NBER WORKING PAPER SERIES

MANAGERIAL QUALITY AND PRODUCTIVITY DYNAMICS

Achyuta Adhvaryu
Anant Nyshadham
Jorge A. Tamayo

Working Paper 25852
http://www.nber.org/papers/w25852

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
May 2019

Thanks to Nick Bloom, Hashem Pesaran, Raffaella Sadun, John Van Reenen, and seminar participants at the NBER, Columbia, Northwestern Kellogg, Harvard, McGill, Michigan, USC, HEC Paris, Clark, Stockholm University, and the MIT/Harvard/Stanford Meeting on Empirical Management for helpful comments. Tamayo gratefully acknowledges funding from the USC Dornsife INET graduate student fellowship. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Managerial Quality and Productivity Dynamics
Achyuta Adhvaryu, Anant Nyshadham, and Jorge A. Tamayo
NBER Working Paper No. 25852
May 2019
JEL No. D24,L2,M11,M12

ABSTRACT

Which managerial skills, traits, and practices matter most for productivity? How does the observability of these features affect how appropriately they are priced into wages? Combining two years of daily, line-level production data from a large Indian garment firm with rich survey data on line managers, we find that several key dimensions of managerial quality, like attention, autonomy, and control, are important for learning-by-doing as well as for overall productivity, but are not commensurately rewarded in pay. Counterfactual simulations of our structural model show large gains from screening potential hires via psychometric measurement and training to improve managerial practices.

Achyuta Adhvaryu
Ross School of Business
University of Michigan
701 Tappan Street
Ann Arbor, MI 48109
and NBER
adhvaryu@umich.edu

Anant Nyshadham
Department of Economics
Boston College
Maloney Hall, 324
Chestnut Hill, MA 02467
and NBER
nyshadha@bc.edu

Jorge A. Tamayo
Harvard Business School
Soldiers Field, Morgan Hall 292
Boston, MA 02163
jtamayo@hbs.edu

1 Introduction

Asymmetric information is a key feature of labor markets around the world. The full set of workers' skills – in both technical and soft dimensions – is notoriously difficult to observe and to contract on for potential employers (Acemoglu and Pischke, 1999; Altonji and Pierret, 2001; Farber and Gibbons, 1996; Lange, 2007). Moreover, the mapping from skills to productivity for a given job may not be easy to decipher by either party, and is likely even harder to learn for potential employers compared to existing employers (Acemoglu and Pischke, 1998; Kahn, 2013; Kahn and Lange, 2014). These frictions can lead to a misallocation of labor and skill and contribute to the vast dispersion in productivity across firms and countries (Bloom and Van Reenen, 2007; Syverson, 2011). Which features of candidate managers – their skills and abilities, personality traits, workplace behaviors, etc. – contribute most to productivity? Which can employers readily observe, and which are obscured during the hiring process? How appropriately are these features priced into wages and what are the implications for the firms' screening and training policies?

These are largely still open questions, in part due to several key empirical challenges. The first challenge is simply that skills, wages, and productivity – all at the individual level – are rarely available in the same data. Second, when such data do exist, one must extract reliable signals of each dimension of skill from a potentially large number of noisily measured and possibly redundant characteristics of workers (Bandiera et al., 2017), and these signals must be linked to productivity in a flexible manner that allows for potential interactions among factors.[1] Third, while assessing mean productivity differences across managerial characteristics is of core importance (Bertrand and Schoar, 2003; Bloom et al., 2018a, 2016; Lazear et al., 2015), in contexts where productivity dynamics are salient – such as the case of learning by doing in manufacturing processes – understanding the role of various dimensions of skill in these dynamics is critical (Arrow, 1962; Benkard, 2000; Jovanovic and Nyarko, 1995; Levitt et al., 2013; Lucas, 1988; Thompson, 2001).[2] This latter challenge also emphasizes the need for data granular enough to capture the evolution of productivity over time.

In this study we seek to overcome these challenges, focusing on the case of production line supervisors in Indian readymade garments factories. Managerial quality plays a key role in firm productivity and

[1]To leverage the full breadth of the managerial survey data collected in this context and to explore agnostically the degree to which different managerial characteristics impact these dimensions of the learning curve, we propose a structural estimation of the learning process using a non-linear latent factor measurement system to obtain the inputs of managerial quality, similar to the one used in recent studies of the cognitive and noncognitive components of the skill production function (Attanasio et al., 2015a,b; Cunha et al., 2010).

[2]This study answers a pointed call made in Levitt et al. (2013) to conduct "research on the complementarities between the learning process and managerial practices."

growth (Bloom et al., 2013, 2018b; Bloom and Van Reenen, 2007, 2011; Karlan et al., 2015; McKenzie and Woodruff, 2013, 2016), and differences in firms' managerial practices explain a substantial portion of the yawning productivity gap across rich and poor countries (Caselli, 2005; Hall and Jones, 1999). Middle managers like the line supervisors we study are often singled out as especially important in facilitating efficient production, and in many low-income country contexts, quality in this tier of the managerial hierarchy is characterized as particularly low (Adhvaryu, 2018; Blattman and Dercon, 2016).

We study the ways in which managerial skills interact with the learning by doing process, a foundational feature of labor-intensive manufacturing. We match granular production data from several garment factories in India to rich information from a survey conducted on the universe of line supervisors employed in these factories to answer the basic question: which managerial skills, traits, and practices contribute most to productivity? Importantly, our survey measures a wide array of features, some of which are easily observable (like industry experience) and some which are likely much more costly or difficult to ascertain at the time of hiring (like personality psychometrics or managerial attention). We then investigate how these features of managers are priced into wages; specifically, whether the features that matter most for productivity have commensurate importance for managers' compensation. Finally, we use structural model estimates to simulate the impacts of screening/hiring policies and management training interventions.

We begin by documenting the presence and scope of learning in our context. Productivity, as measured by the proportion of target production realized by a line per unit time ("efficiency"), is strongly increasing in experience. Efficiency rises by roughly 50% or more over the life of a production run.[3] This pattern is identical irrespective of whether experience is measured as days the line has been producing the current product or cumulative quantity produced to date.[4] Learning curves exhibit strong concavity: learning slows markedly after roughly the first 10 days of an order's production cycle. We also document the presence of retained learning from previous runs of the same style, as well as the depreciation of this retained stock of learning over the intervening time between runs.[5]

[3] Efficiency rises from roughly 40 points when a line first starts production of a garment style to around 60 points by the end of the production run.

[4] Previous studies have addressed possible endogeneity in the dynamics of production decisions and therefore the sequence of productivity shocks or innovations by instrumenting for differences in quantity produced each period with demand shifters or the contemporaneous productivity of other production teams (Benkard, 2000; Levitt et al., 2013; Thompson, 2001). By conducting our analysis using a time-based measure of accrued experience (and documenting qualitatively identical patterns as those obtained using quantity based measures), we circumvent this issue. That is, if production is mean 0 conditional on past productivity and determinants of learning and i.i.d. from a stationary distribution each day of the production run, then this type of endogeneity is not an issue. The similarity in patterns when using time- and quantity-based experience results, as well as robustness of main results to controlling for days left to complete the order, lends support to this assumption.

[5] Experience from previous runs contributes roughly 50% of the productivity gains of an equivalent unit of experience from the current run on average, with each log day of intervening time between runs eroding gains by roughly 15-20% (i.e., retained

Next, we analyze the relative contribution of various dimensions of managerial quality to these productivity dynamics. Our structural estimation procedure isolates each quality dimension's contribution, as well as allows for interactions between dimensions. We also address the common issues of measurement error and redundancy likely to prevail in a large set of survey measures of quality.[6] That is, to leverage the full breadth of the managerial survey data collected in this context and to explore agnostically the degree to which different managerial characteristics impact the learning curve, we propose a structural estimation of the learning process using a non-linear latent factor measurement system to obtain the inputs of managerial quality, akin to recent studies of the skill production function (Attanasio et al., 2015a,b; Cunha et al., 2010).

Our empirical analysis proceeds in three steps. First, we estimate a canonical learning function, taking a form similar to the functions estimated in, e.g., Benkard (2000), Kellogg (2011), and Levitt et al. (2013), except that we allow for the parameters governing the shape of the learning curve to vary by managers. Second, in the spirit of Cunha et al. (2010), we estimate a nonlinear latent factor model using the data from our managerial survey to recover information about the joint distribution of k latent factors of managerial quality and the learning parameters estimated in the first stage. In an exploratory factor analysis, we identify seven distinct factors related to well-studied dimensions of managerial characteristics, falling into three broad categories: *easily screened traits* (tenure and demographics), *costly-to-screen traits* (cognitive skills and personality), and *trainable behaviors and practices* (autonomy and attention). Finally, we draw a synthetic dataset from the joint distribution of these factors and the productivity parameters and estimate a CES-type function for each learning parameter with the factors of managerial quality as arguments.

We find that both easy- and costly-to-screen dimensions of managerial quality contribute to productivity, and that both trainable behaviors and practices as well as less malleable traits are important. Tenure in a supervisory position, managerial attention, and autonomy are important for all elements of productivity dynamics. Cognitive skills and the factor related to internal locus of control matter most for initial productivity. Personality traits and the demographic similarity of supervisors to their workers do not contribute incrementally to initial productivity or the rate of learning, but are substantially correlated with other factors that do. Elasticity estimates reveal that these dimensions of quality are not highly complementary: that is, irrespective of tenure and cognitive skills, managers can achieve higher productivity by exhibiting more autonomy or attentiveness. This implies that screening on or training in these skills

learning is depreciated by roughly 50% after three and a half production weeks away from a style).

[6] That is, many survey measures likely proxy for the same underlying dimensions of managerial quality, but one must identify which measure does so with the strongest signal and purge these measures of this noise to be able to assess contributions to productivity.

may be quite effective in raising productivity.

Analysis of manager pay indicates that some dimensions of managerial quality are also more appropriately priced in the labor market than others. We perform counterfactual simulations of screening (hiring) and training policies using the structural model estimates and compare predicted gains in productivity to predicted increments in pay. Easily screened dimensions like tenure contribute to pay in greater proportion to their impacts on productivity. Harder-to-screen (or less obviously productive) dimensions such as attention and control are less proportionately rewarded. Estimates of pass-through to managers' pay of productivity increases resulting from simulated screening and training experiments are in general modest, ranging from 20% for cognitive skills to 48% for autonomy.

These results suggest substantial information frictions in the labor market for managers. Given the correlation between personality traits and other factors that are important for productivity, such as cognitive skill and autonomy, firms could meaningfully improve the selection of managers via psychometric measurement and screening of candidates. Likewise, given the independent contribution and seemingly low observability of managerial attention in the labor market, providing training to improve this dimension of quality would be profitable for firms.

Our study contributes to a fast-growing economics literature on the importance of management practices in organizations across the world (Adhvaryu et al., 2018a; Aghion et al., 2017; Bandiera et al., 2017; Bloom et al., 2017a, 2013, 2017b; Bloom and Van Reenen, 2007; Macchiavello et al., 2015; McKenzie and Woodruff, 2016; Schoar, 2011).[7] Our work is most closely related to Bloom et al. (2016), who estimate firm production functions that incorporate management as a technology; Bloom et al. (2018a), who study management practice variation across US firms; and Bandiera et al. (2017), who study the link between time use and productivity of CEOs around the world.

We add to this work in four ways. First, existing work is at the level of the firm. We identify a large degree of management practice variation *within* the firm, and show that this variation meaningfully predicts productivity differences across managers. Second, focusing on the level of individual managers lets us determine the pass-through of managerial quality to pay, providing insight into the nature of the labor market for managers in low-income settings. Our findings suggest substantial information frictions

[7] There is, of course, a vast literature in the areas of management and organizational behavior on the relationship between managerial practices and firm performance. We do not attempt to fully review this literature here, but rather highlight that many of the studies in this body of work focus on single practices, or narrowly defined sets of practices, and relate these practices to productivity in an unstructured manner (Bowen and Ostroff, 2004; Cappelli and Neumark, 2001; Collins and Clark, 2003; Collins and Smith, 2006; Combs et al., 2006; Delaney and Huselid, 1996; Hansen and Wernerfelt, 1989; Huselid, 1995). We improve on this work by remaining relatively agnostic about which practices and traits matter and attempting to span a broad set of characteristics, and relate these characteristics to productivity at the line level in a highly structured way that captures key aspects of production dynamics.

in the labor market, particularly with regard to less readily observable dimensions of quality. This is in line with recent work on training and signaling interventions in low-income country labor markets (Adhvaryu et al., 2018b; Alfonsi et al., 2017; Bassi and Nansamba, 2017). Third, the structural estimation procedure we implement allows for counterfactual simulations which yield clear implications for firm hiring and training policies. Finally, we continue the budding investigation into the relative importance of managers versus management practices and contribute additional empirical evidence on which specific skills and practices of managers are most important for productivity (Syverson, 2011).

The rest of the paper is organized as follows. Section 2 explains the garment production process, our data sources, and the construction of key variables. Section 3 presents preliminary graphical evidence of productivity dynamics and heterogeneity by various dimensions of managerial quality. Section 4 develops a structural model to formalize these relationships. Section 5 describes our strategy for estimating the model in three stages and section 6 describes the results. Section 7 discusses checks and robustness, and section 8 concludes.

2 Data

We use data from two main sources for this study. The first source is line-daily data on productivity and specific style (product being produced by each line each day), and the second is survey data on managerial characteristics and practices at the supervisor level that we match to the production lines they manage.

2.1 Production Data

We use line productivity data at the daily level for two years, from July 2013 to June 2015, from six garment factories in Bengaluru, India. The data include the style or product the line is working on, the number of garments the line assembles and the target quantity for each day. Target quantities are lower for more complex garments (since lines can produce fewer complex garments in a given day), and therefore are an appropriate way to normalize productivity across lines producing garments of varying complexity. Our primary measure of productivity is efficiency, which equals garments produced divided by the target quantity of that particular garment per day. Efficiency is the global industry standard measure of productivity in garments.

The target quantity for a given garment is calculated using a measure of garment complexity called the standard allowable minute (SAM). SAM is taken from a standardized global database of garment industrial engineering that includes information on the universe of garment styles. It measures the number of minutes that a particular garment should take to produce. For instance, a line producing a style with SAM of 30 is expected to produce 2 garments per hour per worker on the line. Accordingly, a line of 60 workers producing a style with SAM of 30 for 8 hours in a day will have a daily target of 960 units.[8] If the line produces 600 garments by the end of the day its efficiency would be $600/960 = .625$ for that day. We use daily line-level efficiency as the key dependent variable of interest.[9]

From the productivity data, we can calculate how long a production line has been producing a particular garment style. We can measure learning-by-doing in 2 ways: as a function of the consecutive number of days that a line has been working on a particular style, or as a function of the cumulative quantity the line has produced of that style to date. By conducting our analysis of learning using a time-based measure of accrued experience (while documenting qualitatively identical patterns using a quantity-based measure of experience), we circumvent the issue of endogenous productivity innovations across unit time. That is, serial correlation in production innovations are less concerning when the unit of experience is deterministic like time rather than stochastic like quantity produced to date.[10] We show graphical evidence using quantity-based experience, but use time-based experience as our preferred measure in the structural estimation as it is more robust to endogeneity concerns.[11]

We can also see in the data whether a line is producing a style that it has produced in the past, and how that changes current learning-by-doing. In particular, we define three variables that measure retained prior learning and forgetting: 1) the number of days since the production line last produced the style it is currently producing, 2) the total number of days that the line produced the same style over prior production runs, and 3) the total quantity that the line produced of a particular style prior to the start of the current production run. Of course, these three variables are positive only when lines have produced a particular style more than once and are all 0 when a line is running a style for the first time.

