop in 2007 with the Great Financial Crisis that lasted until 2012.[19] From 2013 on the economy started growing again until reaching pre-crisis growth levels in 2015 and 2016. The growth pattern followed by the Spanish manufacturing sector is similar with far lower (negative) growth rates during the Great Recession. In what follows, we investigate the empirical relationship between firm-level TFP, as estimated using Equation (3), and the Style 2 management score estimated in Section 3.2 for each of these three separate time periods.

[19]Section 4.3 below discusses in detail the Spanish experience during the Great Financial crisis and its aftermath.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.17**	.18**	.17**			
	(.085)	(.082)	(.083)			
$1[\text{style } 2 > \frac{2}{3}]$				.1*	.11**	.11**
				(.054)	(.054)	(.05)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.077	.063	.067
				(.053)	(.047)	(.047)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Firm Productivity 2001	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.52	.57	.58	.52	.57	.58
Adj R-squared	.47	.53	.54	.47	.53	.54
N. of cases	361	344	340	361	344	340

Table 4: Management style and firms' TFP 2002-2006. *Notes.* This table reports the results of estimating Equation (3) using OLS. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

4.2 Management Style and TFP *before* the Great Recession

Our empirical analysis starts by first providing the results of estimating Equation (3) in Table 4 using TFP measures of firms in our sample between 2002 and 2006 and the management style estimated using 2006 plant-level survey data. It is important to highlight that in this first exercise both left-hand and right-hand side variables are contemporaneous and, thus, we are estimating the cross-sectional relationship between TFP, our measure of firm performance, and management style prior to the Great Recession.

Column 1 provides the simple univariate correlation of style 2 intensity with firms' TFP while controlling for firm's productivity in 2001 and adding region and sector fixed effects. In columns 2 and 3, we additionally control for exporting behavior and value chain location, respectively. Across these first three columns, there is a significant correlation between Style 2 intensity and firms' TFP. The estimates' magnitude (between .17 and .18) does not change when adding controls across specifications. Our results show that a one standard deviation change in the management score (0.24) is associated with a change in TFP of 0.04. This is equivalent to an increase of a 9% of a standard deviation in TFP. Alternatively, an increase in style 2 equivalent to the inter-quartile-range of 0.34 would result in a 6% increase in TFP (or a 13% increase of a standard deviation in TFP). The full specification explains between 52% and 58% of the variation in the dependent variable.

Columns 4 to 6 mirror the specifications in columns 1 to 3, respectively, with the only difference of using tercile dummies of the Style-2 management score. Our specifications include dummy variables for the top tercile (Style-2 management score above 0.66) and the mid tercile (Style-2 management score ranging between 0.33 and 0.66), leaving the bottom tercile as the reference group. We find that the firms in the middle tercile of Style 2 intensity are marginally (and statistically insignificantly) more productive than firms in the bottom tercile. In contrast, firms in the top tercile are significantly more productive than firms in the bottom tercile. Having said this, we are unable to statistically reject that the effects are in fact equal for firms in the middle and top terciles.

To sum up, we find a positive association between Style 2 intensity and productivity prior to the Great Recession. That is, more structured management correlates positively with firms' TFP. The Spanish economy was booming up to 2006 and what we observe is consistent with firms being able to leverage structured management to benefit from exploiting economies of scale. Consistent with a large literature (Bloom et al., 2014), structured management style appears to allow firms to more effectively exploit this beneficial economic environment.

4.3 Management Style and TFP *during* the Great Recession

So far, we have established that firms in our sample are managed heterogeneously in that we show a distribution of style 2 management scores in section 3.2. We have also shown that our style 2 management score is meaningful in that it captures differences in structured management across firms in our sample and also because it appears to be correlated with plant productivity. Then, a natural next step is to investigate how these patterns evolve over a longer period of time, for which we have productivity information, taking advantage of the fact that our initial time period was followed by a major recession and its corresponding recovery period.

The Great Recession (2008-2012) followed the Great Financial Crisis that struck in 2007 and 2008. Spain's experience of the aftermath of the crisis was markedly different than that of other countries, such as the US or Germany, where growth rates quickly recovered after a severe short-run contraction. As illustrated in Figure 3, from its peak in 2008, Spain's real GDP fell by an accumulated 8.6% in the following five years until 2013, private final consumption contracted by 14.0% during the same period, and the unemployment rate increased from 9.6% to 26.1%.[20] In terms of the start of the crisis, it is important to note that GDP in manufacturing slowed its growth already in 2007 when GDP growth in Spain's overall economy, much reliant on tourism and the service sector, was still stable, before bottoming out in 2008 and 2009.[21]

Our estimates of firms' TFP are derived from estimating a specification akin to Equation (2) but now using data for the years 2008-2012. Then, we estimate the same regression specification in Equation 3 with TFP in the 2008-12 period and Style 2 management score obtained in section 3.2 using 2006 plant-level survey data. While the choice of asynchronism between dependent and explanatory variables is driven by (a lack of) data availability, it is also important to consider that this exercise is still meaningful because (i) management practices may have long lasting effects, and (ii) structured management, namely higher style 2 management scores, may be associated with higher adjustment costs and, thus, less likely to change over time.[22] We show our results in Table 5.

Following the structure of Table 4, column 1 provides the simple univariate correlation of Style 2 intensity with firms' TFP while controlling for firm's pre-crisis productivity as well as region and sector fixed effects. In columns 2 and 3, we also control for exporting behavior and value chain location, respectively. As in Section 4.2, standard errors are clustered at the industry level.

Unlike in Table 4, we find a significant and negative correlation between Style 2 intensity

[20] See Almunia et al. (2021) for more details on the Spanish experience in the Great Recession.

[21] See also in footnote 15 above. We leave 2007 and 2013 out of our working sample as these were transition years into and out of the financial crisis. Therefore, our main analysis excludes 2007 and 2013 to define 2001-2006 as pre-crisis period and 2008-2012 as crisis period. We demonstrate the (qualitative) robustness of our results to alternative sample definitions in Section 5.

[22] This argument, drawing on Bilicka and Scur (2024), aligns with the idea that, in the short to medium term, management practices are rigid, and that organizational change often faces considerable challenges (Gibbons and Henderson, 2012; Bloom et al., 2014).

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.17*	-.19*	-.19*			
	(.1)	(.1)	(.1)			
$1[\text{style } 2 > \frac{2}{3}]$				-.11*	-.12**	-.12**
				(.056)	(.056)	(.054)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				-.0068	-.013	-.02
				(.059)	(.059)	(.059)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.39	.41	.42	.39	.41	.42
Adj R-squared	.34	.36	.36	.34	.36	.36
N. of cases	379	358	354	379	358	354

Table 5: Firm productivity 2008-2012. *Notes.* This table reports the results of estimating Equation (4) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

and firms' TFP. The estimates' magnitude (between -0.17 and -.19) does not change much when adding controls across specifications. In short, our results show that a one standard deviation change in the management score (0.24) is associated with a change in TFP of 0.04. This is equivalent to a decrease of a 9% of a standard deviation in TFP. Alternatively, an increase in Style 2 equivalent to the inter-quartile-range of 0.34 would result in a 6% decrease in TFP (or a 13% decrease of a standard deviation in TFP). The full specification explains between 38% and 41% of the variation in the dependent variable.

Again, columns 4 to 6 mirror the specifications in columns 1 to 3, respectively, with the only difference of using tercile dummies of the Style-2 management score. Our specifications include dummy variables for the top tercile (Style-2 management score above 0.66) and the mid tercile (Style-2 management score ranging between 0.33 and 0.66), leaving the bottom tercile as the reference group. We find that the firms in the middle tercile of Style 2 intensity are not, from a statistical and magnitude perspective, less productive than firms in the bottom tercile. In contrast, firms in the top tercile are significantly less productive than firms in the middle and bottom tercile.

A potential spurious and alternative explanation for the negative correlation between TFP and management style found in Table 5 given our results in Table 4 would be regression to the mean. This explanation would imply that highly productive firms in the pre-crisis period (those with high scores in management style) would see a decline back to normal TFP levels during the crisis for unrelated reasons to the financial crisis or the adequacy of their management practices to the dire financial outlook. It is important to highlight that we follow the literature (Lazear, 2004; Smeets et al., 2019) and account for this potential alternative explanation by controlling for the pre-period level of TFP, that is, the average TFP in the 2001-2006 period in our regression specifications. Thus we are able to interpret the effect of Style 2 intensity on TFP during crisis holding constant pre-crisis TFP. Put differently, in a scenario of two firms with equivalent pre-crisis TFP, the firm with higher Style 2 intensity does worse during the crisis on average.

4.4 Management Style and TFP *after* the Great Recession

Our final exercise in this section investigates the empirical relationship between TFP during the period 2014-2016 and the Style 2 management score as estimated in Section 3.2. We show results in Table 6 using again the regression specification in Equation 3. Column 1 provides the simple univariate correlation of Style 2 intensity with firms' TFP while controlling for a firm's pre-crisis productivity together with region and sector fixed effects. In columns 2 and 3, we additionally control for exporting behavior and value chain location, respectively. Columns 4 to 6 mirror the specifications in columns 1 to 3, respectively, with the only difference of using tercile dummies of the style-2 management score.

In columns 1 to 3, we find a significant and positive correlation between Style 2 intensity and firms' TFP. The estimates' magnitude vary between 0.28 and 0.34 when adding controls across specifications. Using 0.33 as our base coefficient results, our estimation results imply that a one standard deviation change in the management score (0.24) is associated with a change in TFP of 0.08. This is equivalent to an increase of a 9% of a standard deviation in TFP. Alternatively, an increase in Style 2 equivalent to the inter-quartile-range of 0.34

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.33*	.29	.23			
	(.19)	(.2)	(.2)			
$1[\text{style } 2 > \frac{2}{3}]$				.14	.11	.071
				(.12)	(.13)	(.13)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.16	.16	.14
				(.1)	(.1)	(.11)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.47	.46	.47	.47	.46	.47
Adj R-squared	.41	.4	.4	.41	.39	.39
N. of cases	290	275	272	290	275	272

Table 6: TFP 2014 to 2016. *Notes.* This table reports the results of estimating Equation (4) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

would result in an 11% increase in TFP (or a 25% increase of a standard deviation in TFP). The full specification explains 47% of the variation in the dependent variable.

Our results in columns 4 to 6 show that the firms in the middle tercile of Style 2 intensity are significantly more productive than firms in the bottom tercile. In contrast, firms in the top tercile are not significantly more productive than firms in the bottom tercile. Having said this, we are unable to statistically reject that the effects are in fact equal for firms in the middle and top terciles.

In conclusion, our findings in this section show that those firms using more structured management styles outperformed those firms with less structured management styles during good economic times, namely 2001-2006 and 2014-2016, but they underperformed relative to those with less structured management during the financial crisis between 2008 and 2012. In the section that follows we investigate the mechanisms behind this pattern for higher Style

2 management scores. We also provide robustness checks for our findings in Section 3.2 as well as sections 4.2, 4.3 and 4.4.[23]

5 Mechanisms, additional results and robustness checks

This section first discusses a potential mechanism behind our set of findings above. We posit that firms adopting more structured management practices are also those with corporate culture and intangible assets focused in the long-term survival and performance of their organizations. While we cannot provide one "smoking gun," we are able to provide a collection of facts that together support our proposed mechanism.

In the second half of this section, we provide a number of additional results that demonstrate the robustness of our methodology and results across the sections above.

5.1 Mechanisms

We focus now on the channel through which the intensity of structured management style may affect firm performance over the business cycle. While we are unable to pinpoint a specific mechanism, we provide a set of results that suggest that firms with higher style 2 intensity (more structured approach to management) endogenously self-select into management structures with higher adjustment costs, innately less flexible and more unlikely to adjust to external economic conditions in a timely manner. We argue that this commitment is optimal when structured management is complementary to non-tangible investments such as work culture, worker training and consumer relationships (Blader et al., 2020; Graham et al., 2022a,b). In fact, firms with strong presence of non-tangible investments are willing to sacrifice short-term losses during economic crisis because they focus on long-term performance.

Our explanation for the mechanism behind our results hinges on several independent factors. Next we provide different collections of evidence that support our hypothesis. First, our explanation relies on the assumption that higher intensity of Style 2 management (more structured management practices) are associated with more rigidity and a lower ability to

[23]See Tables A.6, A.7 and A.8 for results when TFP is estimated using methodology by Ackerberg et al. (2015).

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.1***	-.11***	-.1***			
	(.035)	(.036)	(.037)			
$1[\text{style } 2 > \frac{2}{3}]$				-.04	-.045*	-.045
				(.024)	(.026)	(.027)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.018	.015	.015
				(.021)	(.021)	(.021)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Total assets 2006	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	.64	.64	.64			
Adj R-squared	.13	.13	.12	.13	.13	.12
N. of cases	412	389	384	412	389	384

Table 7: Management style and non-fixed assets before the crisis.

Notes. Management style and non-fixed assets before the crisis. The dependent variable is the share of non-fixed assets in 2006. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

adjust to short-term changes in the economic environment. To examine the empirical validity of this assumption, we use information from the SABI dataset to analyze firms' holdings of non-fixed (i.e., rather liquid) assets before the crisis.

Table 7 examines differences in holdings of non-fixed assets across firms with different intensities of Style 2. Columns 1 to 3 show indeed that higher Style 2 intensity correlates with relatively lower holdings of non-fixed assets in 2006. Put differently, a higher Style 2 intensity correlates with relatively more fixed assets, even after controlling for sector and region fixed effects and the total amount of assets in 2006. In columns 4 to 6, we show that the negative correlation in the first three columns comes from those firms in the top tercile of the Style 2 distribution.

