Management practices and firm performance during the Great Recession – Evidence from Spanish survey data[*]

Florian Englmaier[†] Jose E. Galdon-Sanchez[‡] Ricard Gil [§]
Michael Kaiser[¶]

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Abstract

This paper empirically examines whether management practices that work well during an economic boom are also effective in times of economics crisis, using plant-level survey data collected in Spain in 2006 just prior to the Great Recession. By employing *unsupervised machine learning*, we leverage high-dimensional human resource policies at each plant to describe clusters of management practices ("management styles"). We establish a positive correlation of a management style associated with structured management with performance prior to the crisis starting in 2006. Even accounting for firm survival, this correlation turns negative during the financial crisis. Further results suggest that more structured management correlates with relatively higher holdings of non-liquid assets and lower employee turnover. This suggests that a structured management style allows firms to strive during a boom but may be an impediment to adjusting to rapidly deteriorating economic conditions.

JEL codes: M12, D22, C38

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[†]florian.englmaier@econ.lmu.de, LMU Munich, Department of Economics & Organizations Research Group (ORG) & CEPR & IZA & CESifo.

[‡]jose.galdon@unavarra.es, Universidad Publica de Navarra, Department of Economics.

[§]rg73@queensu.ca, Queen's University, Smith School of Business.

[¶]michael.kaiser@econ.lmu.de, LMU Munich, Department of Economics.

1 Introduction

The study of management has been part of Economics almost since the beginning. Already Adam Smith in his books *The Wealth of Nations* and *The Theory of Moral Sentiments* prominently discusses various management topics such as the division and organization of labor, wage setting, incentivizing employees, or interpersonal authority. Yet, rigorous empirical economic research, which documents differences in management and its effect 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 structure and quality 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 these differences in management and how they explain persistent productivity differences, see, e.g. Bloom and van Reenen (2007), has clear implications for policies regarding productivity, growth, and income inequality.

In this paper, we aim to shed light on the ongoing research questions in the literature on the effects of management in economics. First, we empirically document what *bundles* of management practices firms adopt. In the second step, we assess whether and how these bundles affect productivity and firm performance. By evaluating the interplay between management bundles and firm performance before and during the Great Recession, we also speak to whether the effect of management is invariate to changing economic environments. In order to address these questions, we combine two independently collected data sources from Spain. First, we employ a firm survey conducted in 2006 which provides extensive information on manufacturing plants' human resource policies. Second, we match the firms from the survey to 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 the ensuing *Great Recession*.

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—see Milgrom and Roberts (1990, 1995)—which complicates identification of effects of specific management practices. Our approach to the topic 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 firms 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 presence of which 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.

In this paper we focus on the sample of single-plant firms in our data because there is an immediate match between the entity that decides on the adoption of management practices and its performance. In a first step of the analysis, we estimate these latent styles from the survey data on single-plant firms. 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 are argued 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, we label this Style 2 "structured". This classification is also consistent with practices that are typical for this style in the management style distribution.

In a second step, we combine the survey data with administrative balance sheet data that allows us to relate our measure of management style to firms' performance. We then use management style to explain firms' productivity and report two key results. First, we find a systematic and significant positive correlation of a structured management style with firm productivity prior to the Great Recession. Second, this correlation turns statistically significantly negative for firms' performance during the Great Recession. These findings are consistent with an interpretation that structured management helps firms strive in economically benevolent environments, but in times of crisis more flexible and informal styles may have a competitive edge as they are more conducive to short-term adjustments. While, in terms of exploring this interpretation, we are somewhat restricted by our data, we document patterns consistent with it along two margins. First, we document that firms with a less structured management style are adjusting their workforce to a lesser degree during the crisis and, second, that prior to the crisis firms with a more structured management style hold relatively more fixed assets than rather informally run firms.

Employing LDA, i.e., unsupervised machine learning, enables us to utilize all available dimensions of the survey data without prior conceptions of 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—see for instance 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 it can at times 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 the components of the data. Furthermore, our results pass key sanity checks in that the retrieved management styles are meaningful; interpretable; not trivially explained by observable firm characterstics (size, sector, region, etc.); and even, in line with existing literature, correlate significantly with firm productivity.

From a methodological point of view, 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, which exists plentifully, and combine it with a powerful algorithm that allows us to cost-effectively address open questions before starting new and costly—in terms of money, and especially, research time—data collection initiatives.

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 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. This 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 WMS measures of management that validates our findings. In particular, they document higher scores of management practices in multi-plant firms and multinational companies and their subsidiaries. The management score employed in Bloom et al. (2014) captures a more structured approach to management. Analogously, we associate our Management Style 2, which is typically present in multi-plant firms in our sample, with more structured management.

Methodologically speaking, we contribute as well to an emerging 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 on 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 low-dimensional space which facilitates the analysis of the impact of management style—with complementarities embedded in each style—on firm outcomes.

Finally, our paper also contributes to work on the impact of the 2008 financial crisis on firm's management and their performance. Almunia et al. (2020) 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. The paper by Aghion et al. (2020) 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. (2019) 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 those firms with less structure prior to the crisis, but this was no longer true after the crisis.

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* to measure plant and firm performance.[1] In what follows, we describe the survey and its matching with the SABI data.

2.1 Survey data

We first briefly describe how the survey was conducted and its general objective, and then offer details on how we construct the inputs for the unsupervised learning algorithm.

2.1.1 The survey in general

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 firms. The sample is representative of the population of manufacturing plants in Spain with 50 or more employees. In Table 1 we report the sample

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

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.[2] 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 (Bayo-Moriones et al., 2013, 2017).[3]

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 largely 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. 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 other (white-collar) workers and occupations in the plant; and (viii) plant manager characteristics (education, demographics, skill set, etc.).

We discuss summary statistics of firms in the sample in more detail in Section 3.3 when we analyze correlates of firms' management style.

[2]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 firms consists of multiple plants or establishments.

[3]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).

2.1.2 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, we only use variables detailing management policies in our exercise of measuring management practices. 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 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.[4] 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 and no more 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, no management practice ought to be missing in the data. Owing to that restriction, we have to drop 71 plants from the sample. Therefore, our final sample of plants that we use to estimate management style contains 463 firms in the sample of single-plant firms.

2.2 Firm performance data

SABI is a database collected by Informa D&B in collaboration with Bureau Van Dijk. Informa D&B is the only Spanish company that provides online access to the largest database of Business, Financial and Marketing information in the world with more than 350 million companies online in more than 200 countries. 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 linked an entry to all 1003 manufacturing

[4] 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.

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 2010. 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.

From the SABI data, we primarily employ information on revenue, labor force, and assets to construct productivity.[5] We detail the procedure used to construct a measure of firm productivity in Section 4.1. In particlar, we measure output using sales; capital input using total assets; and labor input using the number of employees. Appendix Table A.3 provides summary statistics for the variables used as inputs in the Total Factor Productivity (TFP) estimation for 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 outlining the algorithm we use to that effect. Next, we describe the results and analyze correlates of those results.

3.1 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.

[5]The number of employees is also elicited in the firm survey. The correlation between both measures is $= 0.7$

3.1.1 Estimation setup

The goal of the 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 (econometrically: estimate) 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; see (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 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 supposes that each snippet of text is a mixture of different 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.[6]

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

[6]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.

taken into account when choosing the parameters of unsupervised learning. Finally, the cross-validation exercise in Appendix Figure A.2 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 unlikely to balance the loss of interpretability.

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 practices emblematic of a 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—resulting in all weights being strictly smaller than one.

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.

3.1.2 Estimation results

First, we obtain a distribution over all practices for both styles. In Appendix Figure A.3 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*. Panel (a) 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. In Panel (b) of Appendix Figure A.3 we plot the practices whose loadings quotient across styles is largest. On the far right—practices with a relatively higher loading in Style 1—the algorithm identifies the absence of evaluation systems as well as a narrow focus on ability and personal interviews in the recruitment process. In style 2, human resource department decision making and the importance of evaluations for promotions is emphasized. Note that this analysis does not take into account the importance of those feature in the styles; thus, two practices with relatively low loadings in both styles may feature in this description. We return to the practices with highest single style loadings in more detail below.

Second, we can illustrate firms' style distributions. 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 Appendix Figure A.4 plots the count of firms across the Style 2 continuum. The distribution is bi-modal, and there is a mass of firms that load highly on Style 1. A second mass point is between 0.5 and 0.6, pointing to firms that tend to be rather balanced mixtures of both pure styles. In the analysis, we provide results based on a continuous measure of Style 2 intensity as well as based on indicator variables for terciles.

3.2 Characterizing firms' management styles

Since latent management styles are not ordinal, 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 begin to understand what those styles mean by comparing firms of a certain configuration to a separate set of firms whose management we can characterize *a priori*—that is, without relying on LDA. To this effect, we consider firms with several establishments—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., 2012b,a). 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.[7]

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.[8] 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[9]: 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 1 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, SPFs with Style 2 intensity (from the single-plant sample) also put most mass above 0.5 in the joint estimation. Finally, SPFs with SPF-only sample Style 2 intensity below 0.5 behave 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.