Table 1 presents summary statistics of key variables of interest. We use data from 120 production lines with a total of 153 supervisors.[12] Our sample comprises roughly 50,000 production line-date observa-

[8]That is, the line has 60 minutes $\times$ 8 hours $\times$ 60 workers = 28,800 minutes to make garments that take 30 minutes each, so $28{,}800/30 = 960$ garments by the end of the day.

[9]We run all the same analysis with log quantity as the outcome instead of log efficiency and find qualitatively identical results (see Section 7.3). We keep log efficiency as our preferred outcome as this most closely corresponds to outcomes used in related studies like defect rates in Levitt et al. (2013) and labor per unit produced Benkard (2000) and Thompson (2012).

[10]This issue is discussed and investigated in detail in previous studies. See, e.g., Thompson (2001).

[11]In additional robustness results, we also include days left to the end of each order to control for any *reference point effect* (i.e., productivity increasing as the end of the order approaches). These results are presented in Appendix B and discussed in section 7.3. They appear nearly identical to the main results.

[12]We restrict our analysis to the largest connected set of styles-lines, which includes 120 of the 130 lines for which we have data available. We use the *bgl* toolbox in matlab to extract the largest connected set. Finally, we use an iterative conjugate gradient algorithm suggested by Abowd et al. (2002) to solve for the standard normal equations.

tions, and we observe nearly 2,740 line-style pairings with 88% of lines producing the same style more than once. Mean efficiency is about 0.51 overall, but less than 0.41 on the first day of a new production run. Production runs last for an average of around 15 days and produce on average 6,200 total pieces. Prior experience values are slightly more than the length of time and total quantity of an average order, consistent with lines having on average more than one previous run of experience. On average, the intervening time between runs of the same style on a line is similar in magnitude to the length of a single run.

Table 1: Summary Statistics

	Observations	
Number of line-day observations	49,976	
Number of lines	120	
Number of styles	1,003	
Number of line-style matchings observed	2,742	
Percent of lines producing same style more than once	88%	
Number of supervisors	153	
	Mean	**SD**
Production		
Efficiency	0.512	0.168
Initial Efficiency (first day of production run)	0.407	0.207
Current Experience		
Total length of production run in days	14.927	14.177
Total quantity produced in a line-style run	6196.6	7418.4
Experience from Prior Production Runs		
Total days of prior experience on a given style	19.321	22.690
Total quantity produced on previous runs of the same style	9566.9	12836.0
Intervening days between runs of the same style	15.319	24.001

Note: We keep the largest connected set between lines and styles, which corresponds to 96 lines and 1003 styles. Efficiency is equal to the garments produced divided by the target quantity of that particular garment. The target quantity is calculated using a measure of garment complexity called the standard allowable minute (SAM), which is equal to the number of minutes that a particular garment should take to produce.

2.2 Management Survey Data

Each line is managed by 1 to 3 supervisors who assign workers to tasks and are charged with motivating workers and diagnosing and solving production problems (such as machine misalignment or productivity imbalances across the line) to prevent and relieve bottlenecks and keep production on schedule.

To measure managerial quality, we conducted a survey of all line supervisors. We drew from several sources to construct the management questionnaire, in particular borrowing heavily from Lazear et al. (2015), Schoar (2014), Bloom and Van Reenen (2011) and Bloom and Van Reenen (2010). The survey consisted of several different modules intended to measure both traditional dimensions of managerial skill like job and industry-specific tenure and cognitive skills as well as leadership style and specific managerial practices that have been emphasized in the literature. Additional modules on personality and risk and time preferences were also administered. Overall the survey covered work history, leadership style, management practices, personality psychometrics, cognitive skills, demographic characteristics and discriminatory attitudes.

In order to form a comprehensive assessment of each manager's "quality," we utilize the entirety of the survey in constructing measures to include in the non-linear factor system.[13] We allocate this full set of measures to factors by first conducting exploratory factor analyses within each module of the survey to determine if measures within a module appeared to inform a single factor or multiple factors. We then pool measures across related modules (e.g., leadership style and managerial practices) and perform the exploratory factor analysis again on this pooled set to check that measures are being correctly mapped to the factor for which they are most informative.[14] We follow Cunha et al. (2010), Attanasio et al. (2015b), and Attanasio et al. (2015a) in conducting this exploratory analysis to define factors and determine the mapping of measures to factors. As they do, we perform rotations of the factor loadings to confirm that measures are mapped to the factor they most strongly inform.

We first construct factors that capture the most commonly observed traits of job candidates: work history and demographics. We construct a tenure factor to measure the importance of on-the-job human capital accumulation as emphasized in the long-standing literature on wage growth and productivity. We also construct a demographics factor meant to capture demographic similarity between the supervisor and workers on the line they manage and any discriminatory attitudes the supervisor might have regarding demographic characteristics of their workers.

To inform the tenure factor, we use 4 measures: total years working, years working in the garment industry, years working as a garment line supervisor, and years supervising the current line. In exploratory

[13]In the end, we include all measures from the survey except for a few additional demographic (e.g., mode of transportation to work) and work history (e.g., second sources of income and agricultural experience) variables that were irrelevant to the research questions in this study.

[14]Note that the measurement system we implement allows for the recovered factors to be correlated with each other, so it is permissible for measures to load incidentally onto other factors. However, we ultimately want to identify each factor from the set of measures which load primarily onto that factor. Accordingly, we check for each mapping that the measure most strongly informs the factor to which it is mapped above all other factors.

factor analysis, these four measures load onto a single eigenvector with an eigenvalue greater than 1 indicating that a single factor summarizes their contribution. In additional pooled analyses with other demographic characteristics, cognitive skills, and managerial measures discussed below, this factor persistently appears as distinct from the other factors and all of these four measures consistently inform this factor more strongly than any other. The literature on productivity contributions of industry, firm, and job-specific accrued human capital, is large and well-established (Gibbons and Waldman, 2004; Jovanovic, 1979; Mincer and Ofek, 1982; Mincer et al., 1974; Neal, 1995; Topel, 1991). Any contribution of additional dimensions of managerial quality described below should be measured after accounting for this long-studied dimension.

We collect two measures related to demographics. The first is a simple count of the number of similarities between supervisor and majority of workers on the line in the following dimensions: age, gender, religion/caste, migrant status, and native language. The second measure is a count of the number of demographic dimensions (total of 9) over which the supervisor expressed no discriminatory preference. These measures load onto the same factor in the exploratory analysis and do not load more strongly onto any other factors in additional pooled factor analyses. In pooled factor analyses this factor appears distinct but weak with a positive eigenvector smaller than one. Nevertheless, we include this additional factor as dimensions of ethnic and other demographic similarity and discrimination have been emphasized in the literature (Hjort, 2014).

We next construct three factors meant to capture both cognitive skills reported as useful for production line supervisors and a broad array of non-cognitive skills or personality dimensions and attitudes. The literature on returns to cognitive skills in productivity and earnings is nearly as long-standing and well-established as that for tenure (Boissiere et al., 1985; Bowles et al., 2001). To inform the cognitive skills factor, we use a measure of short-term memory and two measures of arithmetic skill. Digit span recall captures the largest number of digits in an expanding sequence the respondent was able to successfully recall. We use both the number of correct responses on a timed arithmetic test we administered as well as the percent of the attempted problems that had correct responses. Exploratory factor analysis of these three measures yields only 1 factor with a positive eigenvalue. Pooled factor analyses once again show that this factor is distinct from the others and that these three measures inform this factor above all others.[15] Once again, as has been emphasized in recent studies of the returns to cognitive and non-cognitive

[15] The preliminary analyses show that these cognitive skills measures are positively correlated with measures of Autonomy, Attention, Control and Personality discussed below, but an orthogonal varimax rotation confirms that these three measures load more strongly onto a separate factor than those primarily informed by these other measures.

skills (Heckman et al., 2006), we must account for, and even benchmark against, these traditional dimensions of ability when studying additional dimensions of managerial quality like autonomy, personality, and attention.

Recent empirical studies have begun to document the incremental importance of personality psychometrics, alongside cognitive skills and specialized human capital accumulation, for earnings and productivity (Borghans et al., 2008; Heckman and Kautz, 2012). The survey included a standard module for conscientiousness meant to capture commonly measured personality psychometrics.[16] In addition, we collected measures of perseverance, self-esteem, and internal locus of control as well as risk aversion, patience, and Kessler's psychological distress scale.[17]

We started by checking if the two measures of risk and time preferences informed distinct factors. Exploratory factor analysis showed that risk aversion and patience loaded onto the same factor. Analogous factor analysis on the four measures from the personality psychometrics module (i.e., conscientiousness, perseverance, psychological distress, self-esteem, and internal locus of control) revealed two distinct factors. Conscientiousness, perseverance, self-esteem, and psychological distress are highly correlated and load onto a single factor, while internal locus of control loads onto a distinct factor. Factor analysis on the pooled set of measures across these two modules yields two distinct factors with internal locus of control loading clearly onto the same factor as risk aversion and patience.

Finally, we collect survey measures of managerial behaviors and practices emphasized in previous studies. We pool measures from the two management related modules to construct factors. These two modules measured leadership behaviors with respect to "initiating structure" and "consideration" (Stogdill and Coons, 1957) and specific management practices such as production monitoring frequency, problem identification and solving, efforts to meet targets, communication with subordinates and upper level management, and personnel management activities.[18] Additional self-reported measures of issues overcoming worker resistance and motivating workers as well as a self-assessment measure of managerial quality relative to peer supervisors were also collected. We pooled these measures from the two modules together for the exploratory factor analysis to be most agnostic about which dimensions of management styles and practices are being measured by these survey modules. The factor analysis yields two eigenvectors with

[16] Piloting showed that the other "Big Five" modules produced measures that were highly correlated with conscientiousness. This is consistent with what other recent studies have found among blue-collar workers in developing countries (Bassi and Nansamba, 2017). Accordingly, we did not administer the other Big 5 modules and rely on conscientiousness alone.

[17] Modules for risk and time preferences were adapted from those used in the Indonesian Family Life Survey.

[18] The module from which we obtain these measures is taken from the World Management Survey (Bloom and Van Reenen, 2007), adapted to allow for closed responses as opposed to open as piloting revealed closed response questions to be more effective in our setting with frontline supervisors in developing country factories.

eigenvalues above 1.

Both measures of leadership style ("initiating structure" and "consideration") load onto the same factor with initiating structure having the higher loading. "Initiating structure" is said to capture the degree to which a manager plays a more active role in directing group activities; while "consideration" is meant to capture a good rapport with subordinates (Korman, 1966). These two behaviors are often hypothesized to be somewhat distinct from each other, but the factor analysis shows that in our context initiating structure and consideration are highly correlated. Nevertheless, both have been consistently validated as informative measures of successful leadership (Judge et al., 2004). Our two measures of the degree to which the supervisor takes the lead in and responsibility for identifying and solving production problems also load onto this same factor, along with the self-assessment measure of managerial quality relative to peers. Given the higher loading of "initiating structure" and the contributions of our measures of problem identification and solving, we interpret this factor as capturing autonomy on the part of the supervisor, both in terms of leadership style and management practices. The empirical literature on the value of autonomy among lower level managers is small, but a few recent papers on decentralization of management have emphasized the importance of this dimension. Aghion et al. (2017) find that more empowered lower-level management allows for stronger resilience during economic slowdowns. Similarly, Bresnahan et al. (2002) find that the productivity returns to information technology are highest when management is decentralized. Indeed, Bloom and Van Reenen (2011) emphasize managerial autonomy/decentralization as an important dimension of managerial quality, drawing from earlier evidence of the value of autonomy at higher levels of organizational hierarchy (Groves et al., 1994).

The second factor from these management modules reflects contributions from five managerial practice measures: efforts to achieve production targets, production monitoring frequency, active personnel management, communication, and issues motivating workers and overcoming resistance. Each of these is meant to measure effort and attention on the part of the supervisor in accomplishing managerial tasks. The first measures the number of different practices the supervisor engages in to ensure production targets are met. The second records the number of times in a day the supervisor makes rounds of the production line to identify any production problems. The third measures the number of different practices the supervisor engages in to retain workers, motivate low performing workers, and encourage high performing workers. The fourth measures the frequency of communication regarding production with both workers and upper level managers, with a higher value representing less communication. The fifth measures the frequency with which the supervisor reports issues motivating workers and overcoming resistance to initiatives and change. Accordingly, we interpret this factor as capturing managerial attention. The literature on managerial attention is long-standing in theory and has added some recent empirical evidence (Ellison and Snyder, 2014; Reis, 2006). For example, Adhvaryu et al. (2018a) find that more attentive managers are better able to diagnose and relieve bottlenecks that arise from shocks to worker productivity.

Summary statistics for these measures across all 153 supervisors are presented in Table 2. As discussed above, lines have between 1 and 3 permanent supervisors. While we have management characteristics for each manager, productivity data is common across managers of the same line. Co-supervisors generally share all production responsibilities, so it is only appropriate to match the productivity of a given line equally to each of the supervisors responsible.

2.3 Manager Pay

In additional analysis, we explore the degree to which the contributions of various managerial quality measures to productivity dynamics translate into supervisor pay. Given the difficulty in accurately measuring dimensions of managerial quality, as outlined in our approach below, and the complexity and nuance in the relationships between dimensions of quality and various aspects of productivity, we might expect that the firm struggles to appropriately identify and reward supervisor quality. To investigate this, we obtained pay data for each supervisor from the month in which the survey was completed (November 2014).

These data include both monthly salary as well as any production bonus earned by the supervisor when the production line exceeds targets. Summary statistics for these pay variables are reported in the bottom rows of Table 1. Note that there appears only a negligible difference between the monthly salary alone and complete pay inclusive of production bonus. That is, while supervisors can in theory be rewarded for their productivity by way of production bonuses, these bonuses make up only a small fraction of supervisor compensation. Accordingly, in order to appropriately reward supervisor quality in practice, the firm must adjust monthly salary to reflect quality. We explore the degree to which we observe this occurring below.