Second, our explanation also relies on the assumption that higher intensity of Style 2

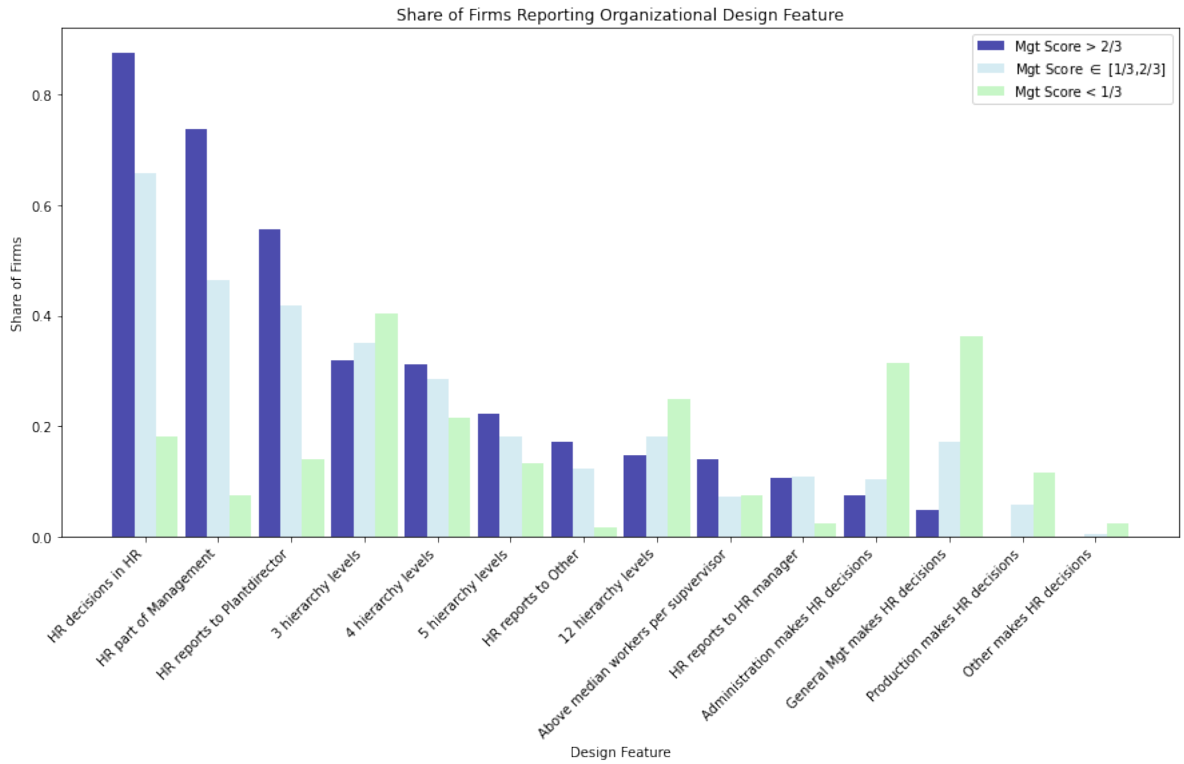


Figure 4: Share of firms with a high ($> \frac{2}{3}$) and low management score ($< \frac{1}{3}$) reporting an organizational design feature.

management (more structured management practices) is associated with practices that are aiming to foster non-tangible investments, that is, a distinct corporate culture. Figure 4 shows differences in formal personnel processes across firms scoring in the top, middle and bottom terciles of intensity of management Style 2. This figure shows the emphasis given to HR management and labor policies in more structured management firms.

Moreover, firms with higher intensity of management Style 2 also have labor policies that aim to avoid layoffs, keep workers under financial duress and lower absolute turnover. While we do not have direct evidence on on-the-job training and firm-specific worker investments, these policies are usually conducive to worker investments specific to the firm and, thus, foster work culture.

In fact, Table 8 examines differences in labor policies across firms when sales drop. The actual question in the plant-level survey asks whether firms under financial duress tend to terminate

	(1)	(2)	(3)	(4)
	Terminate Workers		Keep Workers	
Mgt style 2	-.219**	-.288***	.162*	.213**
	(.086)	(.093)	(.093)	(.102)
Employment		.439*		-.379
		(.240)		(.250)
Constant	.333***	.321***	.639***	.650***
	(.051)	(.054)	(.054)	(.057)
R-squared	.02	.03	.01	.01
N. of cases	415	399	415	399

Table 8: Management style and labor policies when sales fall.

Notes: The dependent variables are indicators taking the value 1 if terminating (columns (1) and (2)) or keeping workers (columns (3) and (4)) are named as strategies to address falling sales. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

workers, namely new workers or offering early retirement, or keep workers through decreasing hours per worker, ending overtime or reallocating workers within the firm. Columns 1 and 2 show that management style 2 firms are less likely to terminate workers. Columns 3 and 4 show that management style 2 firms are more likely to keep workers when sales drop due to external circumstances.

Aside from firm-level labor policies, we can also examine how the firms in our sample actually reacted to the financial crisis in terms of the actual number of employees (intensive margin) and hiring decisions (extensive margin). Table 9 shows that firms with higher intensity of structured management, despite a significantly lower performance during the financial crisis, did not hire significantly less workers than those firms with lower intensity of management Style 2. In fact, Table 10 shows that, if anything, firms with more structured management practices were more likely to hire workers and increase their total number of employees during the financial crisis, that is, they grew despite their worse performance during that period.

Third and finally, our explanation relies as well on the assumption that more structured management practices are associated with a long-term vision and emphasis in business decisions. Table 11 examines the strategic importance that each firm gives to four different

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-1.1	-3.4	-11			
	(7.9)	(8.4)	(9.1)			
$1[\text{style } 2 > \frac{2}{3}]$				-3.9	-5.6	-9.4
				(5.1)	(5.7)	(6.3)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				6.1	4.9	.73
				(4.5)	(4.7)	(4.8)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Total # employees 2006	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	94	93	91	94	93	91
# employees 2006	106	105	103	106	105	103
Adj R-squared	.8	.81	.78	.81	.81	.78
N. of cases	362	341	337	362	341	337

Table 9: Management style and employment.

Notes: The dependent variable is the mean number of employees in 2008-2012.

areas: quality, innovation, cost, and flexibility. The responses to these questions are qualitative and they range between 1 and 4 where 1 is very important and 4 least important. Our results show that management style does not seem to correlate with quality and flexibility. Yet, firms with more structured management appear to focus more on innovation and less on costs than firms with less structured management practices. Because innovation is a long-term process (more so than cutting costs), we find this set of facts consistent with structured management firms being more focused on long-term results than less structured management firms.

Consistently with these findings in Table 11, Table 12 shows that firms with a higher intensity of style 2 management did not reduce their level of investments during the financial crisis despite their worse performance.

Finally, given the evidence in the previous two table, we investigate whether firms with higher Style 2 intensities also have lower exit rates despite their worse performance during

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.21*	.23*	.2			
	(.12)	(.12)	(.13)			
$1[\text{style } 2 > \frac{2}{3}]$				.13*	.13*	.11
				(.075)	(.076)	(.084)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.19***	.19***	.17***
				(.052)	(.057)	(.063)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Total # employees 2006	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	.32	.32	.32			
Adj R-squared	.042	.053	.066	.058	.067	.08
N. of cases	362	341	337	362	341	337

Table 10: Management style and ease of adjustment.

Notes: The dependent variable is an indicator taking the value of 1 if the mean number of employees in 2008-2012 was strictly larger than the mean number of employees in 2001-2006. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

the financial crisis. Table 13 shows that firms with higher intensity of Style 2 are indeed less likely to exit after 2007 and that this effect is mainly coming from those firms in the top tercile of the Style 2 distribution. These table reports logit regressions and controls for sector, region and value chain location fixed effects, as well as the number of employees and the percentage of sales going to exports.

In summary, we have shown evidence that firms in our sample with higher intensity of Style 2 employ labor policies that foster the development of firm culture that yields long-term benefits. These firms are less likely to layoff workers, more likely to hire workers, prioritize investment and innovation over short-term performance and bringing down costs, and they display lower exit rates. Overall, we believe this collection of evidence is consistent with a view that more structured management shows complementarities with intangible assets that

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quality Focus		Innovation Focus		Cost Focus		Flexibility Focus	
Mgt style 2	-.088	-.043	-.840***	-.829***	.659***	.639***	.266	.228
	(.174)	(.184)	(.195)	(.208)	(.205)	(.221)	(.200)	(.219)
Employment		-.036		-.323		-.150		.514
		(.451)		(.655)		(.542)		(.473)
Constant	1.773***	1.739***	3.456***	3.488***	2.129***	2.152***	2.639***	2.618***
	(.092)	(.098)	(.106)	(.116)	(.110)	(.116)	(.111)	(.115)
R-squared	.001	.001	.03	.04	.02	.02	.004	.01
N. of cases	455	438	455	438	455	438	456	439

Table 11: Management style and management priorities.

Notes: The dependent variables rank the importance of a given management focus, taking on values between 1 (very important) to 4 (least important). Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

benefits long-term performance despite shortcomings and rigidities during times of duress, in the case of our paper, during the financial crisis and the Great Recession that followed.

5.2 Additional results & robustness checks

In this section, we aim to address potential shortcomings of our analyses above. We start by running our analysis with all three periods in the same specification (instead of running the specification independently for each period, that is, before, during and after the financial crisis). In Table 14 we run regressions with the full sample. Our specifications here are augmented versions of equation 3, with period-specific dummies and their respective interactions, while still controlling for firm productivity in 2001, the firm location in the value chain, sector, and region fixed effects. Note that we winsorize data at 95% level in columns 1 to 3 and we use the full data in columns 4 to 6.

Our results in Table 14 are consistent with prior findings in sections 4.2, 4.3, and 4.4. While Style 2 management score is positively correlated with TFP during our initial base period, its interaction with the 2008-12 period dummy is negative and larger than the base period coefficient. Finally, its interaction with the post-crisis period dummy is positive. These

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mgt style 2	4.4	8	11	12				
	(5.4)	(8.5)	(9.1)	(9.7)				
$1[\text{style } 2 > \frac{2}{3}]$					2.6	3.8	5.1	5.3
					(3.4)	(4.6)	(5.1)	(5.8)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$					-.33	-1.3	-2.7	-4.5
					(2.2)	(3)	(3.2)	(3.6)
Value Chain	No	No	No	Yes	No	No	No	Yes
Export	No	No	Yes	Yes	No	No	Yes	Yes
Sector FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Region FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Capital Employed 2006	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean DV	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2
Adj R-squared	.083	.13	.092	.059	.076	.12	.12	.11
N. of cases	71	71	65	65	71	71	65	65

Table 12: Management style and capital investments.

Notes: The dependent variable is the difference in means of Total Assets - Depreciation during and pre crisis (in millions of Euros). Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

specifications can explain between 26% and 38% of the TFP variation.[24]

A separate source of concern may be our methodology to estimate differences in management practices styles across firms in our sample. On the one hand, one may argue that some of the practices included in the unsupervised algorithm are structural characteristics of the firms in our sample and, thus, not active management choices. Figure 5 shows the correlation between management Style 2 scores of our original measure and a separate measure leaving out all firm structures. See the values almost perfectly align along the 45-degree line. In

[24] A separate matter that warrants further exploration is our choice of years when defining periods before (2001-2006), during (2008-2012) and after (2014-2016) the financial crisis, leaving out 2007 and 2013 for being transition years with rather heterogenous impact across firms in the Spanish economy and, most notably, in our sample. Tables A.9, A.10, A.11 and A.12 show that including these transition years into our analysis makes our estimation less precise despite the larger amount of observations. Thus, our choice of periods in our analysis is validated.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mgt style 2	-1.2**	-1.1*	-1.1*	-.76				
	(.57)	(.6)	(.63)	(.69)				
$1[\text{sytle } 2 > \frac{2}{3}]$					-.86***	-.8**	-.85**	-.65*
					(.3)	(.33)	(.36)	(.37)
$1[\frac{1}{3} < \text{sytle } 2 \leq \frac{2}{3}]$					-.049	.058	.015	.11
					(.29)	(.31)	(.32)	(.31)
Log N Employees	No	No	No	Yes	No	No	No	Yes
Value Chain	No	No	Yes	Yes	No	No	Yes	Yes
Percent Export	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudeo R-squared	.11	.12	.13	.13	.12	.12	.14	.14
Wald Chi-Squared	39	40	44	44	65	71	79	78
N. of cases	449	427	422	422	449	427	422	422

Table 13: Management style and firm exit.

Notes: This table reports results of logit regressions. The dependent variable is a dummy taking the value of 1 if the firm exits after 2007. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

fact, results are robust to excluding survey questions reflecting structural choices rather than managerial practices for topic modeling.[25]

On the other hand, one may question our choice of methodology itself. While LDA has been used by others (Bandiera et al., 2020), there are alternative available methodologies such as Principal Component Analysis (PCA hereafter) or Structural Supervised-LDA (Hansen et al., 2018). We provide findings of using these alternative methodologies and show consistent results.

Figure 6 shows the management score estimated through LDA (our choice) and PCA are very

[25]See Appendix Tables A.13, A.14 and A.15 for results when using management Style 2 intensity containing all management practices. Some examples of structure variables that do not qualify as practices on their own are the number of hierarchical levels between plant workers and CEO, the number of workers per supervisor or who does HR report to within the organization.

	Firm productivity 95% winsorized			Firm productivity not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
1[During Crisis]	.11**	.12**	.11**	.09	.096	.087
	(.051)	(.052)	(.052)	(.058)	(.059)	(.059)
1[Post Crisis]	-.21**	-.22**	-.22**	-.22**	-.24**	-.23**
	(.091)	(.09)	(.091)	(.1)	(.1)	(.1)
Mgt style 2	.24***	.17**	.14**	.26***	.16*	.14*
	(.066)	(.071)	(.07)	(.075)	(.082)	(.083)
1[During Crisis] X Mgt style 2	-.29***	-.29***	-.27***	-.24**	-.25**	-.23**
	(.098)	(.1)	(.1)	(.11)	(.11)	(.11)
1[Post Crisis] X Mgt style 2	.3*	.29*	.29*	.3	.3	.31*
	(.16)	(.17)	(.17)	(.18)	(.19)	(.19)
Firm Productivity 2001	No	No	No	Yes	Yes	Yes
Win Firm Productivity 2001	Yes	Yes	Yes	No	No	No
1[consumer good]	No	No	Yes	No	No	Yes
1[intermediate good]	No	No	Yes	No	No	Yes
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
R-squared	.29	.38	.38	.26	.34	.35
Adj R-squared	.28	.36	.35	.26	.32	.32
N. of cases	955	955	944	955	955	944

Table 14: Management style and firms TFP 2002-2016

Notes: This table reports the results of estimating Equation (4) using OLS. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

much correlated despite the two different scales (PCA ranges between -8 and +8). Tables A.16, A.17, and A.18 show consistent results with our findings based on LDA above when examining the relationship between TFP and style 2 management score using PCA.