Second, we analyze those practices that carry the highest loadings in both styles. Table 2 reports the five organizational practices with the highest loading in each style. Style 2 exhibits practices that suggest structured management, emphasizing the role of dedicated human resource departments. In Appendix Figure A.3(b) we plot those practices whose loadings' quotient in both styles is largest; that is, those with the highest relative loadings

[7]The second approach to understanding the pure style is by evaluating the style-over-practice distributions which we do below. 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.

[8]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; equivalent Dirichlet priors are employed, and the MCMC parameters are kept constant.

[9]Equivalently, we could have plotted the Style 1 share as well. This would have not affected the conclusions we draw in the following paragraph. These styles are unrelated to the styles estimated in the single-plant sample only. Estimating styles in the joint sample only serves to help understanding the meaning of styles in the single-plant sample.

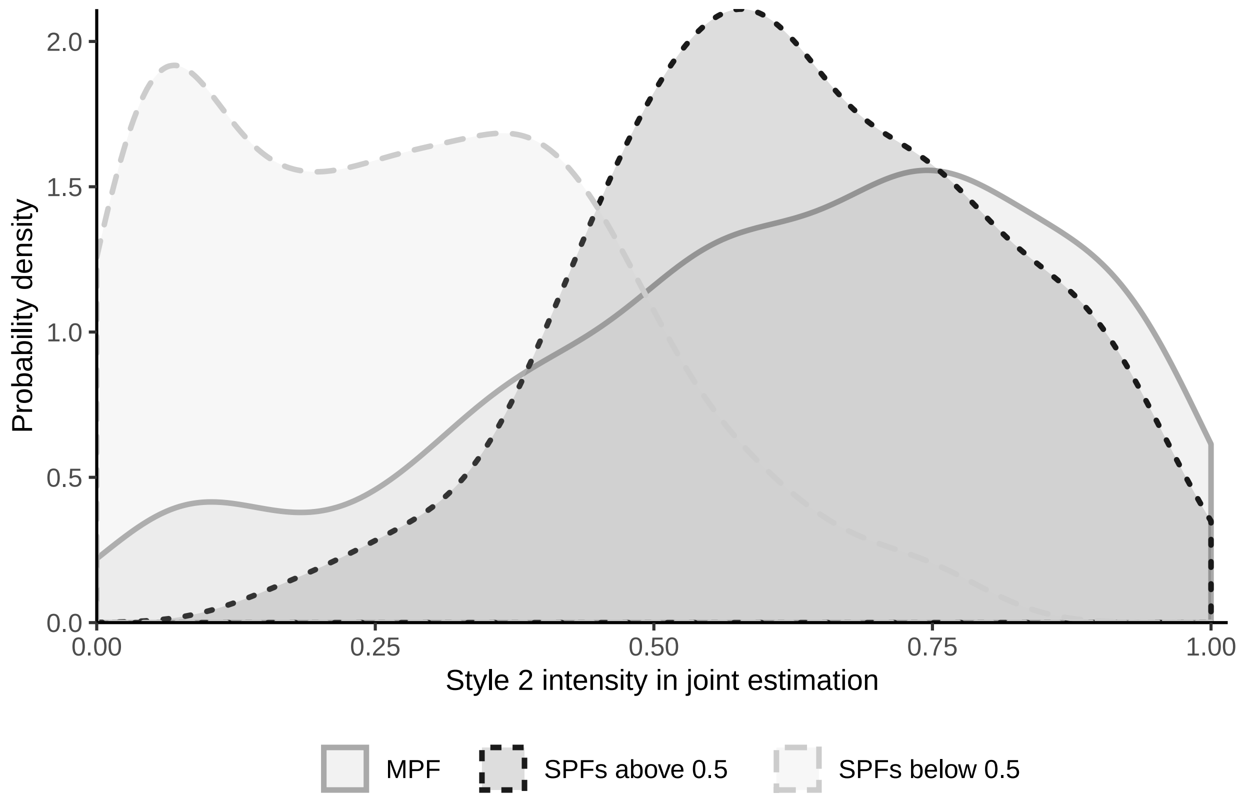

Figure 1: Understanding styles by comparing single- and multi-plant firms. *Notes.* In this figure, we apply the LDA procedure described above to estimate management styles in a pooled sample of single- and multi-plant firms (n=871). We then plot the probability density of the corresponding Style 2 share 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.

in both styles, respectively. This corroborates the notion that Style 2 is exemplified by structured practices, while Style 2 mirrors informal practices. While we would like to emphasize that any label is subjective, we still conclude that Style 2 captures a more *structured* approach to management, and Style 1 represents a more *informal* approach.

3.3 Correlates of management styles

In this section we explore survey data correlates of firms that exhibit high Style 2 intensities 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

Rank	Style 1	Style 2
1	Recruitment with personal interviews	Dedicated HR department
2	Firm uses no evaluation system	HR part of management team
3	White-collar recruitment through interviews	HR executed administrative tasks
4	% white-collar in management $<$ 50%	% white-collar in intermediate management $<$ 50%
5	% of jobs characterized as manual $>$ 50%	HR reports to plant-director

Table 2: Five practices with highest loading in each style. *Notes.* This table lists the five practices with the highest loadings in each style. These are obtained by sorting the respective style-over-practice distribution by practices in descending order of their loading.

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:

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

X_i captures firm characteristics, such as size, export dependency, or a firm's position along the value chain[10]. 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).

In Appendix Table A.1 we provide summary statistics for those variables which we study in this analysis. The average firm has 116 employees although the distribution is highly skewed to the right (skewness $\approx$ 5). Further, the average firm has sales of about €28,639,000 worth of goods and services (also skewed to the right; skewness $\approx$ 7). Firms report sales selectively; only 289 firms report sales in the survey.[11] 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.[12]

The results suggest that both, the number of employees and sales, are positively correlated

[10] Almunia et al. (2020) 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

[11] Reporting sales in the survey is not systematically correlated with Style 2 intensity. A linear regression of an indicator for having reported sales on Style 2 intensity results in a coefficient of 0.004 (SE = .09). Controlling for firm size does not alter this conclusion; in fact, firm size measured by the number of employees is not correlated with the incidence of reporting sales either.

[12] Contrary to Chen and Steinwender (2019), there are only very few family owned firms in our sample and they are reported under the category "other". Note that family owned firms in Spain tend to be multi-plant which is why they are not in our sample here.

	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.

with Style 2 intensity. In Appendix Figure A.5 we zoom 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. Similarly, there is a positive association of Style 2 intensity and export dependency, however, the latter is not substantively explained by the former. 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. Appendix Figure A.6 zooms in on this aspect, and graphically displays lower Style 2 intensity in the consumption good sector. While medians differ, there is ample common support across different locations in the value chain. Finally, there is no discernible effect of ownership status on Style 2 intensity. In Appendix Table A.2 we show how firms' performance correlates with Style 2 intensity. 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. Since these measurements are highly correlated, individual effects are not statistically significant once we jointly include them in a multivariate regression.

The results in Table 3 are obtained from regressions without region nor sector fixed effects. Explanatory power only increases marginally if we include those fixed effects. When region or sector fixed effects are included, the adjusted R^2 in the analogous specification to column 7 increases to 0.24 or 0.23, respectively. When they are jointly included, the adjusted R^2 remains at 0.24.[13] An interesting implication is that there is significant variation in styles within economic sectors.

Thus, overall firm characteristics as elicited in the survey can explain about one quarter of variation in Style 2 intensity. We note a significant positive association between firm size (employees, sales) and Style 2; yet, these characteristics do by far not exhaustively explain variation in Style 2 intensity.

4 Management style and firm performance *before* the Great Recession

This section establishes that the management styles we estimated in the previous paragraph correlate with firms' performance in the period before the Great Recession. We 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

[13] In Appendix Figure A.7 we show a Style 2 breakdown by sectors and region. The boxplot in panel (a) shows that there is "common support" across all sectors; that is, the median and interquartile range of Style 2 intensity is comparable across sectors. The map in panel (b) shows regional heterogeneity but comparable means across most regions.

Total Factor Productivity (TFP), and then projects it into the space of management styles.

4.1 Estimating firms' TFP

We measure firms' performance using TFP which can be interpreted as a firm's 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:

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

Specifically, we use sales in Euro to proxy output, total assets to measure capital input, and the number of employees to measure labor input and estimate Equation (2) using OLS. The underlying, *unbalanced*, panel covers the years 2001-2006.[14]

We obtain a firm's TFP by taking the predicted value of α_i from Equation (2). Appendix Figure A.8 shows the distribution of the estimated $\hat{\alpha}_i$ which is slightly skewed to the right. More importantly, we observe several extreme values indicating relatively (un)productive firms. We account for these in the regression by 95% winsorizing TFP—indicated by the vertical lines in Appendix Figure A.8.

4.2 Results

In this section, we provide evidence that the management style we estimated using firm survey data correlates with firms' TFP. To this effect, we estimate

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

where i indexes a firm located in region r which is active in sector s. $\gamma^2_{i,r,s}$ denotes a firm's management Style 2 intensity, which is a value between 0 and 1. Higher values indicate a stronger Style 2 intensity. The ω_r and ω_s absorb time-invariant variation induced by regions

[14] A total of 446 firms enter the productivity estimation, and the average firm appears 5.5 out of 6 times. 331 firms appear in each year. 11 firms only appear once. We estimate output elasticities of labor and capital to be 0.3 and 0.49, respectively. Below we provide a robustness check focusing only on firms for that we observe the complete panel structure. In this setup, we estimate elasticities of 0.46 and 0.44, respectively.