Table 2: Managerial Quality Measures

	Mean	SD
Tenure		
Total Years Working	12.369	5.125
Tenure in Garment Industry	10.074	4.411
Tenure as Supervisor	4.779	3.117
Tenure Supervising Current Line	1.919	2.055
Demographics		
Demographic Similarity	4.872	2.340
Egalitarianism	3.557	0.961
Cognitive Skills		
Digit Span Recall	6.181	1.847
Arithmetic (Number Correct)	11.517	3.706
Arithmetic (% Correct of Attempted)	0.811	0.181
Control		
Internal Locus of Control	-5.000	3.928
Risk Aversion	3.148	1.462
Patience	2.107	1.289
Personality		
Perseverance	17.899	3.338
Conscientiousness	13.456	4.017
Self-Esteem	8.933	3.418
Psychological Distress	13.664	4.582
Autonomy		
Initiating Structure	42.423	5.479
Consideration	44.765	5.196
Autonomous Problem-Solving	-0.268	1.128
Identifying Production Problems	4.000	1.232
Self-Assessment	8.792	1.462
Attention		
Monitoring Frequency	4.846	0.415
Efforts to Meet Targets	2.852	0.918
Active Personnel Management	8.356	2.014
Lack of Communication	8.128	2.411
Issues Motivating Workers, Resistance	7.953	2.145
Pay		
Gross Salary (monthly)	14895.4	2024.6
Gross Pay with production bonus (monthly)	15079.7	2047.8

Note: Tenure variables are measured in years. Demographic similarity measures the similarities between the managers and the workers (range 0 to 9) and egalitarianism measures the preferences of the managers about the workers of the line (range 0 to 3). Digit span recall measures the number of correct digits a manager remember from a list of 12 numbers; arithmetic (number correct) counts the number of correct answers in a math test with 16 questions; arithmetic (% correct of attempted) is the ratio of the number of correct answers in a math test with 16 questions to the number of questions attempted. Locus of controls is an index from -15 to 1; risk averse and patience are indices from 0 to 4. Perseverance is an index from 9 to 22; conscientiousness captures personality psychometrics from the Big 5 modules (range 3 to 20); self-esteem is an index from 1 to 16; psychological distress refers to Kessler's psychological distress scale (range 10 to 37). Initiating structure capture the degree to which a manager plays a more active role in directing group activities (range 30 to 50) and consideration capture a good rapport with subordinates (range 32 to 55); autonomous problem solving (range -3 to 2) and identifying production problem (range 1 to 7) measure the ability of the managers to identify and solve production problems alone; self-assessment measures one's evaluation of managerial quality relative to peers (range 5 to 10). Monitoring frequency is the number of rounds of the line to monitor production (range 2 to 5); efforts to meet targets is a composite index of dummy variables that measure the activities the supervisors reports engaging in to ensure that production targets are met (range 0 to 5); active personnel management is constructed analogously for activities related to reinforcing high level performance from star and under-performer workers (range 3 to 13); lack of communication measures the frequency of communication regarding production with both workers and upper level managers (range 3 to 18); issues motivating workers, resistance measures the frequency with which the supervisor reports issues motivating workers and overcoming resistance to initiatives and change (range 5 to 18).

3 Graphical Motivation

Before adapting the canonical function shared by most recent empirical studies of learning-by-doing to allow for heterogeneity across managers, we present graphical evidence that illustrates the learning patterns in our empirical context.

3.1 Dynamics of Productivity

We first present figures that depict how efficiency evolves as a function of the number of days that a production line has been producing a particular style consecutively. As an alternative to the number of days that the line has been producing a style, we also present efficiency as a function of the cumulative quantity that the line has produced to date.[19] As noted above, quantity-based experience measures may be subject to endogenous production decisions and serial correlation in production volume. That is, if factory management ramps up production for a series of consecutive days, then higher quantity produced one day (and therefore a larger experience increment) would look like it increased productivity on subsequent days through learning erroneously. On the other hand, when the increment of experience is fixed and deterministic like in time-based experience measures, this concern is less salient. Accordingly, we conduct this preliminary analysis using both a quantity-based measure of experience to conform with the convention set by previous studies and a time-based measure to demonstrate robustness to these endogeneity concerns.[20] We demonstrate the robustness of the empirical patterns across both experience measures here; however, in the main estimation, we present results using the experience defined in days producing a style as our preferred measure.

Figures 1A and 1B show the learning curve for our two measures of experience of the current run: days line has been producing the current style and cumulative quantity of the current style produced to date, respectively. Both figures reflect that productivity, as measured by efficiency, is increasing and concave in the line's current experience. Lines start the production of a new style at around 40% efficiency and approach a maximum of around 60% efficiency. The majority of this roughly 50% rise in productivity over the course of a production run occurs over the first 10 production days or first 3000 units produced of a given style.[21]

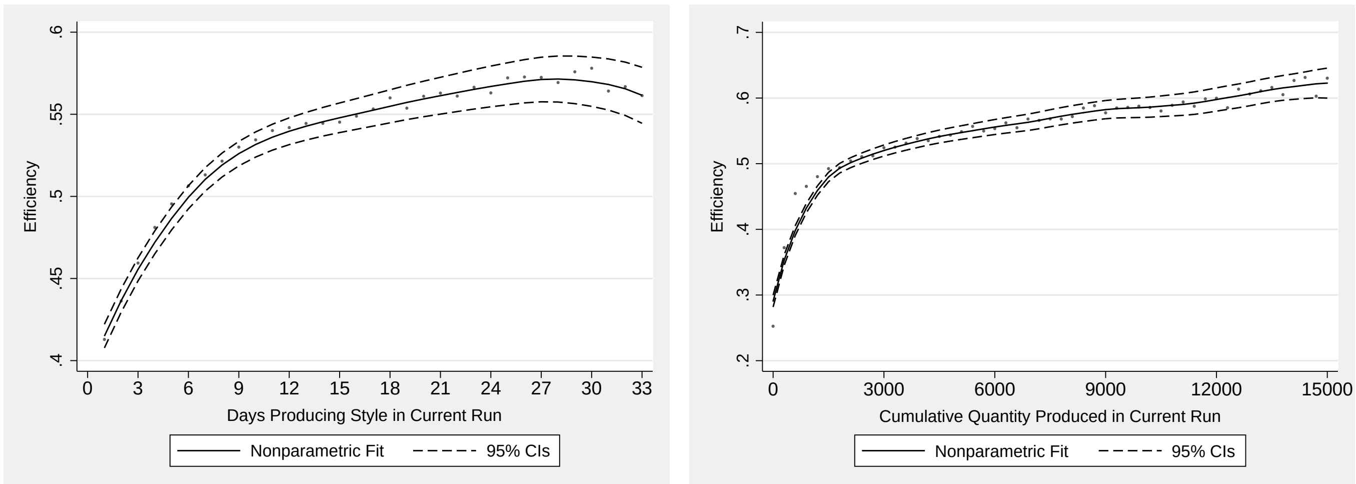
[19]The two are highly correlated, with a correlation of over 0.9, but either may plausibly be considered as the appropriate unit of learning.

[20]We also control for days left to complete production in the current order as an additional check of reference point type dynamics in productivity. The results are presented Appendix B. The additional control does not impact the results and so is not included in the preferred specification.

[21]We also show the full set of results using log(quantity) instead of log(efficiency) as our measure of productivity. We present these results in Appendix C, but find that results are qualitatively identical. Accordingly, we keep log(efficiency) as our preferred

Figure 1A: Efficiency by Days Running

Figure 1B: Efficiency by Quantity Produced



Note: Figures 1A and 1B depict learning curves of efficiency by experience with experience defined by consecutive number of days a style has been running on the production line and cumulative quantity produced to date, respectively. The raw mean of efficiency by bin of experience is depicted in the scatter plot in both figures and the fitted curve (solid line) is the result of a lowess smoothed non-parametric estimation. Dashed lines represent 95% confidence intervals. Experience is trimmed at the 90th percentile in this graphical depiction to ignore outliers, but not from any regression analysis below.

Next, we explore the degree to which learning is retained from the past. That is, if a line has produced a style in the past, are the productivity gains accrued during that production run retained when the line starts producing that style again? Does the line start at higher initial levels of productivity in subsequent runs of the same style? Does it have less to learn to achieve peak productivity? Figures 2A and 2B show learning curves analogous to those depicted in Figures 1A and 1B, respectively, but with the data split into first runs of a style on a line and subsequent runs. Figures 2A and 2B show clearly that productivity gains accrued during first runs of a style are indeed retained, with lines starting at higher initial productivity levels and leaving less scope for additional learning.

The next question, then, is whether this previous retained learning depreciates with the time elapsed between runs of the same style. That is, if a line accrues productivity gains through experience on a first run of a style, does the effect of these gains on subsequent production runs of the same style vary by how much time has elapsed between runs of the same style. We explore this in Figures 3A and 3B by repeating the exercise depicted in Figures 2A and 2B, respectively, but with the sample of subsequent runs of the same style on a line further split by days elapsed since last run. Figures 3A and 3B show clearly that retained productivity gains from prior learning depreciates over the time elapsed before the line produces

measure of productivity as it relates closely to the measures of productivity used in previous studies (e.g., defect rate in Levitt et al. (2013) and labor cost per unit in Thompson (2012)).

Figure 2A: Retention (Prior Days)

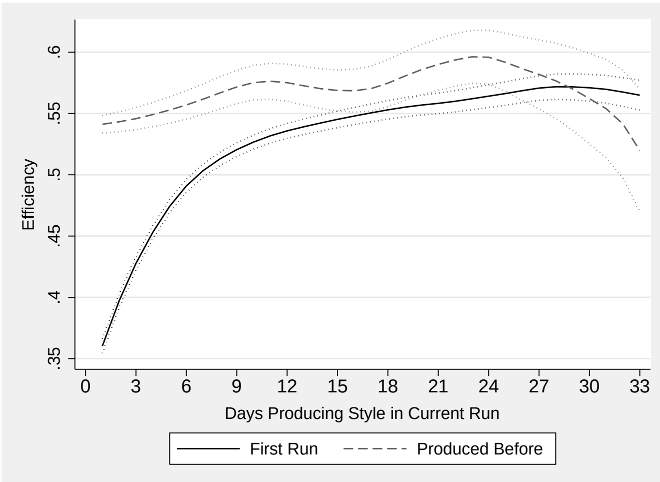
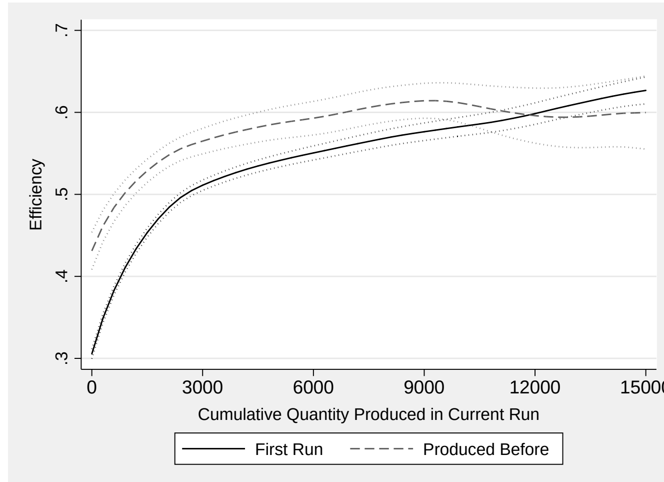


Figure 2B: Retention (Prior Quantity)



Note: Figures 2A and 2B depict the results of repeating the exercise from Figures 1A and 1B, respectively, but separately by whether the line has every produced the same style before. Dotted lines represent 83% confidence intervals to emphasize significant differences between the two curves. Experience is trimmed at the 90th percentile in this graphical depiction to ignore outliers, but not from any regression analysis below.

the same style again. It appears that roughly a third to a half of the productivity value of retained prior learning is depreciated after 12 days (or two full production weeks) of elapsed time between runs of the same style.

Figure 3A: Forgetting (Prior Days)

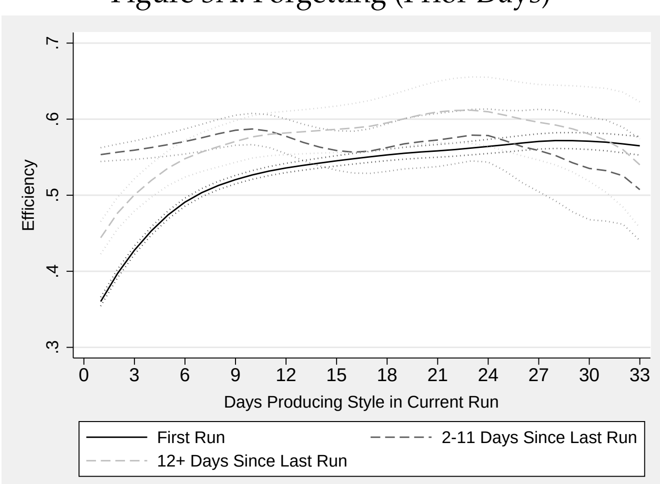
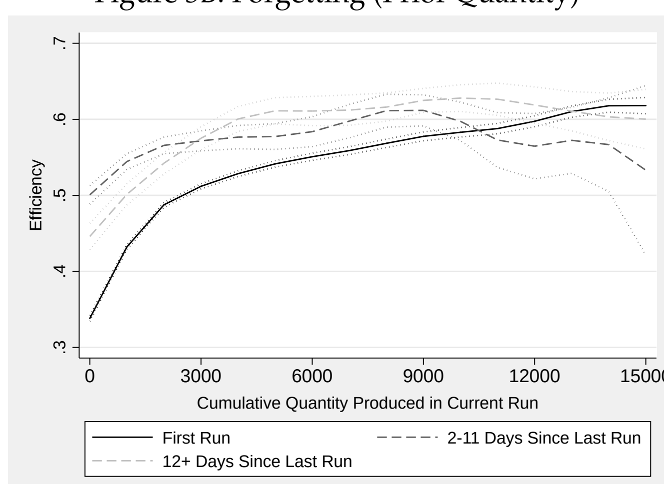


Figure 3B: Forgetting (Prior Quantity)



Note: Figures 3A and 3B depict the results of repeating the exercise from Figures 2A and 2B, respectively, but further splitting previous runs by the number of days that have elapsed since the style was last produced. Dotted lines represent 83% confidence intervals to emphasize significant differences between the two curves. Experience is trimmed at the 90th percentile in this graphical depiction to ignore outliers, but not from any regression analysis below.

In summary, the graphical evidence of the productivity dynamics in line-style production run data closely matches the patterns of learning and forgetting presented in previous studies (Benkard, 2000; Levitt et al., 2013; Thompson, 2012). Accordingly, we start in section 4 with a model nearly identical to those used in these previous studies, differing mainly by allowing production dynamics to be heterogeneous in the characteristics of the line supervisor. As empirical evidence of this heterogeneity is novel to the literature and a main contribution of this study, we present preliminary evidence of heterogeneity in production dynamics by several supervisor characteristics in the next subsection before formalizing the relationships we find in section 4.

3.2 Heterogeneity by Managerial Quality

Having established a clear pattern of learning dynamics in our empirical setting, we next turn to heterogeneity by supervisor quality. As discussed above, we focus on seven dimensions of supervisor characteristics: tenure, demographics, cognitive skills, control, personality, autonomy, and attention. These 7 dimensions of managerial quality have been emphasized in previous literature, as mentioned in section 2.2, and are therefore well-motivated as important aspects on which to focus. Here we provide preliminary evidence that suggests how these characteristics relate to the productivity dynamics shown in the figures above.

Figures 4A and 4B repeat the exercise from Figures 1A, but splitting the sample into lines managed by supervisors with above and below median tenure and cognitive skills, respectively.[22] For this exercise, we use tenure supervising current line as our measure of tenure (Figure 4A) and digit span recall as our measure of cognitive skills (Figure 4B). Figure 4A shows clearly that lines managed by longer tenured supervisors have higher efficiency at the start of a production run and also appear to learn faster over the life of the product run. The pattern is different in Figure 4B with initial levels of productivity appearing higher for lines managed by supervisors with higher cognitive skills, but no apparent difference in productivity later in the product run.