Following Sacher et al. (2024), we also estimate the relationship between TFP and management style using a one-step estimation called structural supervised-LDA and show our findings are

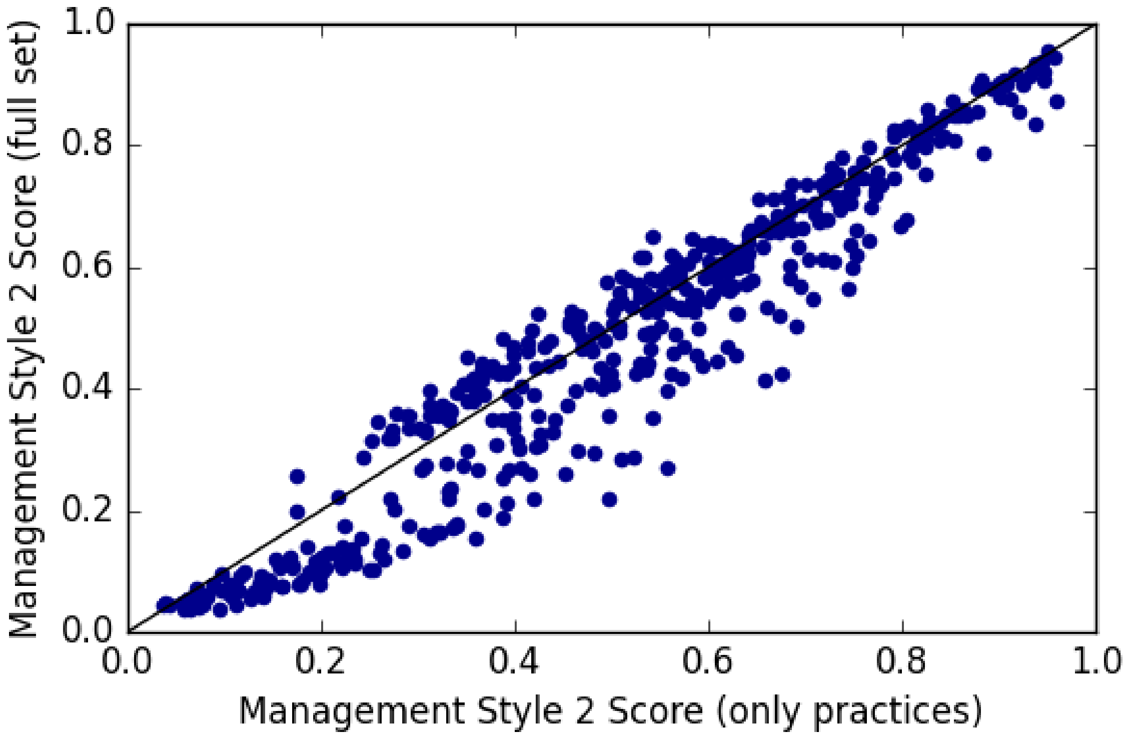


Figure 5: Correlation alternative management style estimation.

Notes: Correlation of preferred estimation of management style (includes only management practices) and alternative estimation including firm structures additionally to management practices.

robust to their alternative estimation methodology. A potential shortcoming of our two-step procedure above is that, in the second step, we implicitly ignore the statistical structure of our first-step estimation. The structural supervised-LDA accounts for the error term structure generated in the first step. Figure 7 shows the distribution of the pre-crisis, crisis and after-crisis management Style 2 coefficients. These results are consistent with our findings in prior sections and strongly support our conclusion that the nature of the relationship between productivity and structured management markedly varies over the business cycle in our sample.

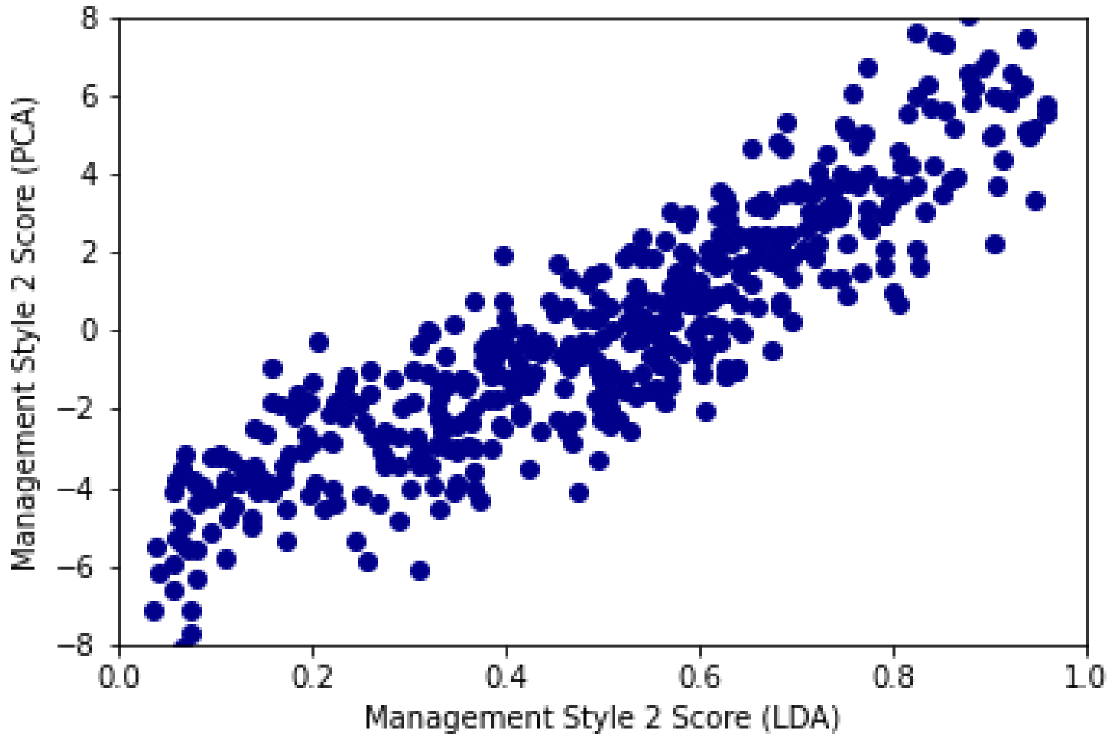


Figure 6: Correlation alternative management style estimation.

Notes: Correlation of preferred estimation of management style (includes only management practices) and estimation using PCA.

6 Conclusion

The study of management and its impact on economic performance is a central part of Economics research. Yet, rigorous empirical economic research documenting the impact of different management practices on performance has shown that management quality and structure as an input of production varies profoundly across countries, across firms within a country, and even across plants within the same firm (Bloom et al., 2019). Understanding the causes and consequences of these differences in management as well as how they explain persistent productivity differences (Bloom and van Reenen, 2007) has clear implications for policies regarding productivity, growth, and income inequality. A particular challenge for empirical studies of management practices has been that, arguably, there exist complementarities

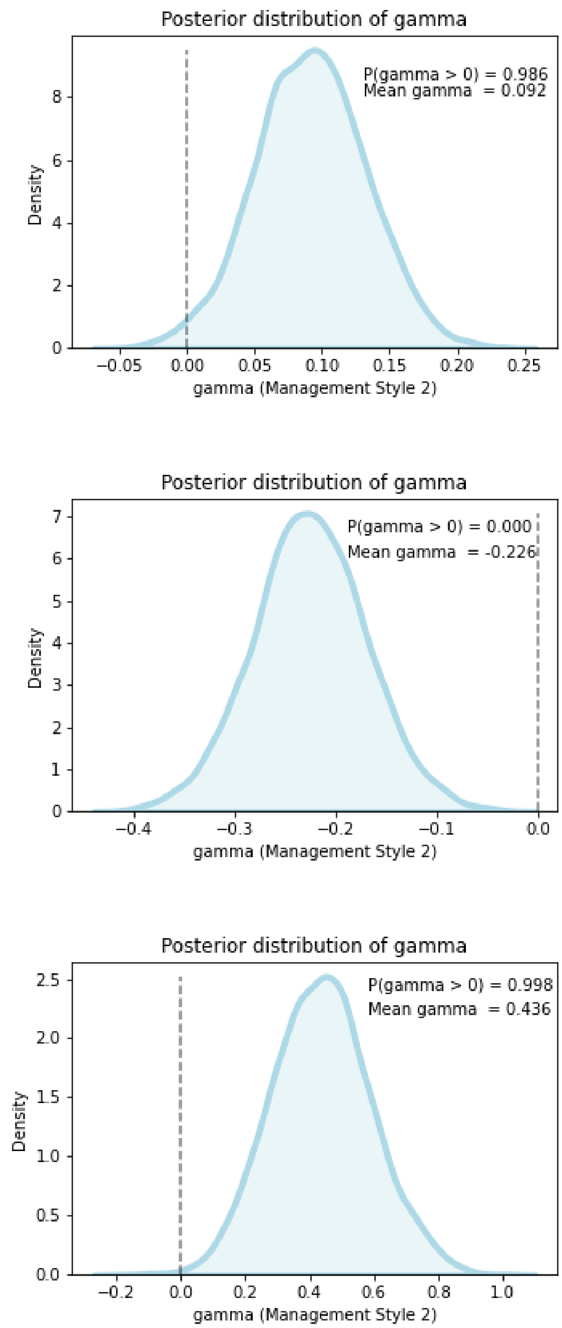


Figure 7: Regression coefficient of management Style 2 on firm productivity before (top), during (middle), and after (bottom) the Great Recession.

between individual practices, leading to sets of practices being adopted jointly by firms (Milgrom and Roberts, 1990, 1995) and, consequently, complicating the identification of effects of specific management practices.

In this paper, our approach to measure the impact of management practices embraces this complementarity. We leverage *unsupervised machine learning*, in particular *Latent Dirichlet Allocations* (LDA), to retrieve low-dimensional latent objects which we term *management styles* from highly dimensional survey data of Spanish manufacturing plants collected in 2006 (Blei et al., 2003; Erosheva et al., 2007)), that is, just prior to the onset of the great financial crisis. Intuitively, the algorithm identifies groups of practices that tend to appear together across firms but whose presence also distinguishes firms from one another. This allows us to classify every firm in our sample as a mixture of two "pure" styles: a rather informal and a rather structured style. The fact that our algorithm retrieves internally consistent clusters of practices is in line with the existence of complementarities that lead to sets of practices being adopted jointly.

The styles are meaningful in that they are not substantively determined by observable firm characteristics. Moreover, they are correlated with firm performance despite the fact that the unsupervised learning algorithm does not force clusters to explain performance (as a supervised algorithm would do). Specifically, consistent with the prior literature (Bloom and van Reenen, 2007), we find positive correlations of a more structured management style with performance prior to the financial crisis. These correlations turn negative during the financial crisis between 2008 and 2012 and turn again positive during the recovery period after 2014. In line with recent studies by Aghion et al. (2021) and McElheran et al. (2020), we conclude that while structured management may fit stable economic conditions, in times of crisis more flexible and informal styles may strive.

In terms of exploring mechanisms supporting this interpretation, we are restricted by our data. We cannot provide irrefutable evidence due to lack of exogenous variation in management practices within firms in our sample. Yet, we are able to document patterns that are consistent with an explanation such that those firms adopting more structured management practices are also those with stronger corporate cultures and intangible assets focused on survival and performance of their organization in the long run. We argue that firms endogenously select into more rigid management structures when they have valuable intangible assets such as strong culture and excellent people management processes.

In our opinion, this selection occurs because there exists strong complementarities between structured management practices and strong cultures. Structured management practices are excellent at generating metrics and quantitative measures of performance. However, these numbers are, by their nature, an incomplete story. They capture outputs but often miss the nuance of context, effort, and unforeseen challenges. Thus, organizations need a high-trust environment to harness the true power of the data generated by structured management practices. Such type of environement can only be cultivated through a strong culture and a stable workforce aligned by a long-term vision. In essence, the data provides evidence, but culture provides the wisdom to interpret it. A stable, vision-aligned culture creates the psychological safety and shared understanding necessary to transform incomplete numbers into collective progress.[26]

Although these practices are characterized by higher firms' short-term adjustment costs, these firms are able to derive higher benefits in the long-run through higher survival rates and higher levels of TFP during good economic times. In fact, we are able to show that firms with more structured management practices are less likely to lay off workers and are less likely to cut investments during the financial crisis, despite lower productivity. We are also able to document the adoption by structured management firms of single management practices that are uniquely designed to foster long-term goals for firm employees and stakeholders.

We see the contribution of our present study as twofold. On the one hand, our empirical exercise is a contribution to the study of the impact of management practices on firm performance. Furthermore, we contribute to that literature by providing evidence that management practices impact on performance may vary across times of economic stability and turmoil. On the other hand, we see our study as a proof of concept. We, as a profession, have access to a large amount of qualitative data and diverse survey data on firm organization and employment practices. Unsupervised learning algorithms, such as LDA, offer a principled way to exploit the entirety of these high-dimensional data and hence a cost effective way to further our understanding of management practices and their intricate relationship to firm performance.

[26] Castro et al. (2024) show that psychological safety (Edmondson, 1999) relates to lower turnover and more innovative behavior and show that it can be improved by guiding middle managers in their 1-to-1 conversations.