	Firm productivity 2001 to 2006 95% winsorized			Firm productivity 2001 to 2006 not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.28***	.26***	.26***	.27***	.25**	.25**
	(.079)	(.082)	(.082)	(.091)	(.098)	(.098)
1[consumer good]			.073			.1
			(.066)			(.081)
1[intermediate good]			.13**			.16**
			(.063)			(.072)
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
Adj R-squared	.023	.13	.14	.017	.11	.12
N. of cases	385	385	379	385	385	379

Table 4: Management style and firms' TFP before the crisis. *Notes.* This table reports the results of estimating Equation (4) using OLS. The dependent variable is a firm's estimated TFP; 95% winsorized in columns 1-3 and non-winsorized in columns 4-6. "Mgt Style 2" is a firm's Style 2 intensity. "1[consumer good]" and "1[intermediate good]" are indicators for firms that are located in the respective location along the value chain. The omitted category is firms producing capital goods. Columns 2,3,5 and 6 contain sector and region fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

and sectors, respectively. In $X_{i,r,s}$, we control for firms' location along the value chain by including indicators for producing consumer goods or equipment—producing capital goods is the omitted category. We cluster standard errors at the three-digit industry level.

We provide the results of estimating Equation (3) in Table 4. Columns 1 and 4 provide simple univariate correlation of Style 2 intensity with firms' TFP. In columns 2 and 5, we add region and sector fixed effects. In columns 3 and 6, we additionally control for value chain location. Columns 1-3 show results based on 95% winsorizing the dependent variable; the remaining columns use non-winsorized outcomes.

Across all columns, there is a significant correlation between Style 2 intensity and firms' TFP. The estimates' magnitude does not change when correlates and fixed effects are included. Unsurprisingly, standard errors are smaller when winsorized data is used on the left-hand side. Style 2 intensity is able to explain about two percent of variation in the dependent variable. The full specification explains 12% of variation. We note that firms producing intermediate goods are more productive than firms producing consumer goods; which in turn are more productive than firms producing capital goods. As pointed out above, the full panel structure of production inputs and output is not available for all years. In Appendix Table A.4 we provide results for the same specifications only using those firms where the full panel is available. The estimates are highly comparable to those in Table 4.

The magnitude of the correlation of about 0.25 corresponds to a one unit change in Style 2 intensity. To put the magnitude in perspective consider a one standard deviation change in Style 2 intensity ($\sigma(\gamma^2) = 0.25$); this corresponds to a 0.0625 change in TFP. This is equivalent to an effect of 13% of a standard deviation in TFP ($\sigma(al\hat{p}ha) = 0.47$). Alternatively, the inter-quartile-range in Style 2 of 0.37 results in a 0.0925 change in TFP; or 20% of a standard deviation in TFP.[15]

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 prior to 2006 and what we observe is consistent with firms being able to benefit from leveraging economies of scale. A structured management style appears to allow firms to more effectively exploit this beneficial economic environment.

5 Management Style and firm performance *during* the Great Recession

In this section we shed light on how management style intensity correlates with firms' performance during the Great Recession (2007-2010) that followed the Great Financial Crisis that struck in 2007. Spains experience of the aftermath of the crisis was markedly different

[15] In Appendix Table A.5 we provide additional results in which we bin management Style 2 intensity into terciles. In the estimation sample of columns 1,2,4 and 5 of Appendix Table A.5, 130 firms' management Style 2 intensity is smaller or equal to $\frac{1}{3}$; 182 firms' Style 2 intensity is larger than $\frac{1}{3}$ but no larger than $\frac{2}{3}$; finally, 73 firms' Style 2 intensity is larger than $\frac{2}{3}$. We show that the firms in the middle tercile of Style 2 intensity are marginally more productive than firms in the bottom tercile. Firms in the top tercile are significantly more productive than firms in the bottom tercile. Finally, we provide p-values for the comparison of firms in the middle and top tercile; we are unable to statistically reject that the effects are in fact equal.

than say in the US or Germany where after a severe contraction in the short-run, growth rates quickly recovered. As illustrated in Appendix Figure A.9, Spain's economy contracted initially at a comparable rate but thereafter its resurgence was markedly slower than that of Germany or the US with GDP starting to grow only in 2011. From its peak in 2008, Spain's real GDP fell by 8.9% in the following five years, bottoming out only in 2013. Private consumption over this period contracted by 14.0% and the unemployment rate increased from 9.6% to 26.9%.[16]

5.1 Setup

Our estimates of firms' TFP are derived from estimating a specification akin to Equation (2) but now using data for the years 2007-2010. We summarize TFP for the period 2007-2010 in Figure A.10. Panel (a) shows a histogram; the distribution looks comparable to the pre-crisis distribution but points to a number of outliers on the right of the distribution. In the analysis, we again account for these by showing estimates based on 95 percent winsorization. In panel (b), we plot the change in TFP between the two periods (2007-2010 vs 2001-2006) relative to the pre-period (2001-2006). The figure suggests a negative relationship which could indicate regression to the mean—highly productive firms in the pre-period see a decline in the post-period. We follow the literature, cf. Lazear (2004); Smeets et al. (2019), and account for this by controlling for the pre-period level of TFP in the regressions.

In the second step we relate firms' productivity in the years 2007-2010 to their management Style 2 intensity, a set of time-invariant controls, and their pre-crisis TFP. In a set of robustness checks, we also provide estimates for the effect of Style 2 intensity on the *difference* in TFP across both periods (pre vs during the crisis). As in Section 4.2, standard errors are clustered at the industry level. In additional results, we show how a censoring approach to missing information due to potentially endogenous firm exit affects the estimates of firm performance during the crisis.

Finally, we turn our focus to channels through which Style 2 intensity affects firm performance during the crisis. While we are unable to pinpoint a specific mechanism, we provide a set of results that suggest that a higher Style 2 intensity leads firms to hold fewer non-liquid assets, and to turn over employees at a lower rate—holding constant a wide set of firm characteristics.

[16] See Almunia et al. (2020) for more details on the Spanish experience in the Great Recession.

5.2 Results

In Table 5 we provide estimates for the conditional correlation of Style 2 intensity and firm performance during the Great Recession 2007-2010. In panel (a) columns 1-3, we see a statistically significant (at 5 percent) negative coefficient, suggesting that firms with higher style intensity fared worse during the crisis. In columns 4-6, we provide estimates without winsorizing the dependent variable, and see that estimates are comparable in magnitude but less precisely estimated. We consider columns 1-3 to be our preferred specification as Figure A.10(a) points to the presence of extreme values in TFP.

In panel (b) of Table 5, we provide results for the case of binning Style 2 intensity into terciles. The point estimates suggest—and the p-values in the table's legend confirms—that the effect is predominantly driven by firms in the top tercile, that is those with the highest Style 2 intensity. The effect of -0.12 in column 3 implies that, on average, the TFP of firms in the top tercile of Style 2 intensity is about a third of a standard deviation lower ($\sigma_{TFP_{'07-'09}} = 0.42$) than those of firms in the bottom tercile.

One may be worried that this reflects regression to the mean, in the sense that firms that did better before the crisis do relatively worse now, and vice versa. Indeed, Figure A.10(b) suggests a comparable relationship in the bivariate reduced form. We account for this phenomenon by controlling for firms' TFP in the year 2001-2006—"pre-crisis TFP" in the tables; cf. Lazear (2004); Smeets et al. (2019). 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.[17]

Another concern one may have is that the least productive firms with high Style 1 intensity had to exit the market during the Great Recession. Thus, what we observe in this period is the set of all firms with high Style 2 intensity, and the subset of relatively more productive firms with high Style 1 intensity.[18] We address this concern in two ways and show

[17] In Table A.6 we show additional results in which we use a firms' difference in productivity across the two periods. The results are qualitatively similar, and show that the difference in productivity levels is more negative if Style 2 intensity is higher. That is, holding pre-crisis productivity constant, a higher Style 2 intensity results in a more negative difference across the two periods.

[18] The data suggests that Style 2 intensity is indeed negatively, but statistically insignificantly, related to firm exit during the crisis. That is, conditional on sector, region, and value chain location fixed effects, we estimate a negative coefficient of -0.047 (SE = 0.056) of Style 2 intensity on firm survival in a linear probability model. The marginal effect at the mean from a logit regression is comparable to this.

	Firm productivity 2007 to 2010 95% winsorized			Firm productivity 2007 to 2010 not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.14**	-.13**	-.13**	-.1	-.092	-.09
	(.069)	(.064)	(.066)	(.081)	(.077)	(.077)
Pre-crisis TFP	.64***	.6***	.62***	.62***	.58***	.6***
	(.061)	(.066)	(.061)	(.09)	(.088)	(.084)
1[consumer good]			-.018			-.012
			(.057)			(.062)
1[intermediate good]			.026			.024
			(.053)			(.056)
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
Adj R-squared	.41	.46	.49	.4	.45	.48
N. of cases	341	341	336	341	341	336

(a) Continuous measure of Style 2 intensity.