We next repeat the exercise using two measures of supervisor personality: internal locus of control (Figure 5A) and psychological distress (Figure 5B). Figure 5A shows a higher initial productivity at the start of new production runs for lines managed by supervisors with higher internal locus of control, but subsequent learning appears indistinguishable. Figure 5B shows lines supervised by more psychologi-

[22]For the rest of this section we the use number of days that a production line has been producing a particular style consecutively as our measure of current experience. The time-based experience measure is preferred given the endogeneity concerns discussed in section 2.1 above.

Figure 4A: Tenure Supervising Current Line

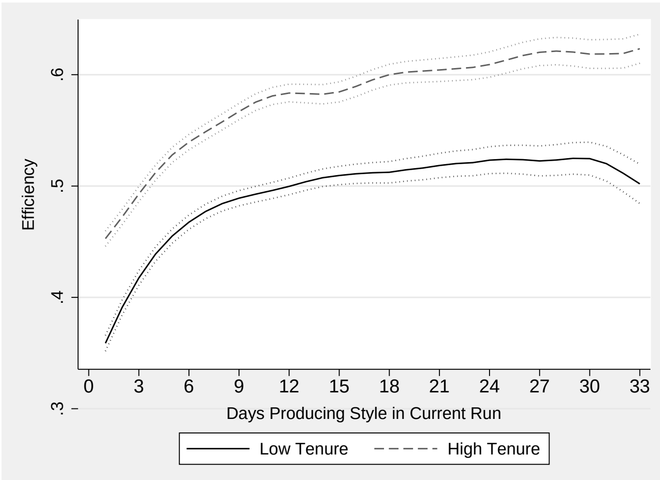
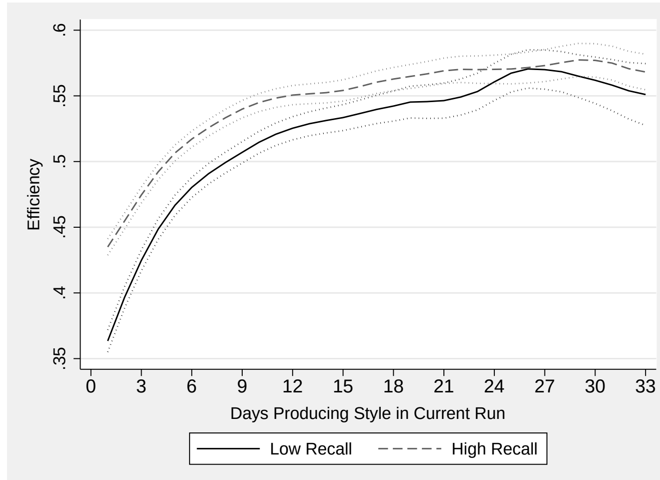


Figure 4B: Digit Span Recall



Note: Figures 4A and 4B depict learning curves of efficiency by current-style experience defined by consecutive number of days a style has been running on the production line. We split the sample into lines managed by supervisors with above and below median tenure defined by years supervising current line (4A); and above and below median cognitive skills defined by digit span recall (4B).The fitted curves (solid and dashed lines) are the result of a lowess smoothed non-parametric estimation. Dotted lines represent 83% confidence intervals to emphasize where the curves are significantly different from each other. The number of days a style has been running is trimmed at the 90th percentile in this graphical depiction to ignore outliers, but not from any regression analysis below.

cally distressed managers start at lower levels of initial productivity, but productivities converge later in the order.

Figures 6A and 6B depict analogous comparisons across lines managed by supervisors with above and below median autonomy and attention, respectively. In Figure 6A, we use an index of autonomous problem-solving measuring the degree to which managers identify and solve production problems on their own. In Figure 6B, we use the manager's reported number of rounds of the line made to monitor production per day as a measure of attention. These figures show a different pattern compared to the two previous graphs. Productivity at the start of a new production run appears indistinguishable across lines managed by more and less autonomous (attentive) supervisors, but subsequent learning appears faster for lines with more autonomous (attentive) supervisors.

In summary, this preliminary graphical evidence confirms that indeed productivity dynamics of the production lines vary by our measures of managerial quality. Furthermore, the figures discussed above suggest that the relationship between managerial quality and productivity dynamics of the line differs by dimension of quality. Some dimensions appear to impact both the initial productivity and the rate of learning (e.g., tenure); others seem to contribute mainly to the initial productivity (e.g., cognition and

Figure 5A: Internal Locus of Control

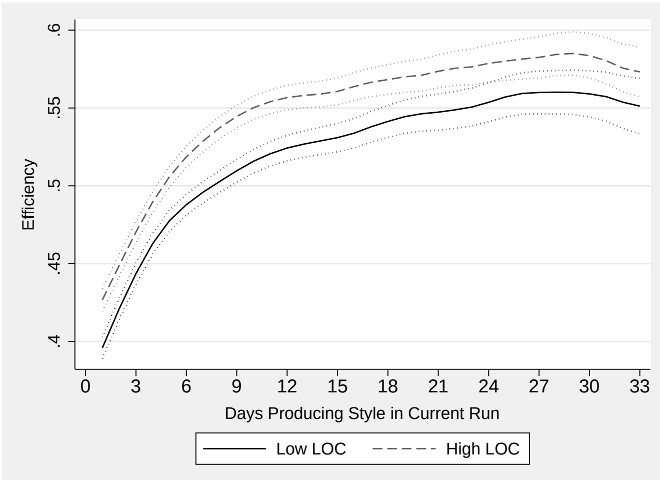
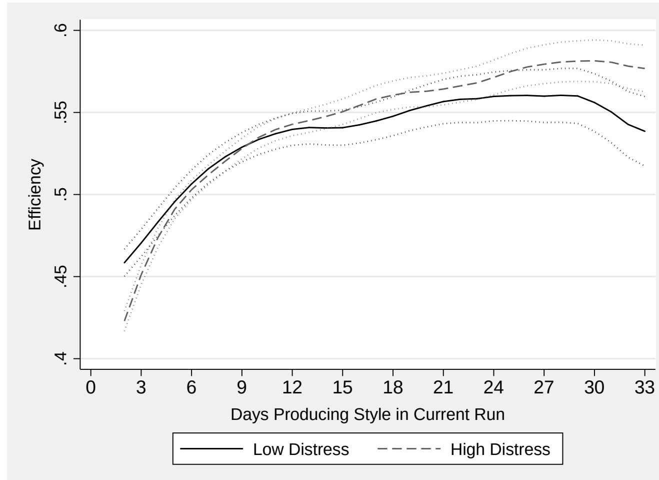


Figure 5B: Psychological Distress



Note: Figures 5A and 5B depict the results of repeating the exercise from Figure 4A, but splitting the sample by supervisor with high and low internal locus of control and psychological distress, respectively. The fitted curves (solid and dashed lines) are the result of a lowess smoothed non-parametric estimation. Dotted lines represent 83% confidence intervals to emphasize where the curves are significantly different from each other. The number of days a style has been running is trimmed at the 90th percentile in this graphical depiction to ignore outliers, but not from any regression analysis below.

Figure 6A: Autonomous Problem-Solving

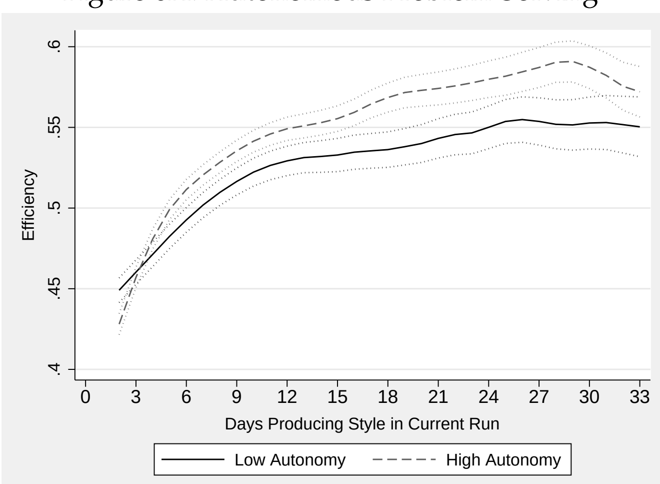
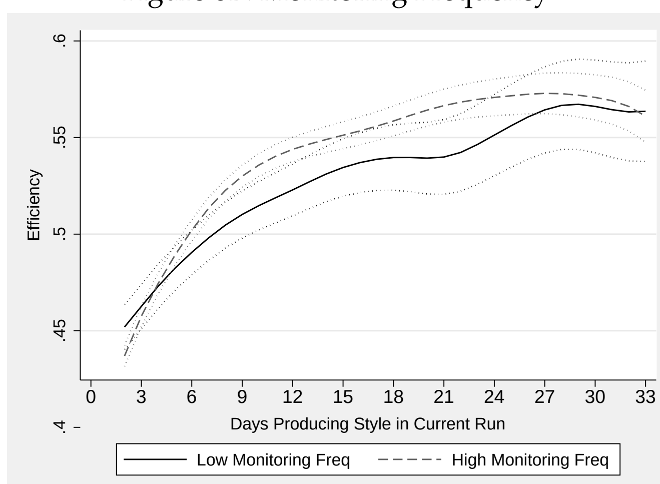


Figure 6B: Monitoring Frequency



Note: Figures 6A and 6B depict the results of repeating the exercise from Figure 4A, but splitting the sample by supervisors with above and below median managerial autonomy and attention skills, respectively. In Figures 6A we use an index of autonomous problem-solving related to the ability of the managers to identify and solve production problems alone. In figure 6B, we use a monitoring frequency index. The fitted curves (solid and dashed lines) are the result of a lowess smoothed non-parametric estimation. Dotted lines represent 83% confidence intervals to emphasize where the curves are significantly different from each other. The number of days a style has been running is trimmed at the 90th percentile in this graphical depiction to ignore outliers, but not from any regression analysis below.

control) or rate of learning (e.g., autonomy and attention).

This preliminary evidence, of course, falls short of a formal investigation of these relationships. That is, ultimately we are interested in investigating the simultaneous, incremental contributions of each of these dimensions of quality to each of the aspects of productivity dynamics present in the line-style production run data (i.e., initial level of productivity, rate of learning, degree of retention, and rate of forgetting). Such an exercise requires a more formal modeling of the learning function that both allows for each quality dimension to flexibly contribute to the various aspects of productivity dynamics and acknowledges the noise and redundancy inherent in survey measures of managerial quality.

4 Model

4.1 Learning Function

In the previous section, we provided evidence of the learning-by-doing process in our garment factory data and showed preliminary results on how managerial quality impacts productivity dynamics. In this section, we build a theoretical framework that formalizes the relationships implied by the preliminary results presented in the previous section.

We start with a learning function with similar intuition and structure to that employed in Levitt et al. (2013),

$$\log\left(S_{ijt}\right) = \alpha_i + \beta_i \log\left(E_{ijt}\right) + \gamma_i \log\left(P_{ij}\right)\left[1 + \delta_i \log\left(D_{ij}\right)\right] + \varepsilon_{ijt} \tag{1}$$

where S_{ijt} is the efficiency of line $i \in \{1, ..., N\}$, producing style $j \in \{1, ..., J\}$ at period $t \in \{1, ..., T\}$.[23] E_{ijt} is the experience that line i has in producing style j at date t in the current production run, as measured by the number of consecutive days spent producing that style. α_i measures the initial level of productivity and β_i the rate of learning of the line i. P_{ij} is line i's experience with style j in the previous production runs (i.e., the number of total days in the prior production run). D_{ij} is the measure of forgetting, which is defined as the number of days since line i last produced style j. γ_i measures the contribution of previous stock learning (retention) and δ_i is the depreciation rate of previous stock learning (rate of forgetting) of

[23]In Appendix C, we present the results of this estimation using log(quantity produced) on the left-hand side instead of log(efficiency). Given that the results are qualitatively identical but with a smaller R-squared, we continue the rest of the estimation using log(efficiency) on the left-hand side. Given that efficiency is measured as the actual quantity produced exceeding minimum quality standards per worker-hour, it is also a closer analogue to the the defect rates and labor cost per unit used in previous studies (Levitt et al., 2013; Thompson, 2012).

line i. ψ_t is a time trend that is included in all specifications.[24] Finally, ε_{ijt}, is an idiosyncratic error term.[25]

Note that the learning function in equation (1) differs primarily from those considered by previous literature (Benkard, 2000; Levitt et al., 2013; Thompson, 2001) in that we allow for the parameters governing the shape of the learning curve (α_i, β_i, γ_i and δ_i) to vary across lines. This is done to reflect the graphical evidence presented in section 3.2 showing that learning curves differ across lines supervised by managers with varying skills and characteristics. However, we cannot tell from the simple exploratory graphs in section 3.2 the functional form these relationships take. Accordingly, we next describe the flexible functional form we use to relate each parameter (α_i, β_i, γ_i and δ_i) to underlying dimensions of managerial quality and to arrive at an estimable model.

4.2 Parameterization of Relationship between Learning and Managerial Quality

Here we impose a structural form to understand how managerial quality affects each of the learning parameters. We assume that there are k *latent* factors that describe managerial quality. We assume that each of the learning parameters depends nonlinearly on these k factors, i.e.,

$$\iota_i = f_\iota(\theta_{1,i}, \theta_{2,i}, ..., \theta_{k,i}) \tag{2}$$

where $\iota \in \{\alpha, \beta, \gamma, \delta\}$ for line $i \in \{1, ..., N\}$, and $\theta_{k,i}$ is the k-th quality factor. Note we assume that the functions for initial level of productivity (f_α), rate of learning (f_β), degree of retention (f_γ) and rate of forgetting (f_δ) take the same set of underlying factors as arguments, but want to allow for the contributions of the factors to differ across these functions.

We assume that f_ι for $\iota \in \{\alpha, \beta, \gamma, \delta\}$ can be approximated by a Constant Elasticity of Substitution (CES) function. The CES form considered here allows us to explore the degree of complementarity or substitutability between the factors included in the function for each learning parameter. That is, we assume that f_ι takes the following functional form,

$$\iota_i = A_\iota[\lambda_{\iota,1}\theta_{1,i}^{\rho_\iota} + \lambda_{\iota,2}\theta_{2,i}^{\rho_\iota} + \cdots + \lambda_{\iota,k}\theta_{k,i}^{\rho_\iota}]^{\frac{1}{\rho_\iota}} \exp(\eta_{\iota,i}) \tag{3}$$

where $\lambda_{\iota,k} \geq 0$ and $\sum_k \lambda_{\iota,k} = 1$ for $\iota \in \{\alpha, \beta, \gamma, \delta\}$ and line $i \in \{1, ..., N\}$. Note that any of the factors can

[24] The time trend is to account for any incidental serial correlation in productivity which may not reflect actual learning. We also show robustness to the inclusion of an additional control for days left to complete the order as a further check against this type confounding of incidental serial correlation with true learning, perhaps through "reference point" mechanisms. This robustness check is presented in Appendix B and does not appear to impact the results.