The same conclusion applies to such data in the fields of economics of innovation, entrepreneurship, and labor relations, or further fields such as advertising, logistics, and urban planning. In our modest opinion, we currently under-exploit the richness of these data, in particular not taking account of clusters and complementarities. Along with a few other contributions (Hansen et al., 2018; Bandiera et al., 2020), our paper documents the potential for the use of this new methodology in exploiting the richness of these existing data sources.

References

Ackerberg, D., Caves, K., and Frazer, G. (2015). Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451.

Aghion, P., Bloom, N., Lucking, B., Sadun, R., and VanReenen, J. (2021). Turbulence, firm decentralization and growth in bad times. *American Economic Journal: Applied Economics*, 13(1):133–169.

Almunia, M., Antras, P., Lopez-Rodriguez, D., and Morales, E. (2021). Venting out: Exports during a domestic slump. *American Economic Review*, 111(11):3611–3662.

Ann, B., Ichniowski, C., and Shaw, K. (2004). Using "insider econometrics" to study productivity. *American Economic Review*, 94(2):217–223.

Bandiera, O., Prat, A., Hansen, S., and Sadun, R. (2020). CEO behavior and firm performance. *Journal of Political Economy*, 128(4):1325–1369.

Bayo-Moriones, A., Galdon-Sanchez, J. E., and Martinez-de Morentin, S. (2013). The diffusion of pay for performance across occupations. *ILR Review*, 66(5):1115–1148.

Bayo-Moriones, A., Galdon-Sanchez, J. E., and Martinez-de Morentin, S. (2017). Performance measurement and incentive intensity. *Journal of Labor Research*, 38(4):496–546.

Bayo-Moriones, A., Galdon-Sanchez, J. E., and Martinez-de Morentin, S. (2025). Does team production rely on more or fewer employee selection procedures? *Forthcoming at British Journal of Industrial Relations*.

Bilicka, K. and Scur, D. (2024). Organizational capacity and profit shifting. *Journal of Public Economics*, 238. Article 105179.

Blader, S., Gartenberg, C., and Prat, A. (2020). The contingent effect of management practices. *The Review of Economic Studies*, 87(2):721–749.

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, 55(4):77–84.

Blei, D. M., Ng, A. Y., and Jordan, M. I. (2003). Latent dirichlet allocation. *Journal of Machine Learning Research*, 3(Jan):993–1022.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R., Patnaik, M., Saporta-Eksten, I., and van Reenen, J. (2019). What drives differences in management practices? *American Economic Review*, 109(5):1648–1683.

Bloom, N., Lemos, R., Sadun, R., Scur, D., and van Reenen, J. (2014). The new empirical economics of management. *Journal of the European Economic Association*, 12(4):835–876.

Bloom, N., Sadun, R., and van Reenen, J. (2012a). Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review*, 102(1):167–201.

Bloom, N., Sadun, R., and van Reenen, J. (2012b). The organization of firms across countries. *Quarterly Journal of Economics*, 127(4):1663–1705.

Bloom, N. and van Reenen, J. (2007). Measuring and explaining management practices across firms and countries. *Quarterly Journal of Economics*, 122(4):1351–1408.

Brynjolfsson, E. and Milgrom, P. (2013). *Handbook of Organizational Economics*, chapter Complementarity in Organizations, pages 11–55. Princeton University Press.

Castro, S., Englmaier, F., and Guadalupe, M. (2024). Fostering psychological safety in teams: Evidence from an rct. CEPR DP 202108.

Currie, J., Kleven, H., and Zwiers, E. (2020). Technology and big data are changing economics: Mining text to track methods. *American Economic Review Papers and Proceedings*, 110:42–48.

Edmondson, A. (1999). Psychological safety and learning behavior in work teams. *Administrative Science Quarterly*, 44:350–383.

Erosheva, E. A., Fienberg, S. E., and Joutard, C. (2007). Describing disability through individual-level mixture models for multivariate binary data. *Annals of Applied Statistics*, 1(2):502–537.

Gibbons, R. and Henderson, R. (2012). *What Do Managers Do?* Princeton University Press.

Graham, J., Grennan, J., Harvey, C., and Rajgopal, S. (2022a). Corporate culture: Evidence from the field. *Journal of Financial Economics*, 146(2):552–593.

Graham, J., Grennan, J., Harvey, C., and Rajgopal, S. (2022b). Corporate culture: The interview evidence. *Journal of Applied Corporate Finance*, 34(4):22–41.

Griffiths, T. L. and Steyvers, M. (2004). Finding scientific topics. *Proceedings of the National Academy of Sciences*, 101(suppl 1):5228–5235.

Hansen, S., McMahon, M., and Prat, A. (2018). Transparency and deliberation within the fomc: a computational linguistics approach. *The Quarterly Journal of Economics*, 133(2):801–870.

Helper, S. and Henderson, R. (2014). Management practices, relational contracts and the decline of general motors. *Journal of Economic Perspectives*, 28(1):49–72.

Ichniowski, C., Shaw, K., and Prennushi, G. (1997). The effects of human resource management practices on productivity: A study of steel finishing lines. *American Economic Review*, 87(3):291–313.

Lamorgese, A., Patnaik, M., Linarello, A., and Schivardi, F. (2024). Management practices and resilience to shocks: Evidence from covid-19. *Management Science*, 70(12):8217–9119.

Lazear, E. P. (2004). The Peter Principle: A theory of decline. *Journal of Political Economy*, 112(S1):S141–S163.

McElheran, K., Ohlmacher, S., and Yang, M.-J. (2020). Strategy and structured management. Forthcoming at Management Science.

Milgrom, P. and Roberts, J. (1990). The economics of modern manufacturing: Technology, strategy and organization. *American Economic Review*, 80(3):511–528.

Milgrom, P. and Roberts, J. (1995). Complementarities and fit strategy, structure, and organizational change in manufacturing. *Journal of Accounting and Economics*, 19(2-3):179–208.

Sacher, S., Battaglia, L., and Hansen, S. (2024). Hamiltonian Monte Carlo for regression with high-dimensional categorical data. Working Paper available at https://arxiv.org/html/2107.08112v2.

Smeets, V., Waldman, M., and Warzynski, F. (2019). Performance, career dynamics, and span of control. *Journal of Labor Economics*, 37(4):1183–1213.

Yang, M.-J., Christensen, M., Bloom, N., Sadun, R., and Rivkin, J. (2025). How Do Chief Execcutive Officers Make Strategy? *Management Science*. Available at https://doi.org/10.1287/mnsc.2023.03924.

	Mean	S.D.	Median	25^{th}	75^{th}	N
	(1)	(2)	(3)	(4)	(5)	(6)
	mean	sd	p50	p25	p75	count
# employees	116	114	85	56	130	463
Sales ['000 EUR]	28639	74308	10000	5000	21941	289
Year plant opened	1970	25	1976	1961	1986	456
% for export	27	28	15	2	45	438
Produces consumer good	.5	.5	1	0	1	458
Produces intermediate good	.29	.45	0	0	1	458
Produces capital good	.22	.41	0	0	0	458
Shared ownership	.67	.47	1	0	1	463
Limited liability	.27	.44	0	0	1	463
Other ownership	.063	.24	0	0	0	463

(a) Summary statistics of firms survey characteristics.

	Mean	S.D.	Median	25^{th}	75^{th}	N
	(1)	(2)	(3)	(4)	(5)	(6)
Sales 2001-2006	17249	29532	9461	5332	18476	505
Log sales 2001-2006	9.2	1	9.2	8.6	9.8	505
Total assets 2001-2006	15327	21794	8422	4374	17393	506
Log total assets 2001-2006	9.1	1.1	9	8.4	9.8	506
# employees 2001-2006	101	82	77	53	116	497
Log # employees 2001-2006	4.4	.67	4.3	4	4.8	497
Sales 2008-2012	18455	28023	9541	4306	20548	457
Log sales 2008-2012	9.1	1.2	9.2	8.4	9.9	457
Total assets 2008-2012	20879	34981	10275	4806	24034	459
Log total assets 2008-2012	9.2	1.3	9.2	8.5	10	459
# employees 2008-2012	95	85	71	43	114	451
Log # employees 2008-2012	4.2	.85	4.3	3.8	4.7	451
Sales 2014-2016	21618	32438	10570	4407	27082	363
Log sales 2014-2016	9.1	1.6	9.3	8.4	10	363
Total assets 2014-2016	22442	32762	12000	4984	28132	371
Log total assets 2014-2016	9.3	1.4	9.4	8.5	10	371
# employees 2014-2016	97	104	66	40	115	355
Log # employees 2014-2016	4.2	.99	4.2	3.7	4.7	355

(b) Summary statistics of TFP inputs.

Table A.1: Summary statistics of survey characteristics and TFP inputs.

Notes. Panel A reports summary statistics of survey-level variables used in the analysis of correlates of firm's Style 2 intensity of Table 3. Panel B provides summary statistics for inputs to the TFP estimation per time period.

	(1) Unmatched SFP mean	(2) Matched SFP mean	(3) Difference diff	p-value
Number of Employees	146.115	113.241	32.874	0.033
Percent of Export in Sales	23.618	27.067	-3.450	0.344
Gender of Plant Manager	1.053	1.077	-0.024	0.456
Age of Plant Manager	48.145	48.529	-0.384	0.745
Absenteeism in 2005	6.118	5.967	0.151	0.836
Number of Workers Quitting in 2005	14.130	11.061	3.069	0.216
Observations	78	456		

Table A.2: Unmatched and Matched Single Plant Firms. *Notes. This table reports summary statistics elicited in the survey for single-plant firms across two samples. Column (1) shows firms with incomplete survey data or without a successful match to SABI. Column (2) shows firms with complete survey data and a valid SABI match, which constitute the final regression sample. Column (3) reports p-values from testing for differences in means between Columns (1) and (2). The reported number of observations refers to the number of employees.*

Year	# Firms Reporting
2001	424
2002	443
2003	449
2004	456
2005	461
2006	457
2008	413
2009	402
2010	395
2011	370
2012	357
2014	349
2015	341
2016	331

Table A.3: Number of Firms Reporting Information Year by Year. *Notes.* This table details the number of firms within our survey that we are able to match to SABI data year by year and that in any given year report their sales, their number of employees and the value of their total assets. We report the number of firms for all years we use in our empirical analysis, that is, 2001 to 2006, 2008 to 2012 and 2014 to 2016.

	Dependent variable: 1[Style 2 intensity available]					
	(1)	(2)	(3)	(4)	(5)	(6)
Log avg # employees '01-'06	-.036					-.028
	(.019)					(.023)
Log avg tot assets '01-'06		-.019				-.019
		(.015)				(.039)
Log avg sales '01-'06			-.023			-.0072
			(.015)			(.039)
Avg net profit '01-'06 [1 mio]				-.018		-.04
				(.016)		(.025)
Avg equity '01-'06 [1 mio]					-.0014	.0067
					(.0021)	(.0044)
% without style measure	14	13	13	13	13	14
Adj R-sq	.0037	.0013	.0018	.001	-.001	.00068
N. of cases	454	513	507	513	513	454

Table A.4: SABI correlates of complete records on Style 2 measure. *Notes.* This table analyzes whether SABI data predicts if firms have complete survey records on management styles such that we can estimate their management style. The dependent variable is thus an indicator equal to 1 if a firm has a style measure, and zero otherwise. The sample size varies as SABI data is not available in all cases either. The line "% without style measure" indicates the percentage of firms without style measure in the respective regression. "Log" refers to the natural logarithm. We employ averages of all available data for a firm across the years 2001-2006. Net profit and equity are not log-transformed since they permit negative measurements. All annual records of sales, assets, profits and equity are 95% winsorized. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	Dependent variable: Style 2 intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
Log # employees 2006	.08***					.051*
	(.023)					(.022)
Log tot assets 2006		.065***				.026
		(.011)				(.024)
Log sales 2006			.071***			.034
			(.011)			(.029)
Net profit 2006 [1 mio]				.011		-.0074
				(.0058)		(.0094)
Equity 2006 [1 mio]					.0046***	-.00029
					(.001)	(.0022)
Adj R-sq	.061	.075	.079	.0027	.029	.099
N. of cases	365	417	412	417	417	364

(a) 2006 SABI data

	Dependent variable: Style 2 intensity					
	(1)	(2)	(3)	(4)	(5)	(6)
Log avg # employees '01-'06	.087***					.03
	(.022)					(.029)
Log avg tot assets '01-'06		.071***				.033
		(.011)				(.032)
Log avg sales '01-'06			.084***			.045
			(.01)			(.034)
Avg net profit '01-'06 [1 mio]				.038***		.00059
				(.01)		(.019)
Avg equity '01-'06 [1 mio]					.0071***	-.0013
					(.0013)	(.0034)
Adj R-sq	.065	.081	.092	.022	.043	.094
N. of cases	391	446	441	446	446	391

(b) 2001-2006 SABI averages.