	Firm productivity 2007 to 2010 95% winsorized			Firm productivity 2007 to 2010 not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
1[sytle 2 > $\frac{2}{3}$]	-.11**	-.11***	-.12***	-.099*	-.099**	-.1**
	(.048)	(.042)	(.043)	(.052)	(.048)	(.048)
1[$\frac{1}{3}$ < sytle 2 $\leq \frac{2}{3}$]	-.033	-.0023	-.0011	-.0083	.025	.027
	(.042)	(.039)	(.041)	(.047)	(.044)	(.045)
Pre-crisis TFP	.64***	.6***	.62***	.62***	.58***	.6***
	(.06)	(.064)	(.059)	(.088)	(.085)	(.081)
1[consumer good]			-.015			-.0091
			(.057)			(.062)
1[intermediate good]			.034			.033
			(.054)			(.057)
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
p: mid vs top tertile	.082	.0076	.0056	.056	.0064	.0052
Adj R-squared	.41	.46	.5	.41	.46	.49
N. of cases	341	341	336	341	341	336

(b) Style 2 intensity in terciles.

Table 5: Style 2 intensity and firm performance during the crisis. *Notes.* This table reports the relationship between management Style 2 intensity and firm performance during the Great Recession. In panel (a), firms' Style 2 intensity is measured by means of the continuous variable. In panel (b), Style 2 intensity is binned in terciles and the first tercile—the 33 percent of firms with the lowest Style 2 intensity—are the omitted category. The dependent variable is a firm's estimated TFP using data from 2007 to 2010; 95% winsorized in columns 1-3 and non-winsorized in columns 4-6. "Mgt Style 2" is a firm's Style 2 intensity. "1[consumer good]" and "1[intermediate good]" are indicators for firms that are located in the respective location along the value chain. The omitted category is firms producing capital goods. We additionally control for firms' TFP using data from 2001-2006 (the dependent variable in Section 4.2; this variable is also winsorized in columns 1-3 but not columns 4-6. Columns 2,3,5 and 6 contain sector and region fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

that it cannot explain our results. The approach we take is similar in spirit to Blundell et al. (2007) in that we try and account for sample selection by simulating a worst-case scenario.

First, we include all firms which we observe before the crisis—Table 4—and *impute* for those we do not see during the crisis their productivity level in the period 2007-2010 to be comparable to the worst performing firm we observe in the data during that period. That is, for those 44 firms we observe before but not during the crisis, we pretend that they are as productive as the least productive firm we do observe. To account for the fact that we are "adding" extreme observations to the data, we now run quantile regressions and estimate the conditional median. We obtain standard errors by drawing 1,000 three-digit-industry-clustered bootstrap samples. We present the finding from this exercise in columns 1-3 of Table A.7. In the most saturated specification, we estimate the conditional median to be -0.19 units lower for a point increase in Style 2 intensity. The effect is statistically significant at the five percent level.

Second, we pretend that the data is in fact censored and that we cannot observe the least productive firms because they had to exit. Thus, for all firms we do not observe in the period 2007-2010 (but do observe before), we impute the fifth percentile of the TFP distribution 2007-2010. In the second step, we estimate a Tobit-model with that fifth percentile being the left-censoring limit. Since the Tobit-model is a linear model, and as such sensitive to outliers, we use the fifth percentile rather than the minimum for imputation. In this setting we report (analytic) standard errors again clustered at the three-digit industry level.

The results in columns 4-6 of Table A.7 display the result of this exercise. Estimates retain a negative sign but are smaller in magnitude than those of Table 5 and do achieve statistical significance at conventional levels. In sum, we interpret the proponderance of negative estimates for Style 2 intensity as rather strong evidence that firms characterized by higher Style 2 intensity suffer more during the Great Recession *ceteris paribus*.

5.3 Mechanisms

At this point it is useful to summarize the results presented thus far. First, we illustrated a novel approach to measuring management from high-dimensional survey data. Based on comparing single-plant and multi-plant firms, and the style-over-practices distributions, we argued that Style 2 in our estimation reflects a more structured approach to management. Second, we reported how this measure of management style significantly correlates with firm performance in the period 2001 to 2006. We show that a higher Style 2 intensity positively affects firm productivity, and speculate that this may have allowed firms to exploit economies of scale during a period of economic expansion in Spain. Finally, in Section 5.2 we show that this correlation reverses its sign during the Great Recession 2007-2010. Firms with management more intensely geared towards Style 2 perform worse during the crisis ceteris paribus.

In this section, we attempt to disentangle the ways and means that could help us understand this sign reversal. We investigate whether a higher Style 2 intensity hampers firms' ability to tackle the challenges of the Great Recession. We analyze two indicators. First, SABI data allows us to distinguish between fixed and non-fixed assets, and we analyze firms' holdings of non-fixed (i.e., rather liquid) assets before the crisis. Second, we analyze changes in the workforce as less rigidly organized firms may be better able to adjust the workforce in the short term.

Table 6 shows the results of this exercise. Columns 1 and 2 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. In columns 3 and 4, we show that Style 2 intensity weakly correlates with lower absolute employee turnover during the crisis. The dependent variable is the difference between the average number of employees of 2007-2010 to 2006. The table legend indicates that the average firm had to lay off about seven workers during the Great Recession. The estimates suggest that—holding constant employment in 2006—a higher Style 2 intensity correlates negatively with employee turnover, albeit these estimates are imprecise and not statistically significantly different from zero. A one standard deviation increase in Style 2 intensity (0.25) implies an about one third increase in turnover as compared to the mean.[19]

[19] This estimates are robust to a number of different specification which we do not report here. Overall, specification that only control sector and region fixed effects lie in between the reported results in terms of magnitude and significance. The results in columns 1-2 become stronger and more statistically significant when we use the raw data for fixed and total assets rather than 95 percent winsorized values. The results in column 3-4 do not change when we control for the natural logarithm instead of the raw value of number of employees in 2006. The same is true for columns 1-2 and the logarithm of total assets in 2006. Finally, taking the difference of the number of employees in 2010 (rather than the average during the crisis) and 2006 produces slightly larger point estimates in columns 3-4.

	Fraction non-fixed assets		Δ # employees	
	(1)	(2)	(3)	(4)
Mgt style 2	-.063*	-.074**	-6.3	-9.9
	(.033)	(.032)	(6.4)	(6.2)
Total # employees 2006			-.085***	-.063*
			(.031)	(.032)
Total assets 2006	.11	.16		
	(.39)	(.35)		
1[consumer good]		-.017		-5.6
		(.028)		(6.6)
1[intermediate good]		-.029		-.093
		(.027)		(5.5)
Sector FE	No	Yes	No	Yes
Region FE	No	Yes	No	Yes
Mean DV	.64	.64	-7.3	-7.3
Adj R-squared	.0027	.12	.069	.079
N. of cases	372	366	354	349

Table 6: Management style and ease of adjustment. *Notes.* This table shows conditional correlations of management Style 2 with pre-crisis holdings of non-fixed assets and employee turnover during the crisis. The dependent variable in columns 1 and 2 is the difference of total and fixed assets divided by total assets. All quantities are measured in 2006 and were 95 percent winsorized prior to entering the ratio. The dependent variable is the average number of employees from 2007-2010 minus the number of employees in 2006. "Mgt Style 2" measures firms' management Style 2 intensity from zero to 1. "1[consumer good]" and "1[intermediate good]" are indicators for firms that are located in the respective location along the value chain. The omitted category is firms producing capital goods. Columns 2 and 4 contain sector and region fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

6 Conclusion

In this paper, we employ an unsupervised learning algorithm to measure clusters of management practices in a Spanish firm survey collected in 2006, i.e., just prior to the onset of the Great Financial Crisis. 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 there being 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. Firm characteristics can explain only about ~ 30 percent of variation in management styles. More importantly, 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, we find positive correlations of a more structured management style with performance prior to the financial crisis. This correlation turns negative during the financial crisis after 2007.

Taking these results seriously, and in line with recent studies by Aghion et al. (2020) 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 somewhat restricted by our data. However, we document patterns that are consistent with structured management being an impediment to firms' short-term adjustment along two margins . First, we document that more structured firms are adjusting their workforce to a lesser degree during the crisis and that, prior to the crisis, more structured firms hold relatively more fixed assets than firms with a more informal management style.

Finally, we see the present 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.

The same applies to such data in the fields of economics of innovation, entrepreneurship, and labor relations, or further afield advertising, logistics, and urban planning. We feel that currently we 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 these rich existing data sources.

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A Appendix

	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

Table A.1: Summary statistics of firms survey characteristics. *Notes.* This table reports summary statistics of survey-level variables used in the analysis of correlates of firm's Style 2 intensity of Table 3. Column 2 reports the standard deviation, while columns 4 and 5 report the 25^{th} and 75^{th} percentile, respectively. "% for export" is a firm's self-reported share of output that is exported abroad. "Produces consumer/intermediate/capital good" are indicator variables equal to one when the firm produces the respective output category, and zero otherwise. "Shared ownership", "limited liability" and "Other ownership" are indicators equal to one when a firm is organized according to the respective ownership structure.