[25] Note that this function also matches closely to that used in and Benkard (2000) and Thompson (2001) with the factor allocations of capital ignored, given the fixed man-to-machine ratio in garment factories.

be irrelevant in any of these functions when $\lambda_{\iota,k} = 0$. ρ_ι determines the elasticity of substitution between the latent factors, which is defined by $\frac{1}{1-\rho_\iota}$, and A_ι is a factor-neutral productivity parameter. Under this technology, $\rho_\iota \in [-\infty, 1]$; as ρ_ι approaches 1, the latent factors become perfect substitutes, and as ρ_ι approaches $-\infty$, the factors become perfect complements.

In summary, we assume a common functional form across the learning parameters $\iota \in \{\alpha, \beta, \gamma, \delta\}$, but we allow the loadings for each latent factor k ($\lambda_{\iota,k}$) and the degree of complementarity (ρ_ι) to differ across learning parameters.

5 Empirical Strategy

Having adapted the canonical learning function to allow different dimensions of managerial quality to flexibly determine the shape of the learning curve, we next develop our strategy for estimating these relationships in the presence of measurement error. Remember that our goal is to be able to estimate equation (3) for $\iota \in \{\alpha, \beta, \gamma, \delta\}$. However, to do so, we must first recover α_i, β_i, γ_i and δ_i for the LHS of equation (3) by estimating equation (1) in our production data, and also extract the k latent factors $\theta_{k,i}$ for the supervisors of each line i from the management survey data.

Accordingly, our empirical strategy consists of three steps. First, we estimate equation (1) line by line to recover α_i, β_i, γ_i, and δ_i for each line $i \in \{1, ..., N\}$ using ordinary least squares. Second, we follow Cunha et al. (2010) Attanasio et al. (2015b), and Attanasio et al. (2015a) in estimating a nonlinear latent factor measurement system using the data from our managerial survey. This step allows us to recover information about the joint distribution (approximated as a mixture of two normals) of k latent factors (θ_k) underlying the multitude of noisy survey measures and the learning parameters estimated in the first stage (α_i, β_i, γ_i, δ_i) using maximum likelihood and minimum distance. We finally draw a synthetic dataset from this joint distribution and estimate equation (3) for $\iota \in \{\alpha, \beta, \gamma, \delta\}$ using nonlinear least squares and bootstrapping to obtain the error distribution.

5.1 First Stage: Productivity Dynamics

5.1.1 Homogenous Learning Function

We start by estimating the conventional model of learning-by-doing assuming homogeneous learning parameters across lines. This model matches the specification used in previous studies on learning-by-doing (Benkard, 2000; Levitt et al., 2013; Thompson, 2001) and is represented by equation (1) with homogenous parameters for α, β, γ, and δ. We perform this estimation by ordinary least squares using different sets of cross-sectional and temporal fixed effects. In particular, we include style fixed effects to account for variation in productivity due to complexity of the style and size of the order, as well as year, month and day of the week fixed effects, to account for common seasonality and growth in productivity across lines.

These estimations serve to validate that the patterns observed in Figures 1A through 3B indeed persist in a more formal regression framework and that the functional form in equation (1) fits the patterns well. We also use these estimations to demonstrate that the patterns of learning and forgetting are robust to varying sets of controls. These controls include time-varying worker characteristics to account for any compositional changes in the workforce of lines and days left to complete the order throughout the run to account for any reference point effects.

5.1.2 Heterogeneous Learning Functions

Next, we estimate the learning function from equation (1) as it is written, allowing for initial levels of productivity, rate of learning, degree of retention and rate of forgetting to vary across lines. That is, we estimate α_i, β_i, γ_i, and δ_i for each line $i \in \{1, ..., N\}$ in a preferred specification including controls for worker characteristics (age, gender, language, tenure, skill grade, and salary) and fixed effects for style and time (year, month, and day of the week). The controls for worker characteristics are meant to account for any compositional differences in the workforce across lines and even within line over the production run or across styles. As we discuss below, balance checks across lines managed by supervisors with differing managerial quality show no systematic compositional differences in the work forces across lines. The style fixed effect in addition to the line-specific learning parameters being estimated amounts to a two-way fixed effect model of lines matched to styles. This two-way fixed effect model is analogous to the worker-firm sorting model studied Abowd et al. (1999) (also known as AKM).[26] Accordingly, we must address, as they do, the potential obstacles to identification of the parameters of interest due to any possible sorting in the match between lines and styles in the data.

First, note that to be able to the identify the line and style fixed effects separately, lines must be observed producing different styles for multiple production runs during the sample period, and each style should be observed being produced by multiple lines (not necessarily contemporaneously). Second, identification is possible only within a group of lines and styles that are connected. A group of lines and styles are connected when the group comprises all the styles that have ever matched with any of the lines in

[26]We have a two-way FE model in which the lines and styles map to the firms and workers, respectively, in the context of the AKM model.

the group, and all of the lines at which any of the styles have been matched during the sample period. Third, we assume that the probability of a style being produced by a certain line is conditionally mean independent of contemporaneous, past, or future shocks to the line. Fourth, we assume that there is no complementarity between lines and styles.

The third and fourth assumptions are quite strong. For example, if the firm is aware of the heterogeneous productivity dynamics depicted in the figures in section 3, it stands to reason that the firm would consider these differences in productivity levels and dynamics when allocating styles so as to optimize overall productivity. This type of sorting on the basis of learning dynamics (and, implicitly, any underlying managerial characteristics) would be a violation of the assumptions inherent in the two-way fixed effect (AKM) model we have proposed. However, if either the firm does not actively measure and analyze these differences in dynamics or the underlying managerial characteristics, or the firm is incapable of practicing this type of optimal allocation of styles to lines due to difficulty in forecasting the arrival of future orders and/or a high cost of leaving lines vacant to await optimally matched orders in the future, then we might expect that assumptions 3 and 4 might actually hold in the data. It is difficult to know which might the be the case, so choose to simply test using Monte Carlo simulation whether the additively separable representation of line and style effects in equation (1) is sufficient to capture any line-style sorting. We also test empirically whether managers of differing quality tend to produce styles of different complexity or orders of differing size on average.

5.1.3 Tests for Sorting Bias: Balance Checks and Monte Carlo Simulations

To establish the validity of this first stage of our strategy, we check for two types of sorting: workers to managers and styles to managers. *A priori*, we may expect the workforce compositions of lines to be relatively homogeneous; lines are comprised of around 70-80 workers, and line assignments are not determined by the line supervisor. Rather, line supervisors log demand for more workers centrally with the firm's Human Resources (which is above the the factory level) and these demands queue and get filled on a first come first serve basis.

To check that indeed this quasi-random line assignment leads to homogenous work-forces across lines on average, we perform balance checks for worker characteristics by managerial characteristics used in our latent factor measurement system. Tables A1-A5 compare different characteristics of the workers (efficiency, skill grade, salary, age, tenure, gender, language, and migrant status) for high and low-type managers defined by the 26 different measures included in the measurement system (summarized in

Table 2). The comparisons in Tables A1-A5 show that the groups are quite balanced across high and low-type managers. Only 29 out of 234 differences are statically significant with significant differences spread across various manager characteristics. Tests of joint significance cannot reject balance overall.[27] We perform similar balance checks for style to manager sorting, checking that the complexity of the style being assigned (measured by the target quantity) and the size of the order (schedule quantity) are balanced across these same managerial characteristics. The comparisons presented in Table A6, once again, show very few (7 of the 52) significant differences, and joint tests fail to reject balance overall.

Nevertheless, to further assess if there is any bias due to endogenous sorting of styles to lines in our estimation of the two-way FE model proposed in equation (1), we use a Monte Carlo experiment (following Abowd et al. (2004)) which relies on the in-sample pattern of the observed relationships between lines and styles. We first estimate the model in equation (1) and keep all the observed characteristics, line and style identifiers, the autocorrelation structure of the residuals, and the estimated coefficients. We generate for each style a *style effect*, and for each line an initial productivity, rate of learning, retention and forgetting (our proposed decomposition of the *line effect*) from a normal distribution which resembles the distribution of the line and style effects as estimated in the first step.[28] Finally, we draw idiosyncratic error terms and construct a simulated outcome based on the simulated fixed effects, the observed characteristics and the simulated error terms, and estimate the model using the simulated data.[29] We repeat the procedure 10,000 times, and compute the percentage mean bias in absolute value for the coefficients of interest (α_i, β_i, γ_i and δ_i). If we find minimal bias, we can conclude that the full set of assumptions imposed in this first stage estimation including those related to sorting are valid in the data and proceed to the next stage of our empirical strategy.

As discussed in section 7 below, we find little evidence of bias in the results of the Monte Carlo experiment. That is, it appears in the data that the firm is not sorting styles to lines on the basis of the relationships between managerial quality and productivity dynamics we find in this study. This is surprising given the clear benefits to the firm from doing so, but seems plausible given the measurement and computational complexities involved in extracting these insights. That is, the firm was not even storing these granular productivity data prior to our intervention, let alone analyzing them, and the measurement

[27] The incidental individual differences do not appear to systematically match to the pattern of findings presented and discussed below.

[28] That is, we compute the mean and standard deviation of the line effect paramters (e.g., initial productivity, rate of learning, retention and forgetting) and style effects. We simulate the new lines and styles effects using these moments. Note that by construction, each line *effect* (initial productivity, rate of learning, retention and forgetting rate) and each style *effect* is endowed with independent effects.

[29] We first assume that the errors are i.i.d. across lines and time, and then relax this assumption by using the autocorrelation structure estimated for the residuals.

of the managerial characteristics was completed first hand by our research team.

Nevertheless, we might imagine that some coarse insights might be gleaned from less rigorous measurement and analysis which might allow the firm to optimize the allocation of styles to lines. Such dynamic optimal assignment would, however, require both predictability of future orders and a willingness to delay the start of an order and leave some lines vacant for some periods of time to achieve a more optimal match of style to line. We find no evidence that lines are left vacant or that lines supervised by managers with differing quality show different patterns of order start and completion. Furthermore, the number of lines completing an order or starting a new order on any given day is rarely more than 1 indicating a limited scope for optimizing the style to line assignment. This evidence is all consistent with a limited predictability of future orders and a high cost of slackness as communicated by factory management.

5.2 Second Stage: Latent Factors of Managerial Quality

We do not directly observe θ_i. Instead, we observe a set of measurements that can be thought of as imperfect proxies of each factor with an error. We adapt from Cunha et al. (2010) a non-linear latent factor framework that explicitly recognizes the difference between the available measurements and the theoretical concept used in the production function. We set the number of the latent factors to $k = 7$, comprised of the following: tenure, demographics, cognitive skills, control, personality, autonomy, and attention. As discussed in section 2.2, we use the original survey module delineations and exploratory factor analyses, following Attanasio et al. (2015a,b) and Cunha et al. (2010), to map the full set of survey measures to these seven factors, each corresponding to dimensions of managerial quality previously proposed and studied in the literature. That is, we let both the intuition of the modules and the data itself determine which are the distinct factors and which measures map to each factor.

Let $m_{l,k}$ denote the lth available measurement relating to latent factor k. Following Cunha et al. (2010) and Attanasio et al. (2015b), we assume a semi-log relationship between measurements and factors such that

$$m_{l,k} = a_{l,k} + \gamma_{l,k} \ln \theta_k + \varepsilon_{l,k} \tag{4}$$

where $\gamma_{l,k}$ is the factor loading, $a_{l,k}$ is the intercept and $\varepsilon_{l,k}$ is a measurement error for factor $k \in K \equiv \{T, D, Ctrl, Cog, P, R, Aut, Att\}$ (tenure, demographics, cognitive skills, control, personality, autonomy, and attention) and measure $l \in \{1, 2, ..., M_k\}$. Thus, for each k we construct a set of M_k measures.

For identification purposes, we normalize the factor loading of the the first measure to be equal to 1 (i.e., $\gamma_{1,k} = 1$ for $k \in K$). Similarly, log-factors are normalized to have mean zero, so a_{lk} is equal to the mean of the measurement. Finally, $\varepsilon_{l,k}$ are zero mean measurement errors, which capture the fact that the m_{lk} are imperfect proxies. Three assumptions regarding the measurements and factors are required for identification. First, we assume that the latent factor and the respective measurement error are independent. Second, we assume that measurement errors are independent of each other. Finally, we assume that each measure is affected by only one factor.[30]

Note that the estimation of (3) requires the construction of a synthetic dataset from the joint distribution of management factors and estimated learning parameters. We follow Attanasio et al. (2015b) and augment the set of latent factors with $\hat{\alpha_i}$, $\hat{\beta_i}$, $\hat{\gamma_i}$ and $\hat{\delta_i}$, estimated in the first stage, and the average of the log of supervisor pay, w_i, for each line i.[31] As we explain later in Section 6, we are able to recover α_i and β_i for 120 lines, which is the largest connected set, but we are only able to recover γ_i and δ_i for 99 lines. The 21 lines for which we cannot recover γ_i and δ_i are those that we do not observe producing more than one style multiple times in the observation period. We restrict the sample in the second stage to the number of managers that are in these 99 lines (129 managers) for which we can estimate the full model.[32] Finally, we assume that the learning parameters from the first stage and the log of supervisor pay are measured with no error.[33] Let $\theta \equiv \left(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \theta_7, \hat{\alpha_i}, \hat{\beta_i}, \hat{\gamma_i}, \hat{\delta_i}, w_i\right)$, thus we can express the *extended* demeaned measurement system in vector notation as,

$$\tilde{M} = M - A = \Lambda \ln(\theta) + \Sigma_{\varepsilon}\varepsilon \tag{5}$$

[30]This assumption can be relaxed to allow some subset of measures to inform more than one factor; however, in our setting, these cross-factor loadings are not well-motivated, as factors come from distinct modules of the survey which were designed to capture different aspects of managerial quality. For identification of the system, we need at least two dedicated measures per factor and at least one measure for each factor conditionally independent of the other measures. See Cunha et al. (2010) and Attanasio et al. (2015b). Note as discussed in 2.2 that in exploratory analyses across pooled sets of measures across modules we find some correlations; however, we always assign the measure to the factor for which its loading is strongest. Note that the factors obtained can be correlated with each other and indeed do appear to be in the final results as shown in the Appendix. Accordingly, this assumption preserves the interpretation of each factor while not restricting that measures assigned to different factors be unrelated.

[31]We use total compensation of the supervisor for the month which includes the monthly salary for November 2014, the month in which the management survey was completed, and any production bonus associated with the productivity of the line.

[32]We use all 120 lines (153 managers) in the first stage. As a robustness check, we estimate the full results in the second and third stage using only the $\hat{\alpha_i}$ and $\hat{\beta_i}$ for all 153 managers lines and omitting the $\hat{\gamma_i}$ and $\hat{\delta_i}$ from the model. The insights regarding the α and β are nearly identical to those in the main results reported below, confirming that restricting attention in the main estimation to the 129 managers of the 99 lines for which we can recover the full set of learning parameters does not meaningfully impact the conclusions we draw.