Table A.5: SABI-data correlates of style intensity. *Notes.* This table reports results from OLS regressions where the dependent variable is a firm's Style 2 intensity, a variable between zero and one. "Log" refers to the natural logarithm. Panel (a) uses SABI data from the year 2006 while panel (b) averages all available data for a firm across the years 2001-2006. Net profit and equity are not log-transformed since they permit negative measurements. All annual records of sales, assets, profits and equity are 95% winsorized. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.37***	.4***	.38***			
	(.11)	(.12)	(.12)			
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.086	.1*	.11*
				(.054)	(.06)	(.059)
$1[\text{style } 2 > \frac{2}{3}]$				.24***	.26***	.25***
				(.059)	(.065)	(.065)
Value Chain	No	Yes	Yes	No	Yes	Yes
Export	No	Yes	Yes	No	Yes	Yes
Firm Productivity 2001	Yes	Yes	No	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.14	.16	.16	.14	.16	.16
Adj R-squared	.075	.083	.084	.075	.081	.082
N. of cases	422	398	396	422	398	396

Table A.6: Firm productivity 2002-2006 using ACF Style 2 estimates. *Notes.* This table reports the results of estimating Equation (4) using OLS. TFP estimated using ACF. All models control for 2001 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.044	-.066	-.083			
	(.096)	(.098)	(.1)			
$1[\text{style } 2 > \frac{2}{3}]$				-.058	-.074	-.084
				(.053)	(.053)	(.055)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.03	.032	.026
				(.062)	(.064)	(.066)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.39	.4	.41	.39	.4	.41
Adj R-squared	.33	.34	.34	.34	.34	.34
N. of cases	343	327	324	343	327	324

Table A.7: Firm productivity 2008-2012 using ACF Style 2 estimates. *Notes.* This table reports the results of estimating Equation (4) using OLS. TFP estimated using ACF. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.39**	.34**	.23			
	(.16)	(.17)	(.17)			
$1[\text{style } 2 > \frac{2}{3}]$				.19*	.16	.1
				(.11)	(.11)	(.11)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.17*	.17*	.14
				(.098)	(.095)	(.11)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.33	.33	.35	.33	.33	.35
Adj R-squared	.26	.24	.27	.25	.24	.26
N. of cases	286	273	270	286	273	270

Table A.8: Firm productivity 2014-2016 using ACF Style 2 estimates. *Notes.* This table reports the results of estimating Equation (4) using OLS. TFP estimated using ACF. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.14*	.15*	.13*			
	(.079)	(.075)	(.077)			
$1[\text{style } 2 > \frac{2}{3}]$				.079	.091*	.083
				(.051)	(.053)	(.05)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.077	.057	.062
				(.049)	(.043)	(.044)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Firm Productivity 2001	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.52	.59	.6	.52	.59	.6
Adj R-squared	.47	.55	.55	.47	.55	.55
N. of cases	355	337	333	355	337	333

Table A.9: Management style and firms' TFP 2002-2007. *Notes.* This table reports the results of estimating Equation (3) using OLS. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.23***	-.24***	-.23**			
	(.088)	(.088)	(.088)			
$1[\text{style 2} > \frac{2}{3}]$				-.14***	-.15***	-.14***
				(.049)	(.05)	(.05)
$1[\frac{1}{3} < \text{style 2} \leq \frac{2}{3}]$				-.025	-.029	-.034
				(.051)	(.052)	(.052)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.4	.43	.44	.4	.44	.44
Adj R-squared	.36	.39	.39	.36	.39	.39
N. of cases	414	391	386	414	391	386

Table A.10: Firm productivity 2007-2012. *Notes.* This table reports the results of estimating Equation (4) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.062	-.093	-.099			
	(.093)	(.095)	(.095)			
$1[\text{style } 2 > \frac{2}{3}]$				-.045	-.059	-.062
				(.055)	(.057)	(.056)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.013	.0071	-.00065
				(.052)	(.053)	(.053)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.45	.47	.47	.45	.47	.48
Adj R-squared	.41	.42	.42	.41	.42	.42
N. of cases	388	366	362	388	366	362

Table A.11: Firm productivity 2008-2013. *Notes.* This table reports the results of estimating Equation (4) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.034	-.044	-.087			
	(.14)	(.15)	(.15)			
$1[\text{style } 2 > \frac{2}{3}]$				-.033	-.045	-.068
				(.088)	(.096)	(.097)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				-.016	-.005	-.023
				(.069)	(.07)	(.07)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.39	.37	.37	.39	.37	.37
Adj R-squared	.32	.29	.3	.32	.29	.29
N. of cases	307	291	288	307	291	288

Table A.12: Firm productivity 2013-2016. *Notes.* This table reports the results of estimating Equation (4) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.2**	.2**	.18**			
	(.085)	(.082)	(.082)			
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.042	.058	.062
				(.046)	(.042)	(.042)
$1[\text{style } 2 > \frac{2}{3}]$				.13**	.13**	.12**
				(.055)	(.059)	(.054)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Firm Productivity 2001	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.52	.57	.58	.52	.57	.58
Adj R-squared	.48	.53	.54	.48	.53	.54
N. of cases	361	344	340	361	344	340

Table A.13: Management style and firms' TFP 2002-2006 using Style 2 with all management practices. *Notes.* This table reports the results of estimating Equation (3) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.17*	-.19**	-.18**			
	(.091)	(.092)	(.093)			
$1[\text{style } 2 > \frac{2}{3}]$				-.14**	-.16**	-.15**
				(.06)	(.061)	(.059)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				-.049	-.051	-.058
				(.052)	(.053)	(.053)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.38	.4	.41	.38	.41	.41
Adj R-squared	.33	.35	.35	.33	.35	.35
N. of cases	388	366	362	388	366	362

Table A.14: Firm productivity 2008-2012 using Style 2 with all management practices. *Notes.* This table reports the results of estimating Equation (4) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.24	.26	.22			
	(.18)	(.18)	(.19)			
$1[\text{style 2} > \frac{2}{3}]$				.077	.073	.041
				(.12)	(.13)	(.13)
$1[\frac{1}{3} < \text{style 2} \leq \frac{2}{3}]$				.041	.07	.058
				(.093)	(.096)	(.098)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.47	.46	.47	.46	.46	.47
Adj R-squared	.41	.4	.4	.41	.39	.4
N. of cases	299	283	280	299	283	280

Table A.15: Firm productivity 2014-2016 using Style 2 with all management practices. *Notes.* This table reports the results of estimating Equation (4) using OLS. All models control for 2001-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.21*	.2*	.18*			
	(.11)	(.11)	(.11)			
$1[\text{style } 2 > \frac{2}{3}]$				.092	.088	.068
				(.059)	(.064)	(.057)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.013	-.013	-.011
				(.055)	(.048)	(.048)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Firm Productivity 2001	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.52	.57	.58	.52	.57	.58
Adj R-squared	.47	.53	.54	.47	.53	.53
N. of cases	361	344	340	361	344	340

Table A.16: Firm productivity 2002-2006 using PCA Style 2 estimates. *Notes.* This table reports the results of estimating Equation (4) using OLS. Management Style estimated with PCA. All models control for 2001 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.18	-.23**	-.23**			
	(.11)	(.11)	(.11)			
$1[\text{style } 2 > \frac{2}{3}]$				-.1	-.12*	-.11*
				(.064)	(.062)	(.061)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				-.049	-.067	-.071*
				(.045)	(.043)	(.042)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.38	.4	.41	.38	.4	.41
Adj R-squared	.33	.35	.35	.33	.34	.35
N. of cases	388	366	362	388	366	362

Table A.17: Firm productivity 2008-2012 using PCA Style 2 estimates. *Notes.* This table reports the results of estimating Equation (4) using OLS. Management Style estimated with PCA. All models control for 2002-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.38*	.34	.27			
	(.21)	(.22)	(.23)			
$1[\text{style } 2 > \frac{2}{3}]$				.23*	.22*	.19
				(.13)	(.13)	(.12)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$				.03	.047	.036
				(.093)	(.09)	(.094)
Value Chain	No	No	Yes	No	No	Yes
Export	No	Yes	Yes	No	Yes	Yes
Pre-Crisis Productivity	Yes	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.47	.46	.47	.47	.47	.47
Adj R-squared	.41	.4	.4	.41	.4	.4
N. of cases	299	283	280	299	283	280

Table A.18: Firm productivity 2014-2016 using PCA Style 2 estimates. *Notes.* This table reports the results of estimating Equation (4) using OLS. Management Style estimated with PCA. All models control for 2002-2006 TFP. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

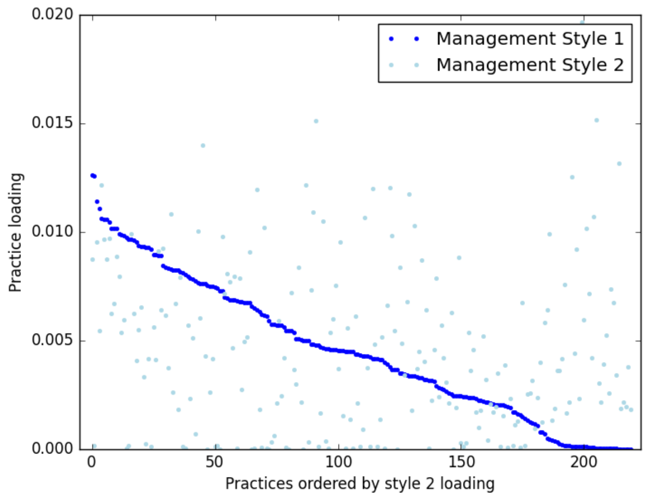


Figure A.1: Style-over-practice distributions.

Notes: In this figure we visualize differences in practices' loadings across both latent style distributions. The distributions were estimated using the single-plant sample alone. Each style is a distribution across 272 observed practices with each practice having a positive weight, and with the sum of weights summing to one. The practices are ordered such that the practice with the highest loading on Style 1 is the far left of the x-axis. The y-axis shows the respective loadings of practices.

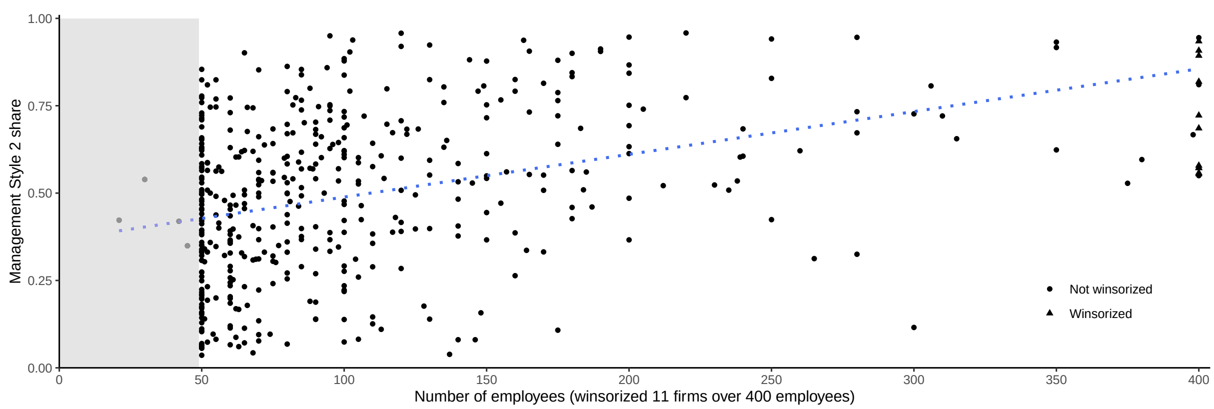


Figure A.2: Style 2 intensity and firms' number of employees. *Notes.* This figure plots the simple univariate relationship between a firm's Style 2 intensity, and its self-reported number of employees from the survey. 11 firms with over 400 employees were winsorized for visual ease; they are represented with triangles rather than circles. The dotted blue line shows the line of linear best fit. Grey dots on the far left of the figure indicate firms that report less than 50 employees.

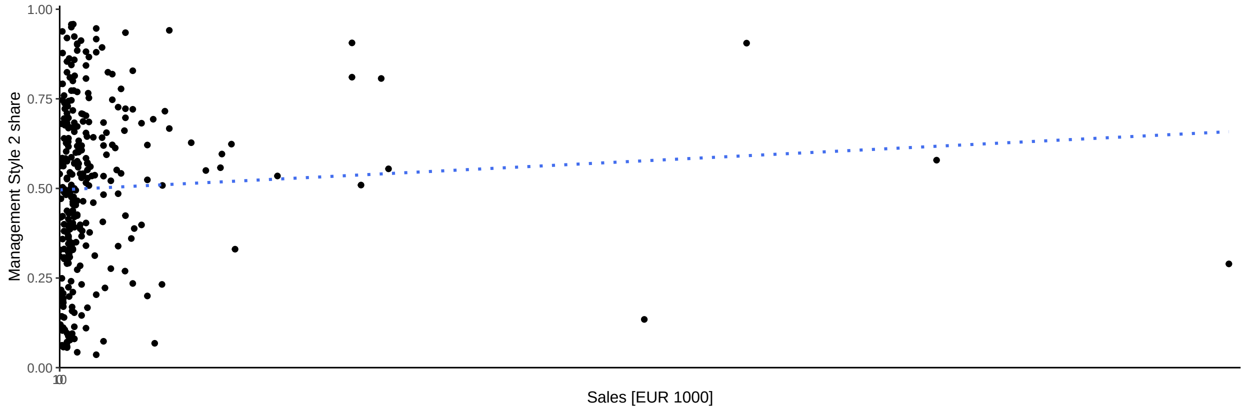


Figure A.3: Style 2 share and annual sales. .

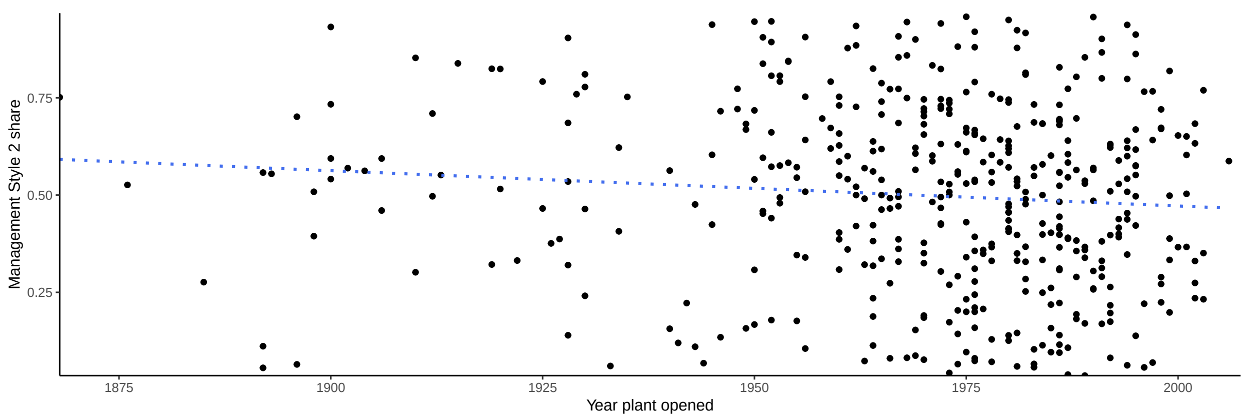


Figure A.4: Style 2 share and year of plant opening. .