	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.2: 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. Pabel (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. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

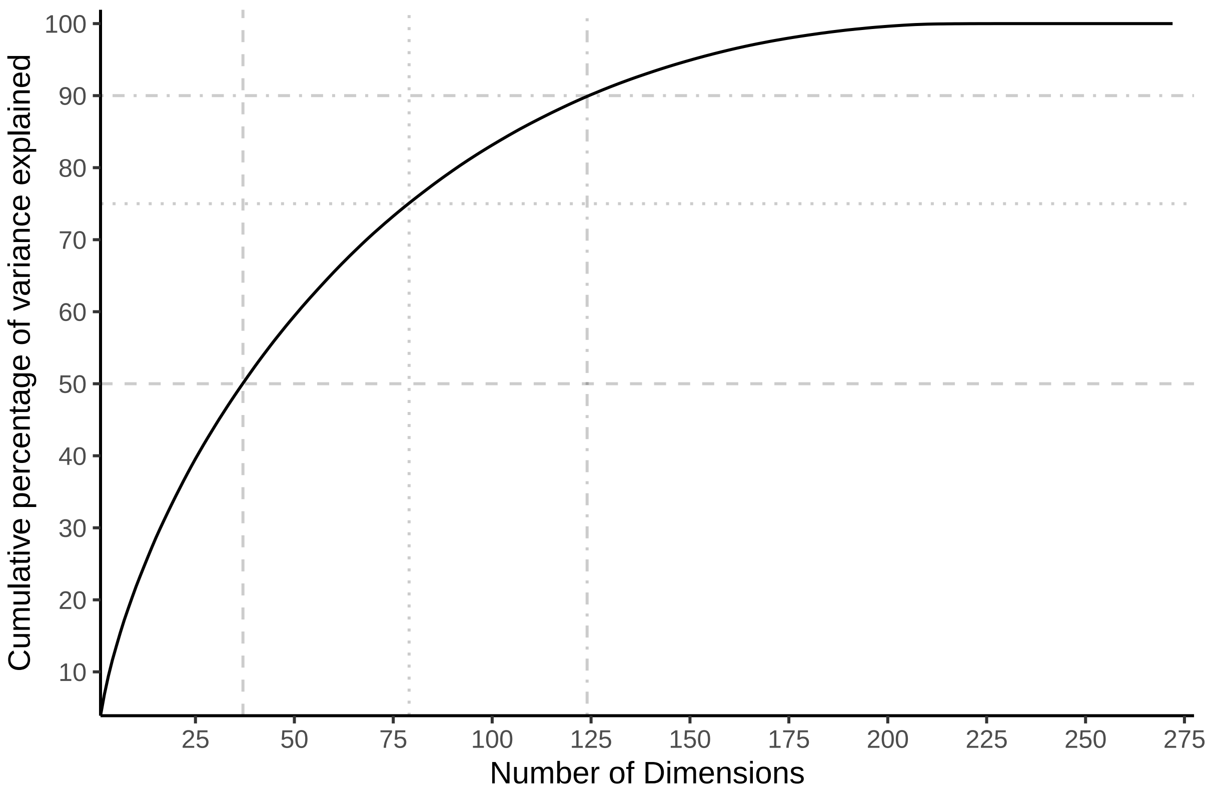


Figure A.1: Cumulative % of variance explained. *Notes.* This figure shows the cumulative percentage of variation explained by the 272 management practice indicators. The results were obtained from running Multiple Correspondence Analysis (MCA) using all indicators. The x-axis contains all indicators ranked from the most to the least explanatory dimension.

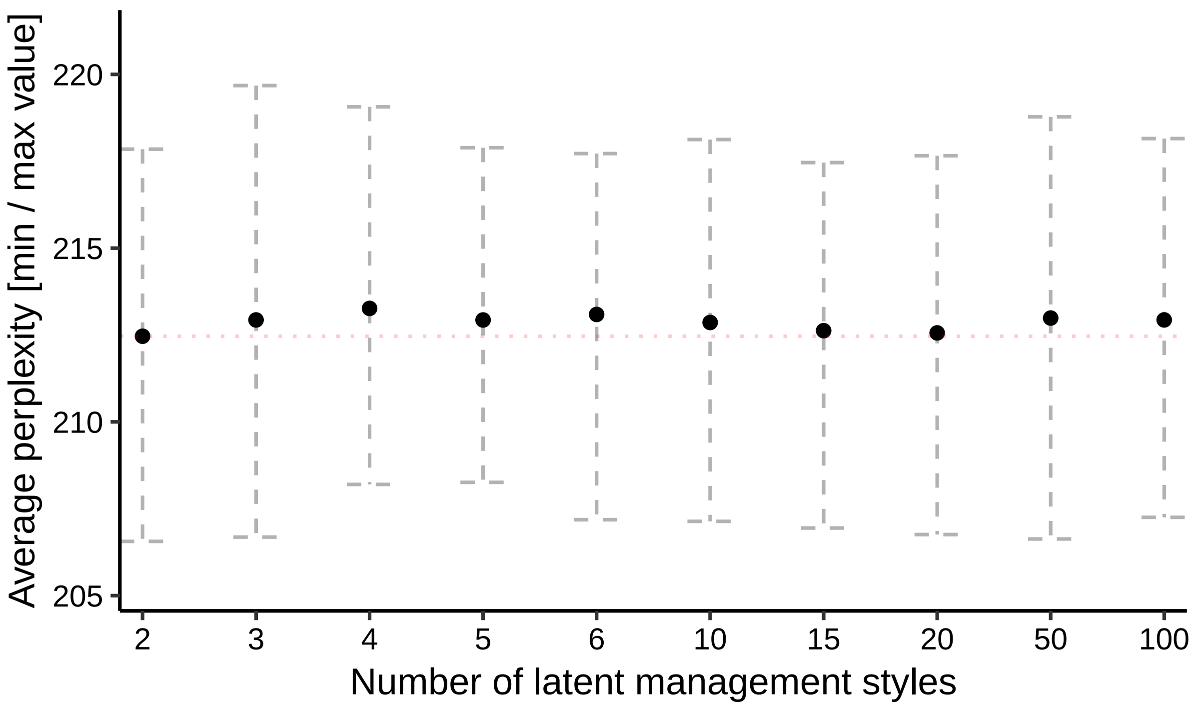


Figure A.2: Cross-validating the number of latent styles. *Notes.* This figure plots the *perplexity* of cross-validated LDA models which vary only in the number of latent styles they estimate. Perplexity is a quantity that measures out-of-sample fit and higher values show better fit. The results are obtained from randomly splitting the sample into ten cross-validation folds. Then nine of those ten folds are used to estimate the model which is then tested on the held-out fold. This procedure is repeated ten times such that each fold is in the training sample exactly nine times, and in the test sample exactly once. The dots show the average perplexity across these ten repetitions for each number of latent styles. The upper and lower end of the error bars show the maximum and minimum perplexity, respectively. The dashed red line shows the average perplexity obtained with the preferred model with two latent styles. The remaining parameters of the estimation are left unchanged and are described in Section 3.1.

	Mean (1)	S.D. (2)	Median (3)	25^{th} (4)	75^{th} (5)	N (6)
Sales 2001-2006	17558	29778	9768	5332	19386	499
Log sales 2001-2006	9.2	.98	9.2	8.6	9.9	499
Total assets 2001-2006	15563	22062	8520	4374	17428	505
Log total assets 2001-2006	9.1	1.1	9.1	8.4	9.8	505
# employees 2001-2006	102	84	77	53	118	452
Log # employees 2001-2006	4.4	.73	4.3	4	4.8	452
Sales 2007-2010	19554	29809	10182	4813	21064	473
Log sales 2007-2010	9.2	1.1	9.2	8.5	10	473
Total assets 2007-2010	21371	39522	10600	4754	23869	479
Log total assets 2007-2010	9.2	1.3	9.3	8.5	10	479
# employees 2007-2010	100	89	73	47	124	439
Log # employees 2007-2010	4.3	.84	4.3	3.9	4.8	439

Table A.3: Summary statistics of TFP inputs. *Notes.* This table provides summary statistics for (time aggregated) inputs to the TFP estimation. The variables are averaged over the corresponding time horizon. "25^{th}" and "75^{th}" denote the respective percentile of the distribution. "Log" refers to the natural logarithm.