[33]This assumption with respect to the pay measure is similar to that imposed by Attanasio et al. (2015b) in their extended measurement system. With respect to the learning parameters, we are including constructed variables in our second stage. From the validity of the identification in the first stage, we regard the error remaining in the constructed variables ($\hat{\alpha_i}$, $\hat{\beta_i}$, $\hat{\gamma_i}$ and $\hat{\delta_i}$) to be near 0 as $T \times N \to \infty$. In our data, $T \times N = 37,192$. Finally, relaxing this assumption would require multiple measures for each of the learning parameters which we do not have.

where Λ is the matrix of factor loadings, ε is a vector of measurement errors and Σ_ε is a diagonal matrix with the standard deviation of the measurement error defined before.[34]

In order to capture complementarities in the learning parameter functions, we follow Cunha et al. (2010) and Attanasio et al. (2015b) in assuming that the joint distribution of the log latent factors, $f(\cdot)$, follows a mixture of two normals,

$$f(\ln\theta) = \tau f^A(\ln\theta) + (1-\tau) f^B(\ln\theta) \tag{6}$$

where $f^i(\cdot)$ is the joint CDF of a normal distribution with mean vector, μ_i, and variance covariance matrix, Σ^i, and mixture weight, $\tau \in [0,1]$, for $i \in \{A, B\}$.[35] Finally, we assume that the log-factors have mean zero, i.e.,

$$\tau\mu^A + (1-\tau)\mu^B = 0 \tag{7}$$

Note that if ε is normally distributed, the distribution of the observed measurements is

$$\mathcal{F}(m) = \tau \cdot \Phi(\mu_{m_A}, \Sigma_{m_A}) + (1-\tau) \cdot \Phi(\mu_{m_B}, \Sigma_{m_B}) \tag{8}$$

where,

$$\mu_{m_A} = \Lambda\mu_A \tag{9}$$

$$\mu_{m_B} = \Lambda\mu_B \tag{10}$$

$$\Sigma_{m_A} = \Lambda^{'}\Sigma_A\Lambda + \Sigma_\varepsilon \tag{11}$$

$$\Sigma_{m_B} = \Lambda^{'}\Sigma_B\Lambda + \Sigma_\varepsilon \tag{12}$$

Estimation in this second stage proceeds in three steps. First, we construct the set of measures for

[34] As we mentioned before we assume that learning parameters and the log of pay are measured with no error. This implies that the corresponding factor loadings are set equal to one in Λ, and the corresponding standard deviations of the error in Σ equal to zero.

[35] The departure from the joint normality assumption is important, otherwise the log of the production function would be linear and additively separable in logs (i.e., Cobb-Douglas, as discussed in Attanasio et al. (2015b)).

each latent factor by matching the appropriate survey modules to each of the seven dimensions of quality previously studied in the literature, as discussed in section 2.2. Second, we use maximum likelihood to estimate an unconstrained mixture of normals for the distribution of measurements.[36] Using equations (7) through (12) as restrictions, we perform minimum distance estimation to recover $\mu^A, \Sigma^A, \mu^B, \Sigma^B$. Finally, we draw a synthetic dataset from the joint distribution of the learning parameters (as well as the log of pay) and factors of managerial quality to produce data for both the LHS and RHS of equation (3).

5.3 Third Stage: Contributions of Managerial Quality to Productivity Dynamics and Pay

Remember that our goal is to estimate equation (3) for $\iota \in \{\alpha, \beta, \gamma, \delta\}$. We first recover the learning parameters (initial level of productivity, rate of learning, retention rate and forgetting rate) for the LHS of equation (3) for each line by estimating the line-specific learning function in equation (1) using ordinary least squares. Second, we estimate a latent factor model similar to Cunha et al. (2010) and Attanasio et al. (2015b) and recover the joint distribution of the latent factors and the learning parameters obtained in the first stage. That is, from the full set of error-ridden survey measures we observe, we recover the RHS of (3). This procedure allows us to construct a synthetic dataset of the factors (RHS) and the learning parameters (LHS). Finally, in the third stage, we estimate equations (3) for $\iota \in \{\alpha_i, \beta_i, \gamma_i, \delta_i\}$ using nonlinear least squares. We bootstrap this third stage 100 times to construct the standard errors of the estimated coefficients. We also repeat this last step with log of mean supervisor pay on the LHS instead, keeping the functional form and set of factors taken as arguments on the RHS the same.

6 Results

In this section, we formally test for the patterns depicted in Section 3. We first report and discuss the results of estimating equation (1) assuming homogeneous learning parameters across lines (i.e., $\alpha, \beta, \gamma, \delta$) to verify that the patterns observed in Figures 1A through 3B persist and are statistically significant in a more formal regression analysis. We then move on to present the results of the regression analysis of the learning function with heterogeneous parameters, and recover α_i, β_i, γ_i and δ_i for each production line. Next, we discuss the measures used in the latent factor model to recover the underlying dimensions of managerial quality and the informative content of each. Then, we present the results of the estimation of equation (3) for $\iota \in \{\alpha_i, \beta_i, \gamma_i, \delta_i\}$ and perform simulations to investigate how productivity dynam-

[36] We use EM algorithm and k-means clustering to select the initial values with uniform initial proportions. We replicate the procedure 10,000 times and select the model with largest loglikelihood.

ics change with increases in each of the dimensions of managerial quality (i.e., tenure, demographics, cognitive skills, control, personality, autonomy, and attention).

We perform two types of simulations: one that mimics focused *training* in managerial practices (assuming independent increases in autonomy and attention) and one that mimics *screening* on productive skills and traits (assuming correlated increases in easily observed traits like tenure and demographics and less commonly measured traits like cognitive skills, control and personality, using the covariance structure between factors to assess what other traits might come along with targeted screening of candidates on each of these dimensions). Finally, we use our procedure to investigate the relationship between the latent factors for managerial quality and the observed pay of supervisors, and perform analogous simulations to recover pass through of productivity contributions of each dimension of managerial quality to pay.

6.1 First Stage: learning parameters

Table 3 presents the results of the learning function with homogeneous learning parameters. Column 1 of Table 3 includes experience from the current run of a style, measured by the number of consecutive days spent producing that style, retained learning from previous runs and its interaction with days since the style was last produced on the line along with style fixed effects and time varying characteristics of the workers on the line (average skill grade, share of the highest skill, average gross salary, average age, share of females, share of workers speaking Kannada, and average tenure) as baseline controls. Column 2 adds additional fixed effects for year, month, and day of week to account for any seasonality in productivity and buyer demand. Column 3 adds the number of days left to the end of the order to control for any reference point effect related to the end of the order.

Table 3 shows that the estimated learning rate is between 0.143 and 0.146. This learning rate implies that productivity will increase on average 50% over roughly 16 days of producing the same style, which is very close to what we inferred from the graphical evidence in Figure 1A. The productivity contribution of retained learning from previous runs is around 0.075, which is just over 50% of contemporaneous learning magnitudes. Every unit of log days since the last run erodes roughly 16-17% of the impact of retained learning such that, after 20 intervening days, 50% of the productive value of retained learning has depreciated.

These results are quite robust to alternative specifications and measures of productivity and experience. Note that the coefficients are very similar across the three specifications when we control for time

Table 3: Learning (Experience in Days)

	Log(Efficiency) (Actual Production/Target Production)		
Log(Number of Days)	0.143	0.143	0.146
	(0.0094)	(0.0093)	(0.0103)
Log(Total Days in Prior Production Runs)	0.0724	0.0745	0.0764
	(0.0176)	(0.0178)	(0.0179)
Log(Prior Days) X Log(Days Since Prior Run)	-0.0118	-0.0124	-0.0133
	(0.0055)	(0.0056)	(0.0056)
Observations	49,976	49,976	49,976
Additional Time Controls	Trend	Trend, Year and Month, and DOW FE	Trend, Year and Month, and DOW FE
Additional Controls	Style FE and Worker Characteristics	Style FE and Worker Characteristics	Style FE, Worker Characteristics and Days left

Note: Standard errors are clustered at the line level.

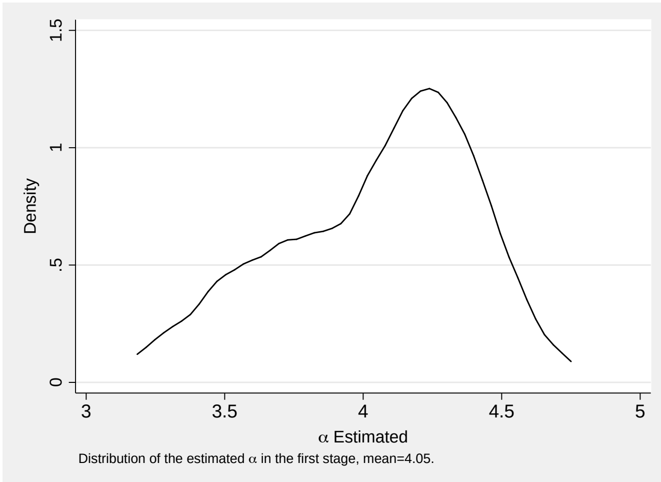
fixed effects and days left to complete the order. In Appendix C we present the analogous results to those in Table 3 using log(quantity produced) on the left-hand side and controlling for log(target quantity) on the right-hand side. Table C1 shows nearly identical results to Table 3. Note that the coefficient on log(target quantity) is close to 1, which suggests that there is no scale effect on the efficiency due to the complexity of different styles. For the rest of the paper, we only present and discuss the results using log efficiency on the left hand side and use the specification in column 2 of Table 3 as our preferred specification in the main results that follow. Full estimation results from these alternative specifications are presented in the Appendix sections B through C

Next, we estimate equation (1) with heterogeneous learning parameters using ordinary least squares line by line.[37] Figures 7A, 7B, 7C, and 7D show the distribution of the estimated initial productivity ($\hat{\alpha}_i$), rate of learning ($\hat{\beta}_i$), degree of retention ($\hat{\gamma}_i$) and rate of forgetting ($\hat{\delta}_i$), respectively. Figures 7A through 7D depict a large degree of variation in each of the parameters governing the shape of the learning function which corresponds well to heterogeneity depicted in Figures 4A through 6B.[38]

[37]For the estimation, we use the largest connected set, which represents 98.5% of the available data

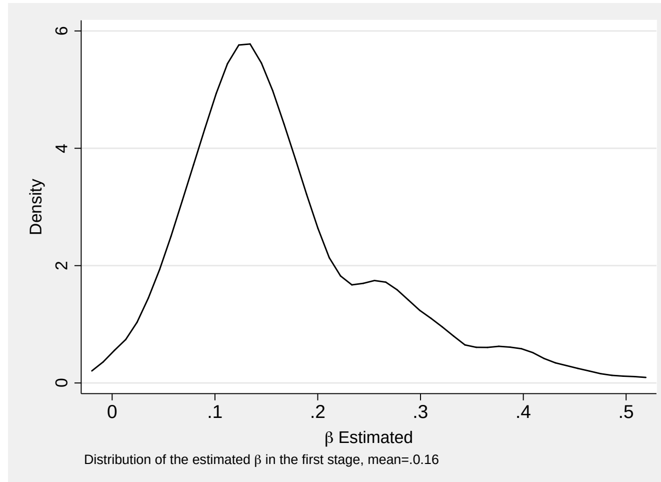
[38]Table A7 shows the correlation of the learning parameters across production lines. As expected, the initial productivity (α) is strongly negatively correlated with the rate of learning (β), as well as weakly negatively and positively correlated with previous experience (γ) and forgetting (δ), respectively. Rate of learning is weakly negatively correlated with both retention (γ) and forgetting (δ).

Figure 7A: Initial Productivity ($\hat{\alpha}_i$)



Distribution of the estimated α in the first stage, mean=4.05.

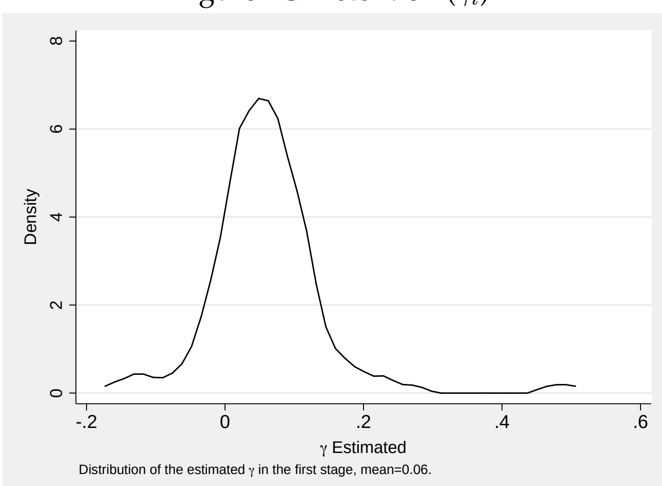
Figure 7B: Learning ($\hat{\beta}_i$)



Distribution of the estimated β in the first stage, mean=.0.16

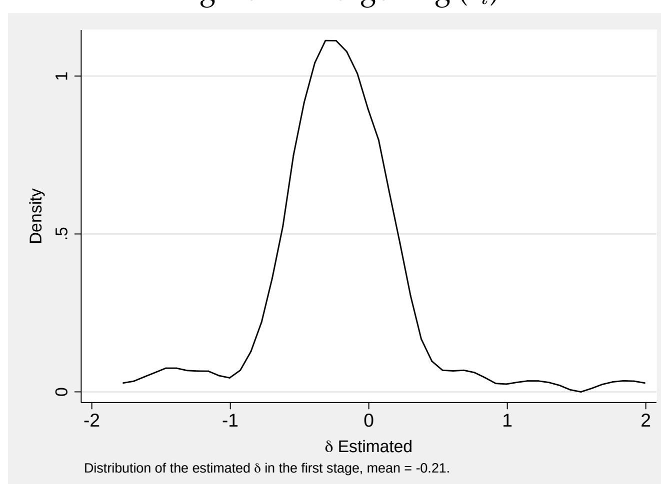
Note: Figures 7A and 7B show the distribution of the estimates of the initial productivity (line-specific intercepts) and the rate of learning (line-specific slopes) for the 120 lines, which is the largest connected set.

Figure 7C: Retention ($\hat{\gamma}_i$)



Distribution of the estimated γ in the first stage, mean=0.06.

Figure 7D: Forgetting ($\hat{\delta}_i$)



Distribution of the estimated δ in the first stage, mean = -0.21.

Note: Figures 7C and 7D show the distribution of the estimates of the retention rate and forgetting rate for the 99 lines for which we are able to recover these parameters.

6.2 Second Stage: managerial quality measures and factors

In this section, we report and discuss the results of the measurement system. Remember from the discussion in section 2.2 that we map the complete set of measures from the different modules of the survey using exploratory factor analysis into the following seven dimensions of managerial quality: tenure, demographics, cognitive skills, control, personality, autonomy, and attention.[39] Table 4 presents the set of measures used to proxy each *latent* factor and the estimated loading for each. To establish the informativeness of each measure, we compute the signal content in each measure (i.e., the variance of the contribution to the latent factor over the residual variance of the measure). Remember that for each factor we normalized the highest loading measure to a loading of 1 such that the loadings of all other measures are relative to that highest loading measure.