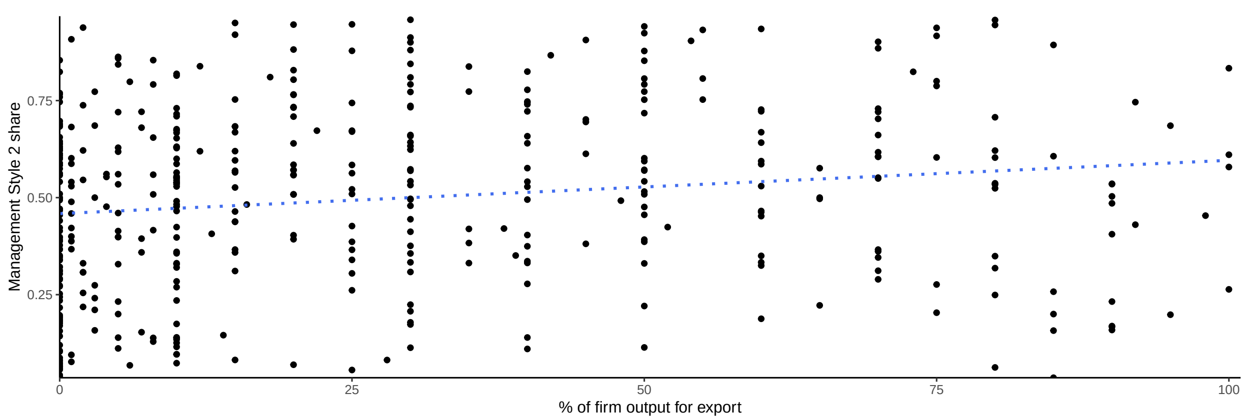


Figure A.5: Style 2 share and percentage of exports over total sales. .

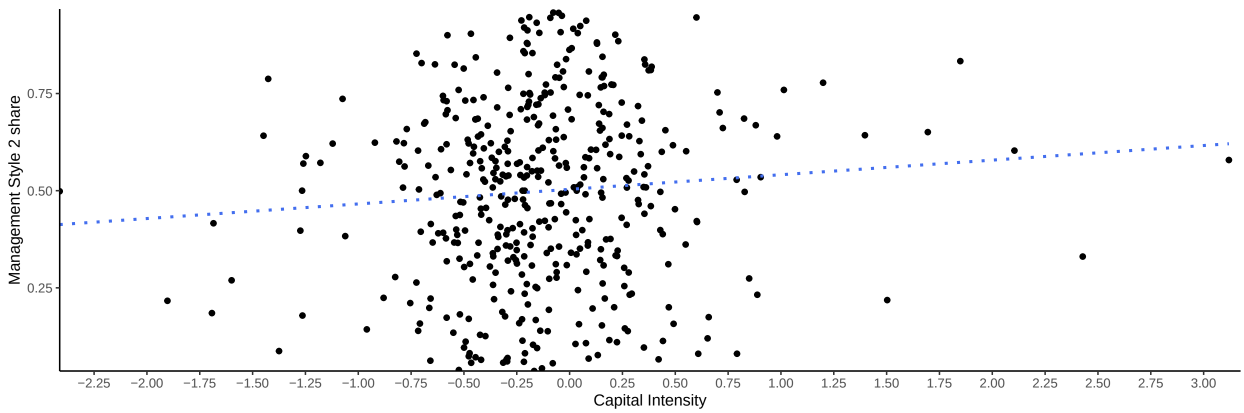


Figure A.6: Style 2 share and capital intensity (assets over total sales).

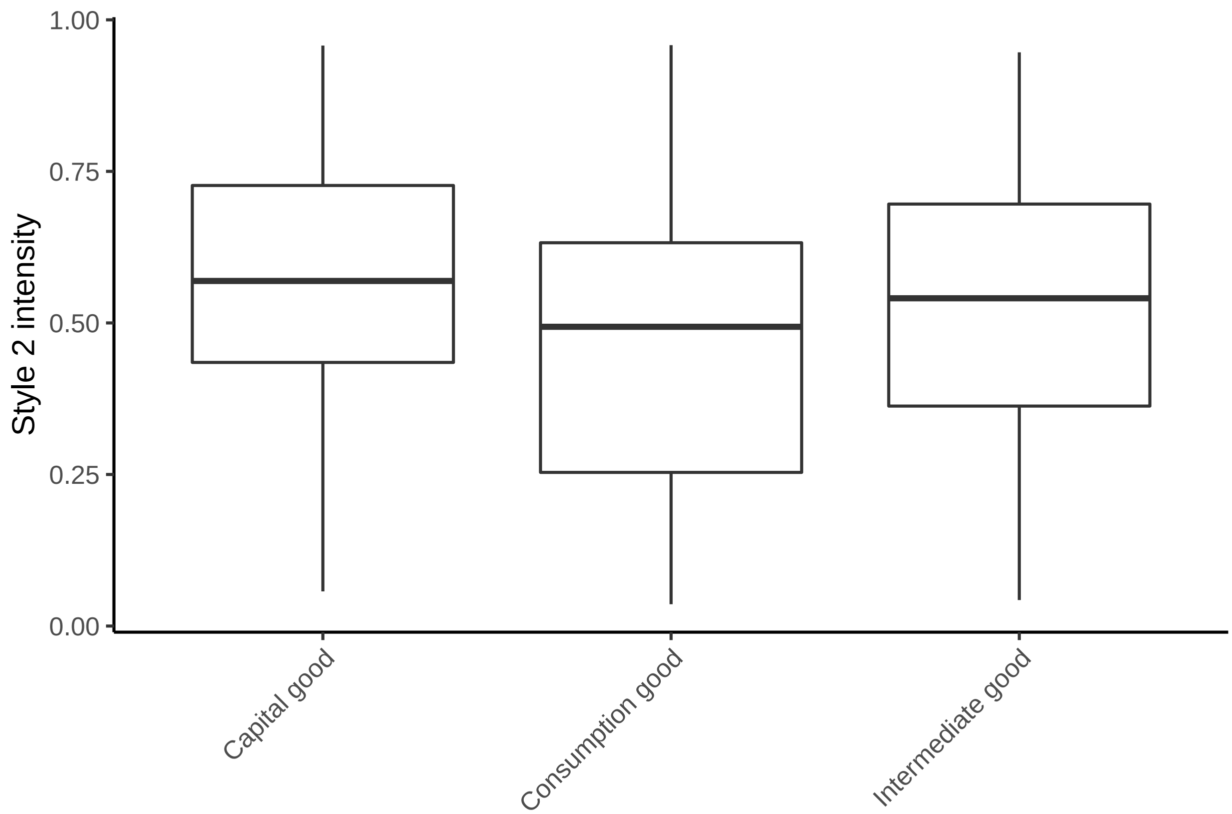


Figure A.7: Style 2 share along the value chain. .

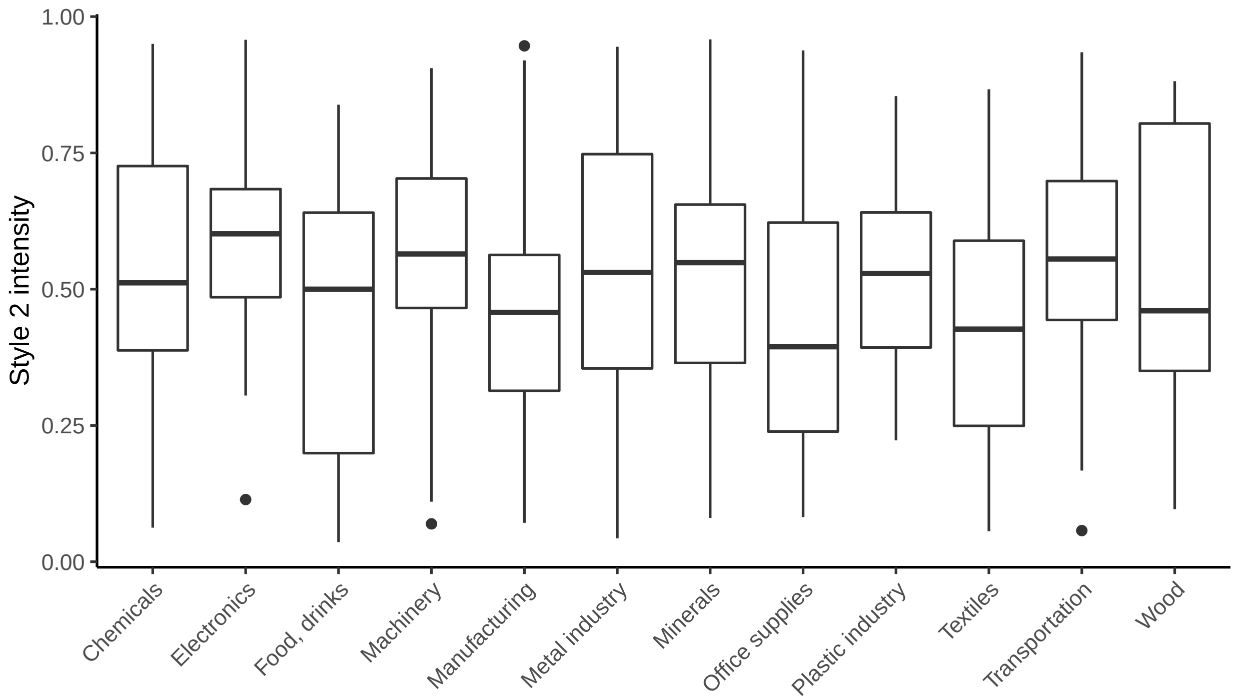


Figure A.8: Style 2 share across different manufacturing sectors. .

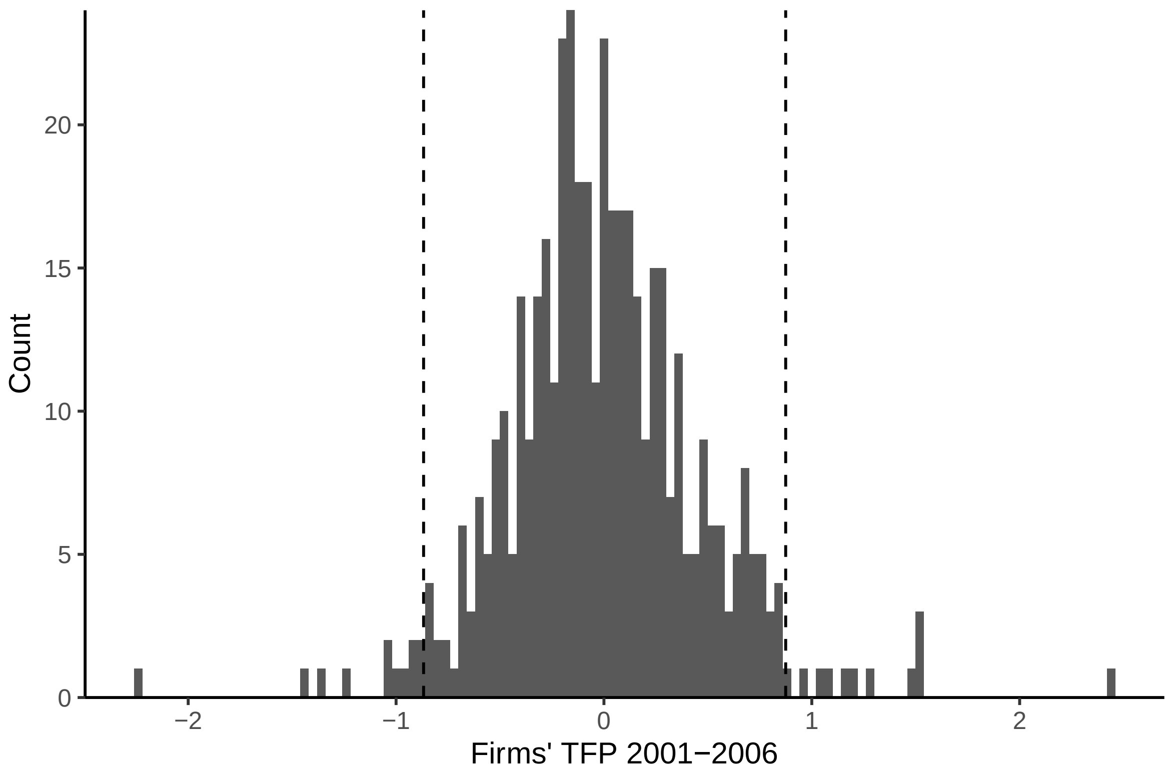


Figure A.9: Firms's total factor productivity 2001-2006. *Notes.* This figure shows a histogram of firms' total factor productivity before the Great Recession using data from 2001-2006. We plot the predicted value of α obtained from estimating Equation (2). The histogram is constructed using a constant binwidth of 0.04. The vertical lines mark the 2.5^{th} and the 97.5^{th} percentile of the distribution. We use these values to winsorize the distribution in some specifications.

B Appendix

Table B.1: Overview of management practices.