	Firm productivity 2001 to 2006 95% winsorized			Firm productivity 2001 to 2006 not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	.3***	.24**	.25**	.3***	.23*	.24**
	(.092)	(.093)	(.093)	(.11)	(.11)	(.11)
1[consumer good]			.071			.13
			(.078)			(.098)
1[intermediate good]			.18**			.24**
			(.082)			(.095)
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
Adj R-squared	.029	.16	.17	.021	.13	.15
N. of cases	288	288	285	288	288	285

Table A.4: Management style and firms' TFP before the crisis—full panel structure. *Notes.* This table reports the results of estimating Equation (4) using OLS, and limiting the sample to those firms for which the full panel to estimate TFP is available—see Section 4.1. "Mgt style 2" is a variable between 0 and 1 and indicates Style 2 intensity. "1[consumer good]" and "1[intermediate good]" are indicators for firms that are located in the respective location along the value chain. The omitted category is firms producing capital goods. Columns 2,3,5 and 6 contain sector and region fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	Firm productivity 2001 to 2006 95% winsorized			Firm productivity 2001 to 2006 not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
$1[\text{style } 2 > \frac{2}{3}]$	.19***	.15***	.16***	.19***	.15**	.16**
	(.056)	(.053)	(.053)	(.06)	(.059)	(.06)
$1[\frac{1}{3} < \text{style } 2 \leq \frac{2}{3}]$	.09*	.11**	.1**	.094*	.12**	.11*
	(.05)	(.049)	(.049)	(.055)	(.056)	(.056)
1[consumer good]			.065			.097
			(.065)			(.08)
1[intermediate good]			.12*			.16**
			(.064)			(.073)
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
p: mid vs top tercile	.068	.37	.28	.097	.52	.41
Adj R-squared	.02	.13	.13	.015	.1	.11
N. of cases	385	385	379	385	385	379

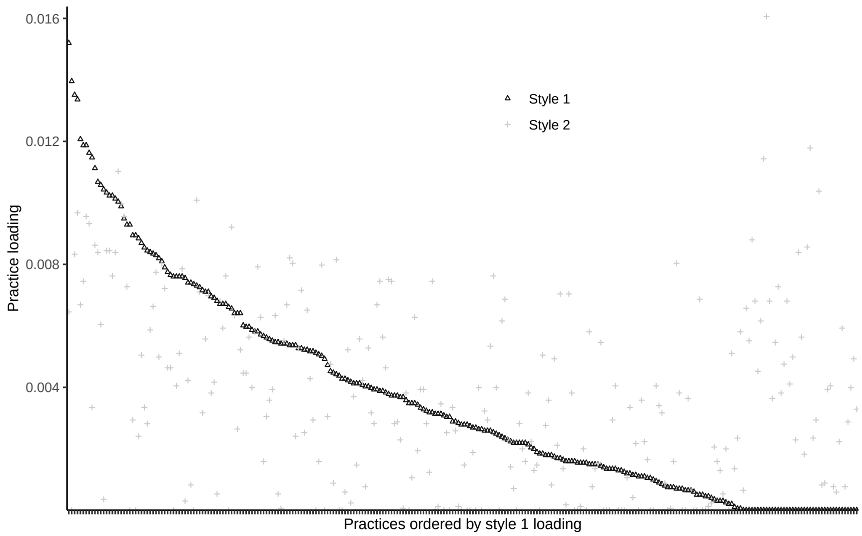
Table A.5: Management style terciles and firms' TFP before the crisis. *Notes.* This table reports the results of estimating Equation (4) using OLS. The dependent variable is a firm's estimated TFP; 95% winsorized in columns 1-3 and non-winsorized in columns 4-6. The indicators bin management style intensity into terciles; the omitted category is the bottom third of Style 2 intensity. "1[consumer good]" and "1[intermediate good]" are indicators for firms that are located in the respective location along the value chain. The omitted category is firms producing capital goods. Columns 2,3,5 and 6 contain sector and region fixed effects. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	Firm productivity (2007 to 2010)-(2001-2006) 95% winsorized			Firm productivity (2007 to 2010)-(2001-2006) not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.14**	-.13**	-.13**	-.1	-.092	-.09
	(.069)	(.064)	(.066)	(.081)	(.077)	(.077)
Pre-crisis TFP	-.36***	-.4***	-.38***	-.38***	-.42***	-.4***
	(.061)	(.066)	(.061)	(.09)	(.088)	(.084)
1[consumer good]			-.018			-.012
			(.057)			(.062)
1[intermediate good]			.026			.024
			(.053)			(.056)
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
Adj R-squared	.2	.27	.28	.22	.28	.29
N. of cases	341	341	336	341	341	336

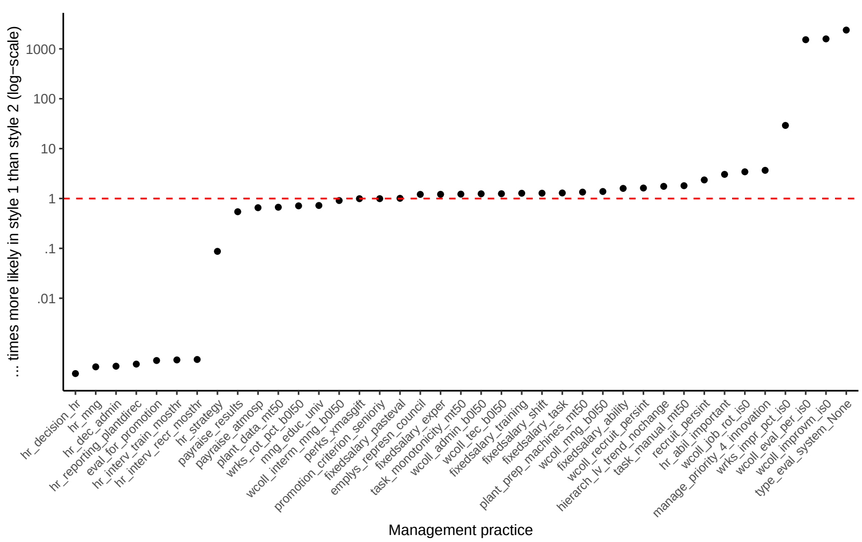
Table A.6: Management style and difference in firm productivity. *Notes.* This table shows results of regressions in which the outcome is the difference between a firm's productivity calculated from 2007-2010 data and its productivity calculated from 2001-2006 data. Both quantities are 95 percent winsorized prior to calculating the difference. "Mgt style 2" is a variable between 0 and 1 and indicates Style 2 intensity. "Pre-crisis TFP" is a firm's productivity calculated from 2001-2006 data. "1[consumer good]" and "1[intermediate good]" are indicators for firms that are located in the respective location along the value chain. The omitted category is firms producing capital goods. Standard errors clustered at the three-digit industry level are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

	Quantile regression			Tobit models		
	Firm productivity 2007 to 2010 95% winsorized			Firm productivity 2007 to 2010 not winsorized		
	(1)	(2)	(3)	(4)	(5)	(6)
Mgt style 2	-.18*	-.17*	-.19**	-.081	-.05	-.051
	(.091)	(.095)	(.097)	(.081)	(.081)	(.083)
Pre-crisis TFP	.75***	.67***	.73***	.55***	.5***	.52***
	(.079)	(.096)	(.094)	(.067)	(.065)	(.065)
1[consumer good]			.13			-.0083
			(.1)			(.083)
1[intermediate good]			.14			.065
			(.098)			(.077)
Sector FE	No	Yes	Yes	No	Yes	Yes
Region FE	No	Yes	Yes	No	Yes	Yes
N. of cases	385	385	379	385	385	379

Table A.7: Management style and firm productivity during the crisis - robustness. *Notes.* This table shows results of regressions which use imputed data to account for possibly endogenous firm exit during the Great Recession. The dependent variable in columns 1-3 is i) a firm's observed productivity level using 2007 to 2010 data, or ii) the productivity level of the least productive firm in that period for those firm we do not observe in that period but do observe in the prior period. The dependent variable in columns 4-6 differs in that we use the firm at the fifth percentile to impute missing values (rather than the least productive). We estimate quantile regressions for the median in column 1-3 and bootstrap standard errors. The bootstrap procedure is replicated 1,000 and draws cluster-robust samples. Standard errors in column 4-6 are analytic and clustered at the three-digit industry level, too. "Mgt style 2" is a variable between 0 and 1 and indicates style 2 intensity. "Pre-crisis TFP" is a firm's productivity calculated from 2001-2006 data. "1[consumer good]" and "1[intermediate good]" are indicators for firms that are located in the respective location along the value chain. The omitted category is firms producing capital goods. Standard errors are reported in parentheses. * (**) [***] denotes statistical significance at the 10% (5%) [1%] level.

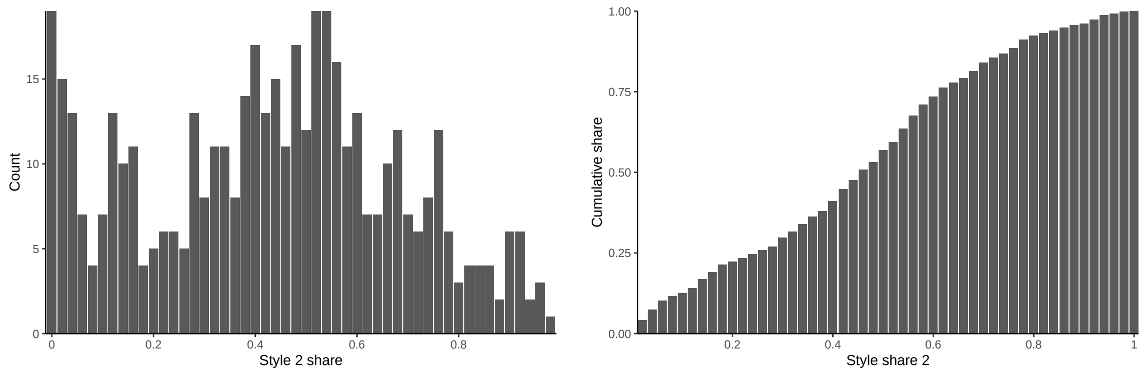


(a) Style distributions.



(b) Differences between styles.

Figure A.3: Style-over-practice distributions. *Notes.* In this figure we visualize differences in practices' loadings across both latent style distributions. The distributions were estimates using the 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. In panel (a),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. In panel (b), we plot the quotient in loadings of the same practice across styles. A high value results from a case in which a practice's loading is higher in Style 1 than in Style 2, and vice versa. We plot the 20 highest ranks on either side breaking ties using the average.