Table 4: Loadings and Signals

Measures				*Latent Factor*				*Signal*
	Tenure	Demographics	Cognitive Skills	Control	Personality	Autonomy	Attention	
Tenure Supervising Current Line	1	0	0	0	0	0	0	0.592
Tenure as Supervisor	0.496	0	0	0	0	0	0	0.200
Tenure in Garment Industry	0.363	0	0	0	0	0	0	0.115
Total Years Working	0.092	0	0	0	0	0	0	0.007
Demographic Similarity	0	1	0	0	0	0	0	0.322
Egalitarianism	0	-0.178	0	0	0	0	0	0.071
Digit Span Recall	0	0	1	0	0	0	0	0.634
Arithmetic	0	0	0.521	0	0	0	0	0.228
Arithmetic Correct (%)	0	0	0.320	0	0	0	0	0.365
Internal Locus of Control	0	0	0	1	0	0	0	0.532
Risk Aversion	0	0	0	0.128	0	0	0	0.007
Patience	0	0	0	0.217	0	0	0	0.015
Conscientiousness	0	0	0	0	1	0	0	0.730
Perseverance	0	0	0	0	1.004	0	0	0.756
Self-Esteem	0	0	0	0	0.910	0	0	0.694
Psychological Distress	0	0	0	0	-0.245	0	0	0.026
Initiating Structure	0	0	0	0	0	1	0	0.833
Consideration	0	0	0	0	0	0.861	0	0.768
Autonomous Problem-Solving	0	0	0	0	0	0.049	0	0.002
Identifying Production Problems	0	0	0	0	0	0.166	0	0.034
Self-Assessment	0	0	0	0	0	0.106	0	0.017
Monitoring Frequency	0	0	0	0	0	0	1	0.529
Efforts to Meet Targets	0	0	0	0	0	0	0.568	0.212
Active Personnel Management	0	0	0	0	0	0	0.972	0.481
Lack of Communication	0	0	0	0	0	0	-0.439	0.136
Issues Motivating Workers, Resistance	0	0	0	0	0	0	-0.127	0.008

Note: The first loading of each factor is normalized to 1. Signal of measure j of factor k is $s_j^k = \frac{(\lambda_{j,k})^2 Var(\ln \theta_k)}{(\lambda_{j,k})^2 Var(\ln \theta_k) + Var(\varepsilon_{j,k})}$. The measures were standardized across all supervisors who were surveyed. Learning parameters (α, β,γ, and δ) and the mean of log pay (including both monthly salary and production bonus) from November 2014 across supervisors of a line are all included in the extended system but measured with no error, i.e., the corresponding factor loadings are set equal to 1 but omitted from this table.

Table 4 shows that the most informative measures for Tenure are years supervising current line and years as supervisor with signals of 59% and 20% and loadings 1 and 0.5, respectively. Tenure in the garment industry is also informative with a loading of .36, but total years working is less informative than the more job and industry-specific measures. For demographics, the loading is largest for demographic similarity with signal of 32%; while the contribution of egalitarianism is negative with a loading of -0.18,

[39]The details of the variable construction are presented in Appendix D.

but less informative (7.1% signal). A negative loading on egalitarianism is as expected, as the factor is informed by demographic similarity and more egalitarianism on the part of the supervisor would likely erode the productive value of any demographic similarity.

For cognitive skills, Table 4 shows that digit span recall, arithmetic (number correct) and arithmetic correct (%) are all quite informative, although the signal is higher for the memory measure (63%) than for the other two arithmetic measures (23% and 37%). With respect to control, internal locus of control has the highest loading and a signal of 53% justifying our naming this factor after this measure. Risk aversion and patience also contribute with loadings of .13 and .22, but both contain much more noise with signals of only 0.7% and 1.5%, respectively. With respect to personality, conscientiousness, perseverance, and self-esteem are all highly informative. The three measures present signal of 73%, 75%, and 69%, respectively, and all have loadings near 1. Psychological distress is less informative than the other three with a loading of -0.24 and a signal of 2.6%. Note that a higher score on the Kessler scale corresponds to more distress, so a negative loading is what we would expect.

For autonomy, the two leadership behavior measures, initiating structure and consideration, are highly informative with loadings of 1 and .86 and signals of 83% and 77%, respectively. Autonomous problem-solving, problem identification, and self-assessment contribute less with loadings of .05, .17, and .11, and are much noisier with signals of only 0.2%, 3.4% and 1.7%, respectively. Note that the sign of the loadings for all measures in these first three factors are positive as would be expected.

Finally, for attention, monitoring frequency and active personnel management are the strongest contributors, both with loadings of roughly 1, and both with strong signals (53% and 48%, respectively). Efforts to meet targets also contributes strongly with a loading of .57, but is less precise with a signal of 21%. Lack of communication and issues motivating workers both contribute with loadings of -.44 and -.13, but appear quite noisy with signals of 13% and 0.8%, respectively. Note that we would expect less communication with workers and upper management regarding production and more issues motivating workers and overcoming resistance to initiatives to both indicate less managerial attention or effort, so negative loadings for these measures is what we would expect.

It is important to note in summary the heterogeneity in the amount of information contained in each measure for each factor. This demonstrates the importance of allowing for measurement error in the system. Note also that even measures with low loading and high degree of noise are valuable to the system in efforts to purge informative measures of error.

6.3 Third Stage: productivity contributions of managerial quality

Table 5 reports the estimates of the CES functions for the initial level of productivity, the rate of learning, retention, and rate of forgetting. We see in column 1 that the initial level of productivity is most strongly impacted by attention and control, followed by tenure, autonomy, and cognitive skills. The estimated coefficients for demographics and personality are not significantly different from zero.

Table 5: Contributions of Managerial Quality to Productivity Dynamics

	Initial Productivity (α)	Rate of learning (β)	Retention (γ)	Forgetting (δ)
Tenure	0.193	0.266	0.300	0.402
	(0.027)	(0.018)	(0.023)	(0.023)
Demographics	0.022	0.000	0.001	0.046
	(0.017)	(0.000)	(0.003)	(0.024)
Cognitive Skills	0.058	0.039	0.055	0.000
	(0.025)	(0.021)	(0.023)	(0.000)
Control	0.251	0.138	0.098	0.000
	(0.052)	(0.038)	(0.050)	(0.000)
Personality	0.002	0.001	0.007	0.121
	(0.011)	(0.006)	(0.015)	(0.058)
Autonomy	0.134	0.214	0.200	0.162
	(0.023)	(0.019)	(0.026)	(0.053)
Attention	0.341	0.343	0.341	0.269
	(0.027)	(0.019)	(0.022)	(0.031)
Productivity Parameter	1.036	1.044	1.041	1.058
	(0.036)	(0.019)	(0.023)	(0.031)
Complementarity Parameter	-0.214	0.119	0.106	0.009
	(0.155)	(0.061)	(0.078)	(0.083)
Elasticity of Substitution	0.824	1.135	1.119	1.009
Std. Dev. of Dep. Variable	0.2982	0.1055	0.8461	0.1623
First Stage	log(Eff)	log(Eff)	log(Eff)	log(Eff)

Note: Standard errors in parentheses based on 100 bootstrap replications.

For the rate of learning, we find that attention and tenure still contribute strongly along with autonomy which contributes more to the rate of learning than to initial productivity. That managerial practices illustrating greater attention to production issues and autonomy in implementing changes would be important for rapid learning is quite consistent with our understanding of how supervisors enable learning by doing in this context. That is, the main ways in which production line supervisors can improve the productivity of their lines over the life of a production run are to monitor for machine calibration issues and bottle necks, reorganize the sequence of operations, and adjust allocations of workers to machine operations to relieve production imbalances. Control, on the other hand, contributes nearly half as strongly to the rate of learning as compared to its contribution to initial productivity. Similarly, the cognitive skills contribution to the rate of learning is smaller than its contribution to initial productivity. Once again, personality and demographics exhibit no discernible contribution.

Table 5 shows that the pattern of contributions to retention are quite similar to those for learning. That is, attention and tenure contribute most strongly and autonomy contributes more strongly to retention than to initial productivity. Cognitive skills contribute more strongly to retention than the rate of learning, consistent with the memory-based measure digit span recall being the most informative measure underlying this factor. Control contributes less to retention than to learning and initial productivity. Personality and demographics continue to be insignificant.

With respect to forgetting, we find that tenure contributes most strongly, consistent with the idea that supervisors who have more experience switching between orders and revisiting styles they have produced in the past are better at recalling and reimplementing nuanced technical details learned during previous productions runs.[40] Autonomy and attention contribute less strongly to forgetting than other learning parameters, while control and cognitive skills do not contribute to forgetting. We find a positive and significant contribution of personality to the rate of forgetting, consistent with the personality factor being most informed by perseverance and conscientiousness. We also see in column 4 that the contribution of demographics is marginally significant though small in magnitude.

For all the CES functions across the learning parameters, we find that the complementarity parameter is close to zero and not generally statistically significant, except for the rate of learning which is positive and weakly significant. This indicates that the different dimensions of managerial quality are not strongly complementary in their contributions to productivity. That is, the factors appear only weakly complementary in initial productivity and weakly substitutable in learning, indicating that a deficiency in one dimension of managerial quality does not impact the productive contributions of other dimensions. For example, a shorter tenured and/or less cognitively skilled supervisor can still benefit greatly from training in autonomy and/or attention.

Overall, given the complex relationships between the factors and productivity at different points along the learning curve, it is difficult to evaluate the composite impacts of higher stocks of different dimensions of managerial quality on productivity from the estimates in Table 5. Additionally, the relative value of screening on or training in these different dimensions is also hard to evaluate without considering how

[40] Note that a larger positive contribution to δ here indicates a slower rate of forgetting.

variable is each factor in the population. In order to perform this type of comparison, simulations of productivity under supervisors with higher values of different factors would be most informative.

Two different types of simulations can be conducted corresponding to whether the increased stock is achieved by screening candidate supervisors on particular dimensions of quality which can be measured at the time of hiring (e.g., tenure, demographics, cognitive skills, control, or personality) or whether it is achieved through focused training in specific practices or behaviors (e.g., autonomy or attention). In the case of screening on existing stocks of skills or traits, the manager who is hired with higher stock of one dimension (e.g., tenure) will come along with different stocks of other dimensions which are correlated in the population. On the other hand, in the case of focused training (in, e.g., attention), one can imagine being able to improve the behavior or increase the frequency of the practice independently. Accordingly, we conduct screening simulations assuming correlated changes in stocks of different dimensions of quality for both frequently observed traditional dimensions like tenure and demographics and less readily measured but still screenable dimensions like cognitive skills, control, and personality. For trainable practices like autonomy and attention, we conduct simulations in which independent increases are achieved.

6.3.1 Screening Simulations

In this section, we simulate the contribution of a one standard deviation (SD) increase in each of the dimensions of quality which are able to be measured and screened on at the time of hiring: both commonly observed factors – tenure and demographics – and less frequently measured factors – cognitive skills, control, and personality. Specifically, we substitute the estimated function of each learning parameter presented in Table 5 into the first stage (equation 1) and compute the impact of an increase of one standard deviation of each factor (as estimated in the second stage) on productivity at all points along the learning curve. We first evaluate productivity with each factor in each learning parameter fixed to its mean (baseline), and then increase sequentially each factor by one standard deviation.

Given that these dimensions on which candidates can be screened may be correlated with other dimensions of quality, we use the covariance structure of the factors in the population and compute the impact of an increase of factor i by δ_i, i.e., $E\left(\ln \boldsymbol{\theta} | \ln \theta_i = \delta_i\right)$ where $\delta_i = \sqrt{\sigma_{ii}}$ and $\sigma_{ii} = var\left(\theta_i\right)$. The computation of $E\left(\ln \boldsymbol{\theta} | \ln \theta_i = \delta_i\right)$ depends on the nature of the multivariate distribution assumed for $\ln \boldsymbol{\theta}$, thus

$$E\left(\ln \boldsymbol{\theta} | \ln \theta_i = \delta_i\right) = \left(\sigma_{1i}/\sigma_{ii}, \cdots, \sigma_{Ki}/\sigma_{ii}\right)' \delta_i$$

where $\sigma_{ij} = var(\theta_i, \theta_j)$. This procedure is similar to the generalized impulse response functions proposed in the time series context by Pesaran and Shin (1998).[41] This type of correlated shock is more analogous to what might result from a screening intervention in which supervisors with a SD more of a given factor than the average candidate would come along with more or less of the other correlated factors as well.

We present the correlation structure between factors used in these screening simulations in Table A9 in the Appendix. The cognitive skills factor is positively correlated with all other factors, most strongly with control (.335) and personality (.326). Personality is strongly positively correlated with autonomy (.852), as well as moderately correlated with control (.358) and demographics (.255). Demographics is correlated with all factors except for tenure, most strongly with control (.476), autonomy (.383), and attention (.308).

Figure 8A: Screening on Tenure

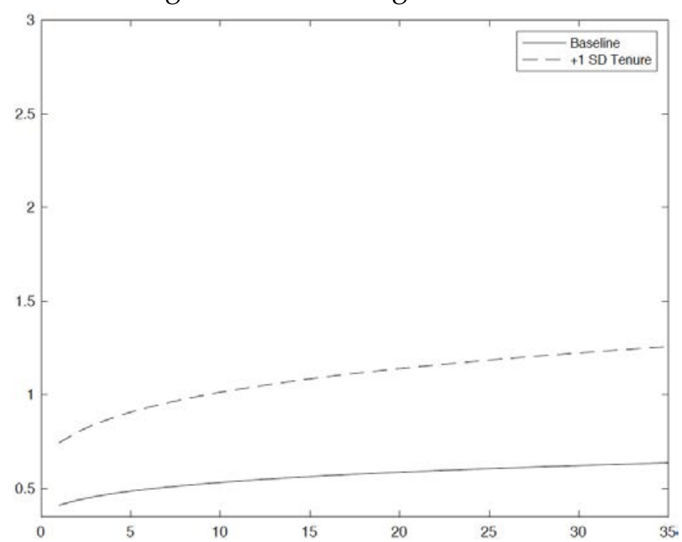
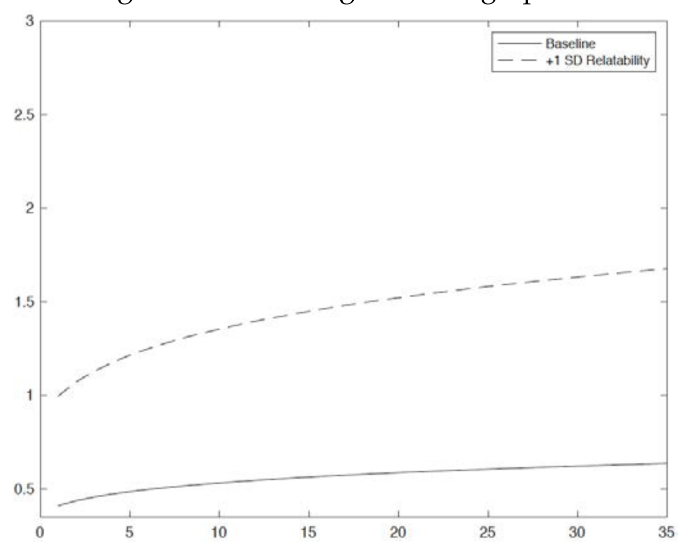


Figure 8B: Screening on Demographics



Note: Figures 8A and 8B show the contribution of Tenure and Demographics to the learning curve (log efficiency), respectively. We fix the learning parameters to their mean and increase sequentially each factor by one standard deviation using the covariance structure.