Practice indicator	#	Question text	Answer	Mean
manage_priority_1_cost	A.10	How important are these factor to manage the plant?	First priority: Cost	0.22
manage_priority_1_flexibility	A.10	How important are these factor to manage the plant?	First priority: Flexibility	0.14
manage_priority_1_innovation	A.10	How important are these factor to manage the plant?	First priority: Innovation	0.13
manage_priority_1_quality	A.10	How important are these factor to manage the plant?	First priority: Quality	0.51
manage_priority_2_cost	A.10	How important are these factor to manage the plant?	Second Priority: Cost	0.30
manage_priority_2_flexibility	A.10	How important are these factor to manage the plant?	Second Priority: Flexibility	0.24
manage_priority_2_innovation	A.10	How important are these factor to manage the plant?	Second Priority: Innovation	0.17
manage_priority_2_quality	A.10	How important are these factor to manage the plant?	Second Priority: Quality	0.28
manage_priority_3_cost	A.10	How important are these factor to manage the plant?	Third Priority: Cost	0.27
manage_priority_3_flexibility	A.10	How important are these factor to manage the plant?	Third Priority: Flexibility	0.33
manage_priority_3_innovation	A.10	How important are these factor to manage the plant?	Third Priority: Innovation	0.22
manage_priority_3_quality	A.10	How important are these factor to manage the plant?	Third Priority: Quality	0.17
manage_priority_4_cost	A.10	How important are these factor to manage the plant?	Forth Priority: Cost	0.21
manage_priority_4_flexibility	A.10	How important are these factor to manage the plant?	Forth Priority: Flexibility	0.29
manage_priority_4_innovation	A.10	How important are these factor to manage the plant?	Forth Priority: Innovation	0.47
manage_priority_4_quality	A.10	How important are these factor to manage the plant?	Forth Priority: Quality	0.03
num_certification_is1	A.18-20	Is plant certified with ISO 9000? + Some other certification? + . ISO 14000?	1 Certification?	0.38
num_certification_mt1	A.18-20	Is plant certified with ISO 9000? + Some other certification? + . ISO 14000?	More than 1 Certification?	0.33
num_certification_is0	A.18-20	Is plant certified with ISO 9000? + Some other certification? + . ISO 14000?	0 certifications?	0.29
recruit_personality	B.5	What of these tools are used in recruitment?	Personality	0.14
recruit_iq	B.5	What of these tools are used in recruitment?	IQ	0.07
recruit_genknowl	B.5	What of these tools are used in recruitment?	General Knowledge test	0.21
recruit_persint	B.5	What of these tools are used in recruitment?	Personal Interview	0.90
recruit_groupdyn	B.5	What of these tools are used in recruitment?	Group Dynamics	0.03

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Practice indicator	#	Question text	Answer	Mean
recruit_outsourced	B.5	What of these tools are used in recruitment?	Outsourced	0.03
hire_prim_age	B.6	Which of these factors does this plant take into account when hiring?	Primary: Age	0.05
hire_prim_education	B.6	Which of these factors does this plant take into account when hiring?	Primary: Education	0.16
hire_prim_experience	B.6	Which of these factors does this plant take into account when hiring?	Primary: Experience	0.54
hire_prim_personality	B.6	Which of these factors does this plant take into account when hiring?	Primary: Personality	0.05
hire_prim_qualification	B.6	Which of these factors does this plant take into account when hiring?	Primary: Qualification	0.12
hire_prim_teamwork	B.6	Which of these factors does this plant take into account when hiring?	Primary: Teamwork	0.06
hire_second_age	B.6	Which of these factors does this plant take into account when hiring?	Secondary: Age	0.12
hire_second_education	B.6	Which of these factors does this plant take into account when hiring?	Secondary: Education	0.24
hire_second_experience	B.6	Which of these factors does this plant take into account when hiring?	Secondary: Experience	0.14
hire_second_personality	B.6	Which of these factors does this plant take into account when hiring?	Secondary: Personality	0.09
hire_second_qualification	B.6	Which of these factors does this plant take into account when hiring?	Secondary: Qualification	0.23
hire_second_teamwork	B.6	Which of these factors does this plant take into account when hiring?	Secondary: Teamwork	0.15
emplys_train_outside_amed	B.7	Percentage of workers got training outside of the plant and paid by the firm in 2005.	Percentage ¿ 50%	0.51
managers_fromwithin_all	B.9	How many supervisors and middle managers in the plant have previously been plain workers in the plant?	All	0.27
managers_fromwithin_bot_p20	B.9	How many supervisors and middle managers in the plant have previously been plain workers in the plant?	Bottom 20 %	0.12
managers_fromwithin_none	B.9	How many supervisors and middle managers in the plant have previously been plain workers in the plant?	None	0.03
managers_fromwithin_p21p40	B.9	How many supervisors and middle managers in the plant have previously been plain workers in the plant?	21 % - 40 %	0.11
managers_fromwithin_p41p60	B.9	How many supervisors and middle managers in the plant have previously been plain workers in the plant?	41 % - 60 %	0.09
managers_fromwithin_p61p80	B.9	How many supervisors and middle managers in the plant have previously been plain workers in the plant?	61 % - 80 %	0.17

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Practice indicator	#	Question text	Answer	Mean
managers_fromwithin_top_p20	B.9	How many supervisors and middle managers in the plant have previously been plain workers in the plant?	Top 20 %	0.19
vacant_spots_how_no_pref	B.10	How do you fill in vacant spots in the plant? 4 options.	No preference	0.07
vacant_spots_how_only_extern	B.10	How do you fill in vacant spots in the plant? 4 options.	Only external candidates	0.02
vacant_spots_how_only_internal	B.10	How do you fill in vacant spots in the plant? 4 options.	Only internal candidates	0.50
vacant_spots_how_pref_extern	B.10	How do you fill in vacant spots in the plant? 4 options.	Prefer external	0.02
vacant_spots_how_pref_internal	B.10	How do you fill in vacant spots in the plant? 4 options.	Prefer internal	0.37
promotion_criterion_equal	B.11	When promoting workers, rank seniority and merit.	Equally	0.19
promotion_criterion_merrit	B.11	When promoting workers, rank seniority and merit.	Merit	0.02
promotion_criterion_seniority	B.11	When promoting workers, rank seniority and merit.	Seniority	0.76
fin_discl_wrks_no	B.12	Do you publicly and periodically report financial status of the plant to workers?	No	0.33
fin_discl_wrks_reps	B.12	Do you publicly and periodically report financial status of the plant to workers?	Periodically?	0.39
fin_discl_wrks_yes	B.12	Do you publicly and periodically report financial status of the plant to workers?	Yes	0.28
emplys_represn_council	B.13	Are plant workers represented somehow?	Council	0.75
emplys_represn_delgates	B.13	Are plant workers represented somehow?	Delegates	0.12
emplys_represn_none	B.13	Are plant workers represented somehow?	No representation	0.11
emplys_represn_other	B.13	Are plant workers represented somehow?	Other form of representation	0.02
labor_agreement_collect_branch	B.14	Describe labor conditions in the plant? Type of labor agreement in place.	Sectoral agreement	0.52
labor_agreement_collect_firm	B.14	Describe labor conditions in the plant? Type of labor agreement in place.	Firm level agreement	0.38
labor_agreement_other	B.14	Describe labor conditions in the plant? Type of labor agreement in place.	Other	0.09
union_influence_high	B.15	Describe union influence on worker behavior.	High influence	0.29
union_influence_low	B.15	Describe union influence on worker behavior.	Low influence	0.33
union_influence_medium	B.15	Describe union influence on worker behavior.	Medium Influence	0.18
union_influence_veryhigh	B.15	Describe union influence on worker behavior.	Very high Influence	0.03
union_influence_verylow	B.15	Describe union influence on worker behavior.	Very low influence	0.12
lowprod_tol_below6	B.16	Tolerance towards worker of continuous low productivity.	Tolerance below 6	0.43
workers_incentivepay_mt0	C.1	Does any manufacturing worker receive variable pay/incentives?	More than 0	0.44

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Practice indicator	#	Question text	Answer	Mean
share_variablepay_11to20	C.2	Of those receiving variable pay, what percentage of their pay is variable?	11 - 20%	0.21
share_variablepay_1to10	C.2	Of those receiving variable pay, what percentage of their pay is variable?	1 - 10%	0.15
share_variablepay_21to30	C.2	Of those receiving variable pay, what percentage of their pay is variable?	21 - 30%	0.05
share_variablepay_30plus	C.2	Of those receiving variable pay, what percentage of their pay is variable?	31%+	0.06
share_variablepay_none	C.2	Of those receiving variable pay, what percentage of their pay is variable?	None	0.49
incentivepay_indivperf	C.3	What type of incentives are used, what percentage of workers receive these, and what percentage of their pay comes from this incentive?	Individual performance	0.32
incentivepay_firmperf	C.3	What type of incentives are used, what percentage of workers receive these, and what percentage of their pay comes from this incentive?	Firm performance	0.08
incentivepay_teamperf	C.3	What type of incentives are used, what percentage of workers receive these, and what percentage of their pay comes from this incentive?	Team performance	0.17
fixedsalary_task	C.4	What determines the fixed part of the workers compensation?	Type of task	0.80
fixedsalary_training	C.4	What determines the fixed part of the workers compensation?	Training	0.77
fixedsalary_tenure	C.4	What determines the fixed part of the workers compensation?	Tenure	0.61
fixedsalary_pasteval	C.4	What determines the fixed part of the workers compensation?	Past evaluations	0.65
fixedsalary_exper	C.4	What determines the fixed part of the workers compensation?	Experience	0.76
fixedsalary_ability	C.4	What determines the fixed part of the workers compensation?	Ability	0.79
fixedsalary_shift	C.4	What determines the fixed part of the workers compensation?	Shift	0.67
fixedsalary_personal	C.4	What determines the fixed part of the workers compensation?	Personal circumstances	0.45
payraise_inflation	C.6	What determines wage increases?	Inflation	0.57
payraise_recruit	C.6	What determines wage increases?	Recruiting and retention	0.44
payraise_results	C.6	What determines wage increases?	Firm results	0.49
payraise_atmosp	C.6	What determines wage increases?	Keeping good environment	0.54
payraise_compete	C.6	What determines wage increases?	Salaries of competing firms	0.38

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Practice indicator	#	Question text	Answer	Mean
payraise_law	C.6	What determines wage increases?	Law/labour agreements	0.61
payraise_hq	C.6	What determines wage increases?	Headquarter	0.25
workers_buyequity	C.7	Can workers buy equity on the firm?	Buy Equities of the firm or not	0.05
perks_discounts	C.9	Do you use these perks in your plant?	Discount for the final product	0.32
perks_family	C.9	Do you use these perks in your plant?	Family-based help	0.26
perks_xmasgift	C.9	Do you use these perks in your plant?	Christmas gift	0.80
perks_pension	C.9	Do you use these perks in your plant?	Pension	0.09
perks_lifeinsur	C.9	Do you use these perks in your plant?	Life insurance	0.26
perks_healthinsur	C.9	Do you use these perks in your plant?	Health insurance	0.11
type_eval_system_None	C.11	Does the firm use formal or informal evaluation systems? Both?	None	0.61
type_eval_system_both	C.11	Does the firm use formal or informal evaluation systems? Both?	Both	0.22
type_eval_system_objective	C.11	Does the firm use formal or informal evaluation systems? Both?	Objective / formal	0.15
type_eval_system_subjective	C.11	Does the firm use formal or informal evaluation systems? Both?	Subjective / informal	0.03
eval_frequency_semester_more	C.13	How often?	More than semester	0.17
eval_frequency_trimester	C.13	How often?	Trimester	0.23
wrk_eval_sup	C.14	Who evaluates the workers?	Supervisor?	0.18
wrk_eval_mng	C.14	Who evaluates the workers?	Manager	0.15
wrk_eval_hr	C.14	Who evaluates the workers?	HR	0.11
eval_for_salary	C.15	Evaluation results affect the workers salary increases, on-the-job training, promotion, firing?	Salary	0.25
eval_for_onjobtrain	C.15	Evaluation results affect the workers' salary increases, on-the-job training, promotion, firing?	On job training	0.20
eval_for_promotion	C.15	Evaluation results affect the workers' salary increases, on-the-job training, promotion, firing?	Promotion	0.32
eval_for_firing	C.15	Evaluation results affect the workers' salary increases, on-the-job training, promotion, firing?	Firing	0.24
hierarch_lv_trend_diminishing	D.1	What's the trend in the number of hierarchical levels in the plant?	Down	0.19
hierarch_lv_trend_increasing	D.1	What's the trend in the number of hierarchical levels in the plant?	Up	0.13
hierarch_lv_trend_nochange	D.1	What's the trend in the number of hierarchical levels in the plant?	Same	0.68
hierarchy_lev_12	D.2	How many hierarchical levels between supervisor and plant manager?	12 levels?	0.19

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Practice indicator	#	Question text	Answer	Mean
hierarchy_lev_3	D.2	How many hierarchical levels between supervisor and plant manager?	3 levels?	0.36
hierarchy_lev_4	D.2	How many hierarchical levels between supervisor and plant manager?	4 levels?	0.27
hierarchy_lev_5p	D.2	How many hierarchical levels between supervisor and plant manager?	5 levels?	0.18
wrksperspv_hl12_amed	D.3	What is the number of workers under one same supervisor?	12?	0.11
wrksperspv_hl3_amed	D.3	What is the number of workers under one same supervisor?	3?	0.18
wrksperspv_hl4_amed	D.3	What is the number of workers under one same supervisor?	4?	0.15
wrksperspv_hl5p_amed	D.3	What is the number of workers under one same supervisor?	5?	0.09
spv_coord_vimp	D.4a	What characterizes the job of a supervisor?	Coordination	0.65
spv_prod_vimp	D.4a	What characterizes the job of a supervisor?	Production	0.38
spv_deal_vimp	D.4a	What characterizes the job of a supervisor?	Problem solving	0.48
spv_spv_vimp	D.4a	What characterizes the job of a supervisor?	Supervision	0.47
spv_quality_vimp	D.4a	What characterizes the job of a supervisor?	Quality	0.47
spv_comm_act_vimp	D.4a	What characterizes the job of a supervisor?	Information flow	0.38
spv_comm_lev_vimp	D.4a	What characterizes the job of a supervisor?	Upstream communication	0.44
degr_spvision_high	D.5	How would you describe the degree of control/supervision of plant workers?	High amount of supervision	0.40
degr_spvision_low	D.5	How would you describe the degree of control/supervision of plant workers?	Low amount of supervision	0.06
degr_spvision_medium	D.5	How would you describe the degree of control/supervision of plant workers?	Medium amount of supervision	0.54
wrks_rot_pct_is0	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Rotation: 0%	0.21
wrks_rot_pct_b0l50	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Rotation: Between 0 and 50%	0.62
wrks_rot_pct_mt50	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Rotation: More than 50%	0.17
wrks_team_pct_is0	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Work in teams: 0	0.32
wrks_team_pct_b0l50	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Work in teams: between 0 and 50%	0.42
wrks_team_pct_mt50	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Work in teams: more than 50%	0.26