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

Figure A.4: 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.

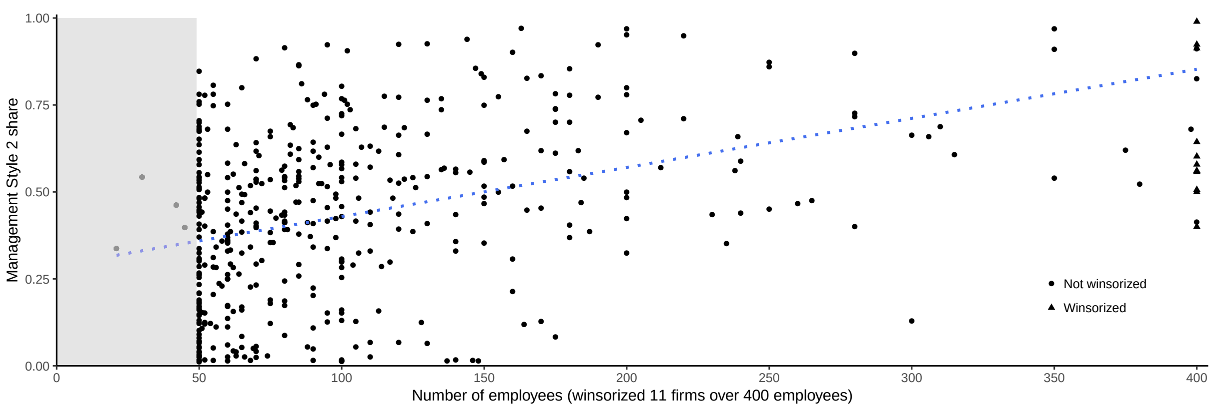


Figure A.5: Style 2 intensity and firms' number of employees. *Notes.* This figure plots the simple univariate relationship between a firm's Style 2 intensity, and its self-reported number of employees from the survey. 11 firms with over 400 employees were winsorized for visual ease; they are represented 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.

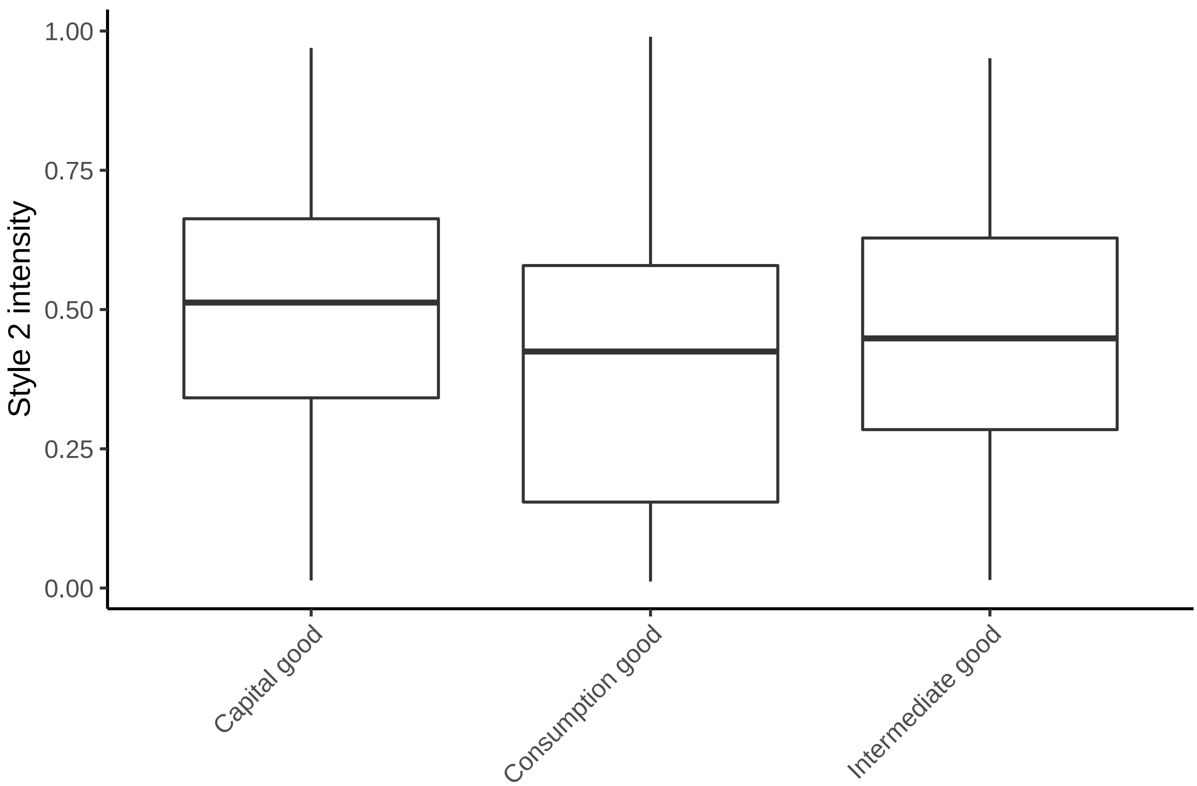
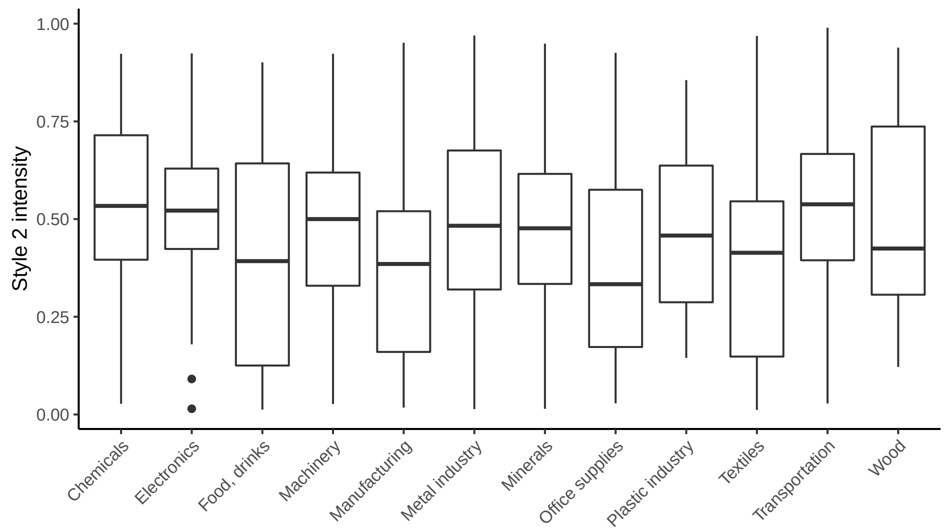
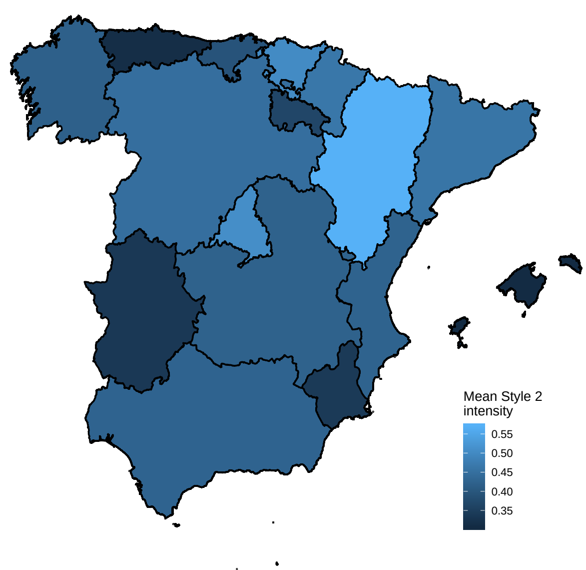


Figure A.6: Style 2 intensity and firms' position in the value chain. *Notes.* This figure shows a box-and-whisker plot of Style 2 intensity relative to firms' position in the value chain. Firms indicate to be producing one of "consumption", "intermediate" or "capital" good in the survey. The horizontal bar within a *box* represents the median; the upper and lower hinge report the largest and small value within 1.5 times the interquartile range, respectively. Dotted values report values beyond the hinges but smaller than three times the interquartile range.



(a) Sectors.



(b) Regions.

Figure A.7: Sectoral and regional variation in style 2 intensity. *Notes.* This figure plots the observed Style 2 intensities across sectors and regions. Panel (a) shows a box-and-whisker plot of Style 2 intensity relative to firms' sector of operation. Firms self-report in which sector they are active. The horizontal bar within a *box* represents the median; the upper and lower hinge report the largest and small value within 1.5 times the interquartile range, respectively. Dotted values report values beyond the hinges but smaller than three times the interquartile range. Panel (b) shows a map of Spanish regions with color intensity reflecting firms' average Style 2 intensity.

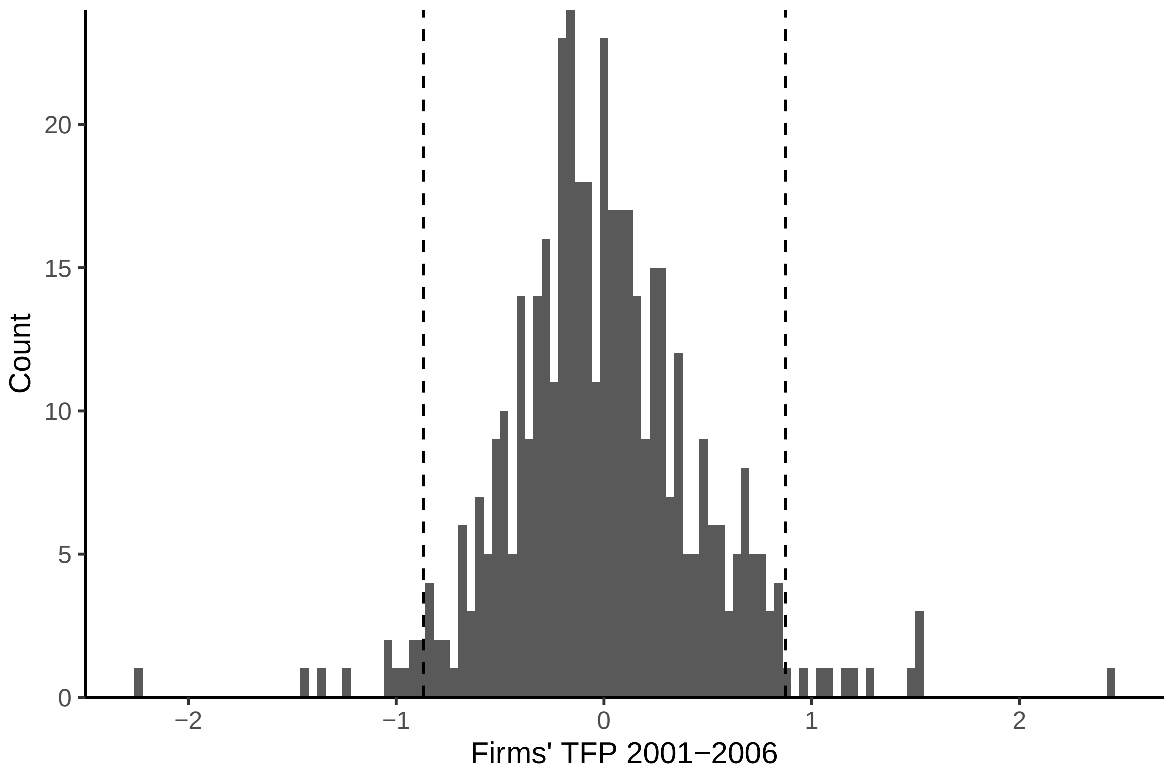


Figure A.8: Firms's total factor productivity 2001-2006. *Notes.* This figure shows a histogram of firms' total factor productivity before the Great Recession using data from 2001-2006. We plot the predicted value of α obtained from estimating Equation (2). The histogram is constructed using a constant 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.

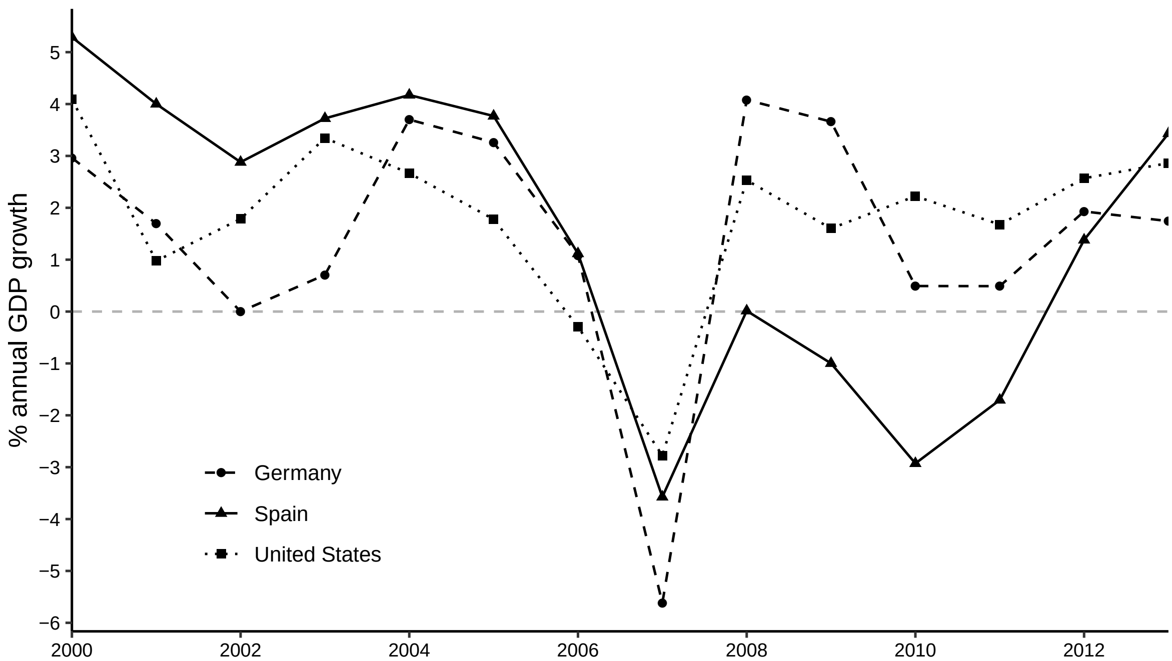
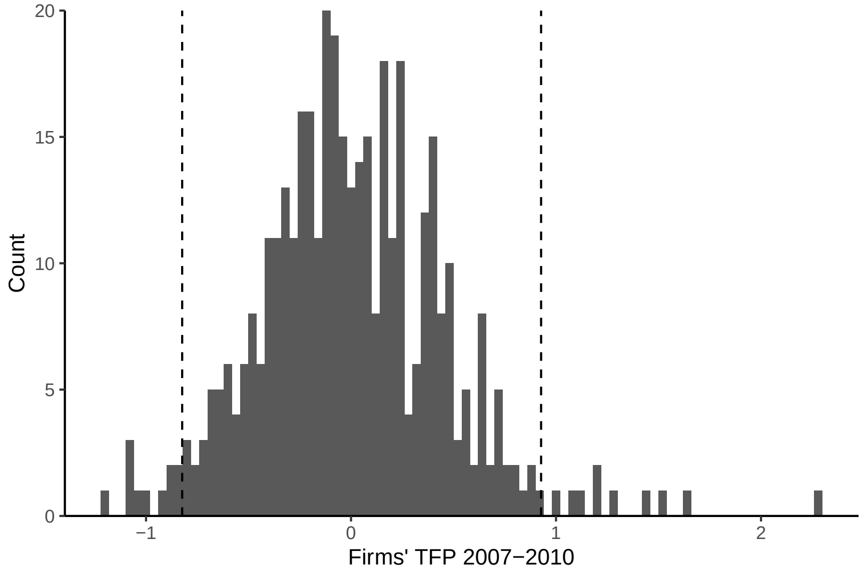
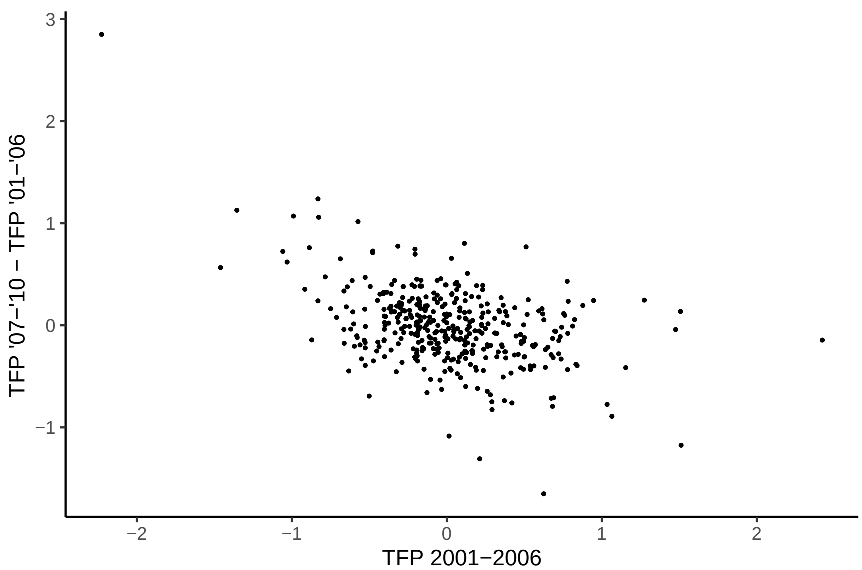


Figure A.9: The Great Recession's impact on GDP growth for select countries. *Notes.* This figure plot year-to-year GDP growth (in percent) for Germany, Spain and the United States. The data on which this figure is based is taken from the World Bank's World Development Indicators.



(a) TFP 2007-2010.



(b) Δ TFP relative to pre-crisis levels.

Figure A.10: TFP during the Great Recession. *Notes.* This figure presents firms' estimated TFP using data from 2007-2010. In panel (a) we show a simple histogram of firms' TFP using a binwidth of 0.04. Panel (b) is a scatter plot where we plot firms' TFP before the crisis (2001-2006 data) on the x-axis, and TFP during the crisis (panel (a) quantity) on the y-axis.

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