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Practice indicator	#	Question text	Answer	Mean
wrks_impr_pct_is0	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Contribute to improvement in processes: 0	0.47
wrks_impr_pct_b0l50	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Contribute to improvement in processes: between 0 and 50%	0.41
wrks_impr_pct_mt50	D.6	Percentage of workers that rotate jobs, work in teams, contribute to improvement in processes?	Contribute to improvement in processes: more than 50%	0.12
plant_prep_machines_is0	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Prepare machines they use: 0	0.14
plant_prep_machines_b0l50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Prepare machines they use: between 0 and 50%	0.13
plant_prep_machines_mt50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Prepare machines they use:	0.73
plant_maintenance_is0	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Do maintenance: 0	0.21
plant_maintenance_b0l50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Do maintenance: between 0 and 50%	0.22
plant_maintenance_mt50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Do maintenance: More than 50%	0.57
plant_data_is0	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Analyse Data: 0	0.22
plant_data_b0l50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Analyse Data: between 0 and 50%	0.25

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Practice indicator	#	Question text	Answer	Mean
plant_data_mt50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Analyse Data: More than 50%	0.53
plant_work_orga_is0	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Organize their workload autonomously: 0	0.24
plant_work_orga_b0l50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Organize their workload autonomously: between 0 and 50%	0.30
plant_work_orga_mt50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Organize their workload autonomously: More than 50%	0.47
plant_pace_is0	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Set their own pace: 0	0.20
plant_pace_b0l50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Set their own pace: between 0 and 50%	0.22
plant_pace_mt50	D.7	To what extent plant workers prepare machines they use, do maintenance, analyze data, organize their workload autonomously, set their own pace?	Set their own pace: More than 50%	0.58
task_monotonicity_is0	D.8	Jobs of plant workers are monotone, complex, manual?	Monotone: 0	0.07
task_monotonicity_b0l50	D.8	Jobs of plant workers are monotone, complex, manual?	Monotone: between 0 and 50%	0.17
task_monotonicity_mt50	D.8	Jobs of plant workers are monotone, complex, manual?	Monotone: More than 50%	0.76
task_tec_complexity_is0	D.8	Jobs of plant workers are monotone, complex, manual?	Complex: 0	0.12
task_tec_complexity_b0l50	D.8	Jobs of plant workers are monotone, complex, manual?	Complex: between 0 and 50%	0.34
task_tec_complexity_mt50	D.8	Jobs of plant workers are monotone, complex, manual?	Complex: More than 50%	0.54
task_manual_is0	D.8	Jobs of plant workers are monotone, complex, manual?	Manual: 0	0.03
task_manual_b0l50	D.8	Jobs of plant workers are monotone, complex, manual?	Manual: between 0 and 50%	0.20
task_manual_mt50	D.8	Jobs of plant workers are monotone, complex, manual?	Manual: More than 50%	0.77

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Practice indicator	#	Question text	Answer	Mean
hr_absent_important	E.8	Rate the importance of HR goals?	Reduce absenteeism: Important	0.37
hr_absent_medium	E.8	Rate the importance of HR goals?	Reduce absenteeism: Medium importance	0.49
hr_absent_unimportant	E.8	Rate the importance of HR goals?	Reduce absenteeism: Unimportant	0.13
hr_moti_important	E.8	Rate the importance of HR goals?	Motivate employees: Important	0.47
hr_moti_medium	E.8	Rate the importance of HR goals?	Motivate employees: Medium importance	0.47
hr_moti_unimportant	E.8	Rate the importance of HR goals?	Motivate employees: Unimportant	0.06
hr_costs_important	E.8	Rate the importance of HR goals?	Reduce labor cost: Important	0.48
hr_costs_medium	E.8	Rate the importance of HR goals?	Reduce labor cost: Medium importance	0.48
hr_costs_unimportant	E.8	Rate the importance of HR goals?	Reduce labor cost: Unimportant	0.04
hr_climate_important	E.8	Rate the importance of HR goals?	Improve morale: Important	0.51
hr_climate_medium	E.8	Rate the importance of HR goals?	Improve morale: Medium importance	0.44
hr_climate_unimportant	E.8	Rate the importance of HR goals?	Improve morale: Unimportant	0.06
hr_retention_important	E.8	Rate the importance of HR goals?	Retention: Important	0.43
hr_retention_medium	E.8	Rate the importance of HR goals?	Retention: Medium importance	0.51
hr_retention_unimportant	E.8	Rate the importance of HR goals?	Retention: Unimportant	0.06
hr_recruit_important	E.8	Rate the importance of HR goals?	Recruitment: Important	0.42
hr_recruit_medium	E.8	Rate the importance of HR goals?	Recruitment: Medium importance	0.51
hr_recruit_unimportant	E.8	Rate the importance of HR goals?	Recruitment: Unimportant	0.07
hr_red_wrks_important	E.8	Rate the importance of HR goals?	Reduce number of workers: Important	0.26
hr_red_wrks_medium	E.8	Rate the importance of HR goals?	Reduce number of workers: Medium importance	0.18
hr_red_wrks_unimportant	E.8	Rate the importance of HR goals?	Reduce number of workers: Unimportant	0.56
hr_abil_important	E.8	Rate the importance of HR goals?	Improve training and ability: Important	0.50

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Practice indicator	#	Question text	Answer	Mean
hr_abil_medium	E.8	Rate the importance of HR goals?	Improve training and ability: Medium importance	0.42
hr_abil_unimportant	E.8	Rate the importance of HR goals?	Improve training and ability: Unimportant	0.08
hr_strategy	F.1	Is there a strategic plan in the plant detailing HR goals?	There is a strategic plan	0.33
hr_decision_admin	F.3	Where are HR decisions made?	Administration	0.15
hr_decision_genmgt	F.3	Where are HR decisions made?	General management	0.19
hr_decision_hr	F.3	Where are HR decisions made?	HR	0.59
hr_decision_other	F.3	Where are HR decisions made?	Other	0.01
hr_decision_prod	F.3	Where are HR decisions made?	Production?	0.06
hr_dec_admin	F.4	Does this department do other clerical tasks?	Yes?	0.42
hr_mng	F.5	HR department is part of managing team?	Yes?	0.43
hr_reporting_hrmgr	F.6	Who does the HR department report to?	HR manager	0.09
hr_reporting_othermgr	F.6	Who does the HR department report to?	Other manager	0.11
hr_reporting_plantdirec	F.6	Who does the HR department report to?	Plant director	0.38
hr_interv_recr_equal	F.7	Who intervenes in the following HR decisions?	Recruitment: Equal	0.20
hr_interv_recr_higherups	F.7	Who intervenes in the following HR decisions?	Recruitment: Highre-ups	0.08
hr_interv_recr_mosthr	F.7	Who intervenes in the following HR decisions?	Recruitment: Mostly HR	0.31
hr_interv_empl_equal	F.7	Who intervenes in the following HR decisions?	Retention: Equal	0.25
hr_interv_empl_higherups	F.7	Who intervenes in the following HR decisions?	Retention: Higher-ups	0.13
hr_interv_empl_mosthr	F.7	Who intervenes in the following HR decisions?	Retention: Mostly HR	0.20
hr_interv_prom_equal	F.7	Who intervenes in the following HR decisions?	Promotion: Equal	0.25
hr_interv_prom_higherups	F.7	Who intervenes in the following HR decisions?	Promotion: Higher-ups	0.15
hr_interv_prom_mosthr	F.7	Who intervenes in the following HR decisions?	Promotion: Mostly HR	0.18
hr_interv_eval_equal	F.7	Who intervenes in the following HR decisions?	Evaluation: Equal	0.27
hr_interv_eval_higherups	F.7	Who intervenes in the following HR decisions?	Evaluation: Higher-ups	0.14
hr_interv_eval_mosthr	F.7	Who intervenes in the following HR decisions?	Evaluation: Mostly HR	0.17
hr_interv_train_equal	F.7	Who intervenes in the following HR decisions?	Training: Equal	0.21
hr_interv_train_higherups	F.7	Who intervenes in the following HR decisions?	Training: Higher-ups	0.07
hr_interv_train_mosthr	F.7	Who intervenes in the following HR decisions?	Training: Mostly HR	0.32
wcoll_recruit_personality	G.1	What tools are used for recruitment and selection of white-collar employees?	Personality	0.22
wcoll_recruit_iq	G.1	What tools are used for recruitment and selection of white-collar employees?	IQ	0.16
wcoll_recruit_genknowl	G.1	What tools are used for recruitment and selection of white-collar employees?	General knowledge test	0.27
wcoll_recruit_persint	G.1	What tools are used for recruitment and selection of white-collar employees?	Personal Interview	0.89

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Practice indicator	#	Question text	Answer	Mean
wcoll_recruit_groupdyn	G.1	What tools are used for recruitment and selection of white-collar employees?	Group Dynamics	0.08
wcoll_recr_outsourced	G.1	What tools are used for recruitment and selection of white-collar employees?	Outsourced	0.07
wcoll_eval_per_is0	G.2	Percentage of white-collar workers that undergo an evaluation process?	0%	0.39
wcoll_eval_per_b0l50	G.2	Percentage of white-collar workers that undergo an evaluation process?	between 0 and 50%	0.26
wcoll_eval_per_mt50	G.2	Percentage of white-collar workers that undergo an evaluation process?	More than 50%	0.35
wcoll_train_is0	G.3	Percentage of white-collar workers that got training in 2005 paid by the firm.	0%	0.16
wcoll_train_b0l50	G.3	Percentage of white-collar workers that got training in 2005 paid by the firm.	Between 0 and 50%	0.47
wcoll_train_mt50	G.3	Percentage of white-collar workers that got training in 2005 paid by the firm.	More than 50%	0.37
wcoll_vac_no_pref	G.5	How are white-collar workers promoted? Criteria.	No preference	0.14
wcoll_vac_only_extern	G.5	How are white-collar workers promoted? Criteria.	Only external	0.12
wcoll_vac_only_internal	G.5	How are white-collar workers promoted? Criteria.	Only internal	0.32
wcoll_vac_pref_extern	G.5	How are white-collar workers promoted? Criteria.	Prefer external	0.07
wcoll_vac_pref_internal	G.5	How are white-collar workers promoted? Criteria.	Prefer internal	0.34
autoeval_efqm	A.21	Auto-evaluation of EFQM?	Yes?	0.15
wcoll_info_all	G.7	How often white-collar workers are informed of the financial status of the plant?	All information	0.48
wcoll_info_no	G.7	How often white-collar workers are informed of the financial status of the plant?	No information	0.23
wcoll_info_reps	G.7	How often white-collar workers are informed of the financial status of the plant?	Periodically?	0.29
wcoll_job_rot_is0	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Change jobs: 0	0.62
wcoll_job_rot_b0l50	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Change jobs: between 0 and 50%	0.33
wcoll_job_rot_mt50	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Change jobs: more than 50%	0.05
wcoll_team_is0	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Work in teams: 0	0.32

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Practice indicator	#	Question text	Answer	Mean
wcoll_team_b0l50	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Work in teams: between 0 and 50%	0.31
wcoll_team_mt50	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Work in teams: more than 50%	0.38
wcoll_improvm_is0	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Contribute to improvement of processes: 0	0.40
wcoll_improvm_b0l50	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Contribute to improvement of processes: between 0 and 50%	0.33
wcoll_improvm_mt50	G.8	Percentage of white-collar workers that change jobs, work in teams, contribute to improvement of processes?	Contribute to improvement of processes: more than 50%	0.27
wcoll_mng_is0	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Management: 0	0.03
wcoll_mng_b0l50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Management: 1 - 50%	0.94
wcoll_mng_mt50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Management: 51%+	0.03
wcoll_tec_is0	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Technicians: 0	0.02
wcoll_tec_b0l50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Technicians: 1 - 50%	0.85
wcoll_tec_mt50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Technicians: 51% +	0.13
wcoll_admin_is0	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Clerical: 0	0.02
wcoll_admin_b0l50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Clerical: 1 - 50%	0.87
wcoll_admin_mt50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Clerical: 51%+	0.11

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Practice indicator	#	Question text	Answer	Mean
wcoll_interm_mng_is0	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Intermediate management: 0	0.13
wcoll_interm_mng_b0l50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Intermediate management: 1-50%	0.84
wcoll_interm_mng_mt50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Intermediate management: 51%+	0.03
wcoll_sale_is0	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Salesforce: 0	0.35
wcoll_sale_b0l50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Salesforce: 1 - 50%	0.62
wcoll_sale_mt50	G.9	Percentage of white-collar workers that belong to management, technicians, clerical, intermediate management, salesforce.	Salesforce: 51%+	0.03
mng_age_young	H.1	Age	Young or not	0.23
mng_educ_belowSecond	H.2	Highest degree obtained.	Below secondary school	0.10
mng_educ_second	H.2	Highest degree obtained.	Secondary school	0.19
mng_educ_univ	H.2	Highest degree obtained.	University education	0.69
mng_tenure_b5	H.4	Years on the job.	Below 5 years	0.23
mng_tenure_5to15	H.4	Years on the job.	From 5 to 15 years	0.32
mng_tenure_mt15	H.4	Years on the job.	More than 15 years	0.38
mng_prev_sameplant	H.5	Where did he/she work before?	Same plant or not	0.44
mng_equ	H.7	Does he/she own equity?	Owns equity	0.58
mng_sex_female	H.9	Gender.	Male recorded as 1	0.08