Figures 8A and 8B show the contribution to the learning curve of screening supervisors on tenure and demographics, respectively. We plot simulated curves with 1 SD above mean tenure and demographics, alternately, as well as the corresponding augmented stocks of all other factors as given by the covariance structure between factors and compare these curves to the baseline learning curve evaluated with each factor at its mean value. In the simulations, we evaluate the learning curves with previous experience and days since last run of the same style at average levels observed in the data to reflect contributions to

[41] See also Pesaran (2015).

all parameters of the learning curve, including retention and forgetting.

Figure 9A: Screening on Cognitive Skills

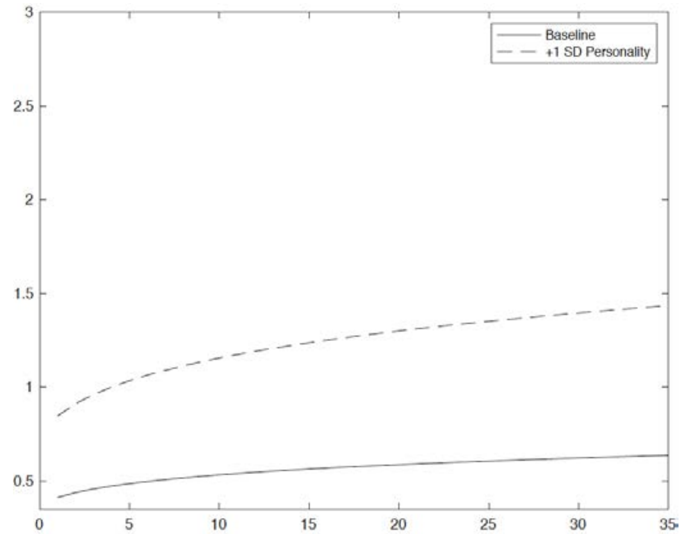


Figure 9B: Screening on Control

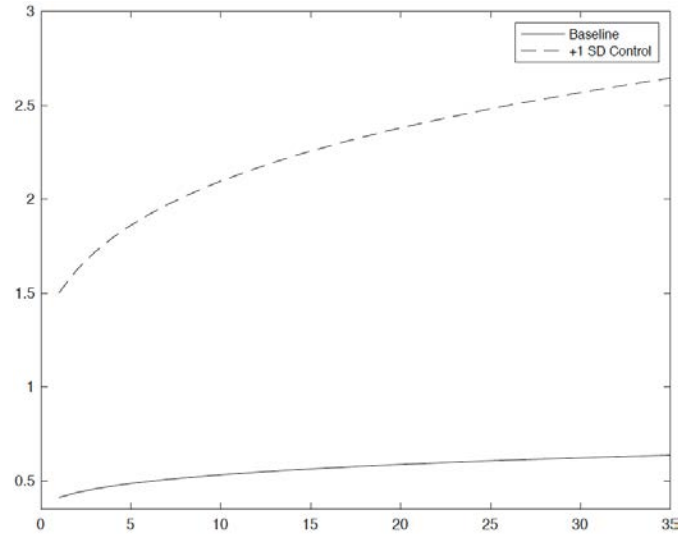
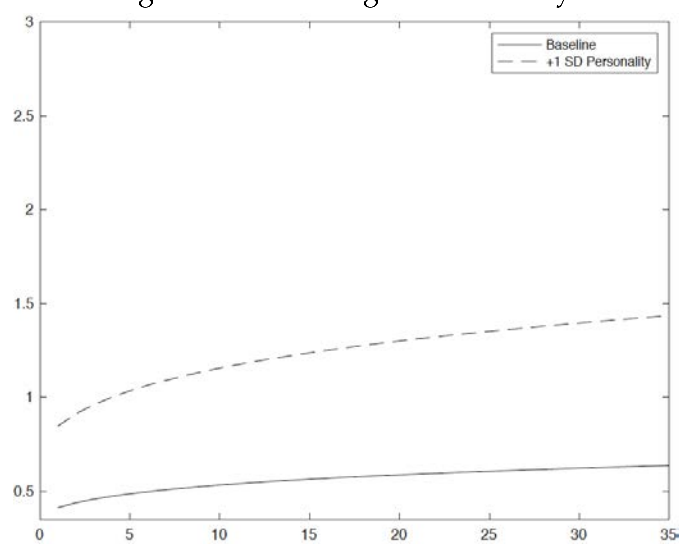


Figure 9C: Screening on Personality



Note: Figures 9A and 9C show the contribution of control and personality to the learning curve (log efficiency), respectively. We fix the learning parameters to their mean and increase sequentially each factor by one standard deviation.

We repeat the exercise for less frequently observed dimensions cognitive skills, control, and personality and present the comparisons between simulated learning curves to baseline learning curves in Figures 9A through 9C. For example, if we compare productivity on day 15 (the mean length) of the order, a supervisor with one SD of control more than the average supervisor will achieve productivity of roughly 2.2 as compared to roughly .5 for the average supervisor. The day 15 comparisons for personality, cognitive skills, and demographics depict increases from .5 to 1.3, 1.4, and 1.5, respectively; while the analogous exercise for tenure shows an increase in productivity to roughly 1.1.

Table 6: Screening Simulation: Contributions to Productivity

Factor	Mean
Easily Screened	
Tenure	0.684
	(0.0497)
Demographics	0.943
	(0.0614)
Costly to Screen	
Cognitive Skills	0.910
	(0.0523)
Control	1.379
	(0.0427)
Personality	0.783
	(0.0482)

Note: Table 6 shows the impact on productivity of an increase of each factor by one standard deviation. We use the covariance structure of the factors to compute the impact on productivity.

Overall, we find across these screening simulations that account for correlations between factors of managerial quality that control has the largest impact, followed by demographics and cognitive skills. Personality shows the next largest impact, with tenure having the smallest impact. These contributions are summarized in 6, which presents differences in average productivity across days of a production run between simulated curves and baseline curves along with bootstrapped standard errors. Simulated gains in productivity range from 68% from screening on tenure to 138% for screening on control, with all contributions being large and precisely estimated.

6.3.2 Training Simulations

Next, we simulate the contribution of a one standard deviation (SD) increase in the two factors corresponding to behaviors and practices in which supervisors can be trained – autonomy and attention. Assuming the potential for focused training in these behaviors and practices, we impose that increases in these factors can be achieved independent of other factors. That is, we assume that a potential intervention on attention or autonomy affect only the *treated* factor.

In Figures 10A and 10B, we observe that attention has larger impact on productivity than does autonomy, though both show large gains in productivity. When comparing productivity on day 15 across curves we see that a simulated, focused increase in autonomy of 1 SD increases productivity from .5 to roughly 1; while that for attention increases productivity to around 1.5. Table 7 presents average productivity gains from these simulated trainings and corresponding bootstrapped standard errors. Estimates indicate a precisely estimated gain of 60% from training in autonomy, similar in magnitude to screening on tenure in the above simulations, and a gain of 112% from training in attention, a larger simulated gains than screening on cognitive skills or demographics but not as large as the gain from screening on control.

Of course, the decisions of which policy – screening or training – and which dimensions to prioritize depend also on corresponding impacts on the wages needed to retain these higher quality supervisors. For that, we must conduct the analogous third stage estimation for observed pay of supervisors as well as corresponding simulations, and compare results with these productivity results.

Figure 10A: Training in Autonomy

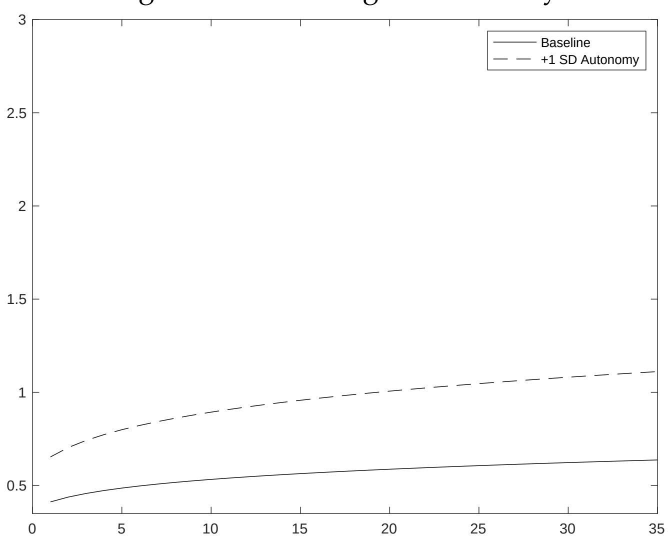
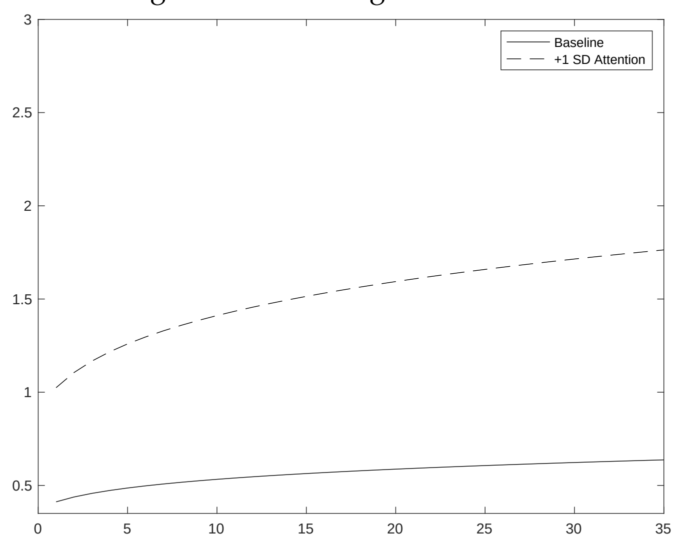


Figure 10B: Training in Attention



Note: Figures 10A and 10B show the contribution of autonomy and attention to the learning curve (log efficiency), respectively. We fix the learning parameters to their mean and increase sequentially each factor by one standard deviation, assuming that the shocks to the factors are independent.

Table 7: Training Simulation: Contributions to Productivity

Factor	Mean
Autonomy	0.603
	(0.05)
Attention	1.123
	(0.0495)

Note: Table 7 shows the impact on productivity of an increase of autonomy and attention by one standard deviation. We assume that the intervention only affects the specific dimension of managerial quality considered.

6.4 Third Stage: Contributions of Managerial Quality to Pay

Having estimated the contributions of the seven latent factors to the learning parameters and simulated impacts of skill increases on composite productivity, we next test if there exists a relationship between these seven factors and supervisor pay. If pay reflects the marginal productivity of labor, as a standard model of a perfectly competitive labor market would predict, we may expect similar results to the ones presented in Table 5. However, imperfect information on the part of the employer (or competing employers) regarding quality of the managers, particularly less easily measured or observed dimensions of quality, may lead the firm to rely just on the observable characteristics, like tenure or demographics to determine the pay scheme (or only force the firm to reward these observable dimensions). Furthermore, if the firm's market power approaches a monopsony, the firm may not have incentives to adjust the pay fully in response to productivity.

To test the link between the seven latent factors and supervisor pay, we follow the same approach as we did for productivity. We use data on salary paid by the firm to each of the managers during the month of the survey, November 2014, and include the monetary bonuses that are associated with the productivity of the lines. Remember that we included the log of this pay measure in the measurement system in stage 2 of our empirical strategy. Accordingly, we can draw synthetic datasets from the joint distribution of factors and supervisor pay just as we did for the learning parameter analysis above. Finally, we estimate an analogue to equation (3) with log of supervisor pay as the outcome.

Table 8 presents the results of this analysis of supervisor pay. Attention and tenure are reflected most strongly in supervisor pay, followed by autonomy. Control, personality, and cognitive skills are not strongly reflected in pay; all three estimates are statistically insignificant from 0, consistent with a limited effort (or ability) to measure these traits. The demographics factor also has no measurable impact on pay, perhaps due to efforts against discrimination. Note, that overall the pattern of results in Table 8 is not entirely consistent with the rank of factors' contributions to productivity. For example, control showed fairly large impacts on productivity in the screening simulation but is not reflected in pay. To best assess the relative pass-through of productivity contributions of factors to pay, we should perform analogous simulations for pay to the productivity simulations summarized in Tables 6 and 7, and compare results across pay and productivity simulations for each factor.

Table 8: Contributions of Managerial Quality to Pay

	Pay
Tenure	0.311
	(0.015)
Demographics	0.000
	(0.000)
Cognitive Skills	0.025
	(0.017)
Control	0.048
	(0.030)
Personality	0.007
	(0.014)
Autonomy	0.248
	(0.018)
Attention	0.362
	(0.017)
Productivity Parameter	1.045
	(0.017)
Complementarity Parameter	0.066
	(0.049)
Elasticity of substitution	1.071
Std. Dev. of Dep. Variable	0.1011

Note: Standard errors in parentheses based on 100 bootstrap replications.

6.4.1 Screening Simulations: Pass-through of Productivity to Pay

In this section we compare the contribution to productivity vs. supervisor pay of a simulated 1 SD increase in each of the factors on which supervisor candidates can be screened. For productivity, we simply use the coefficients from Tables 6 and 7 along with corresponding bootstrapped errors. For analogous pay simulations, we substitute the estimated coefficients of factors presented in Table 8 back into the estimating equation (3) using the mean value of each factor at baseline and an increase of one standard deviation of each factor sequentially to simulate pay for the higher skilled supervisors. We once again perform this pay simulation assuming increases in the factor on which candidates are being screened comes along with augmented stocks in other factors according to the measured covariance structure. Finally, we compute the pass-through of productivity to pay by dividing the simulated change in pay by the simulated change in productivity for the one SD increase in each factor.

Table 9 presents results form this comparison for both commonly observed dimensions – tenure and demographics – and less readily measured dimensions – cognitive skills, control, and personality. We see that tenure exhibits the strongest pass through to pay: more than 30%. Demographics, though just as easily and frequently observed in the hiring process as tenure, has lower pass-through to pay, likely due to efforts against discrimination. The less readily measured dimensions – cognitive skills, control, and personality–all exhibit lower pass-through to pay as compared to Tenure.

Table 9: Screening Simulations: Pass-through of Productivity to Pay

	Contribution to Productivity	Contribution to Pay	Pass-through
	Easily Screened		
Tenure	0.684	0.2105	30.77%
	(0.0497)	(0.0123)	
Demographics	0.9434	0.1837	19.47%
	(0.0614)	(0.0152)	
	Costly to Screen		
Cognitive Skills	0.91	0.2015	20.03%
	(0.0523)	(0.0133)	
Control	1.3787	0.2762	27.48%
	(0.0427)	(0.0115)	
Personality	0.783	0.2152	22.14%
	(0.0482)	(0.0112)	

Note: The contributions are the percentage change in productivity and pay of an increase of one standard deviation of each factor, and associated changes in all other factors as given by the covariance structure among factors. We compute the pass-through of productivity to pay, dividing the contribution to pay by the contribution to productivity. Standard errors in parentheses are based on 100 bootstrap replications.

6.4.2 Training Simulations: Pass-through of Productivity to Pay

Finally, we repeat the above exercise for the simulations of training in autonomy and attention. Table 10 shows that although training in attention produces larger gains in productivity than autonomy, both dimensions of managerial quality command similar wage premia. That is, the pass-through of productivity gains from autonomy to pay is much larger (48%) than that for attention (27%). These results indicate that the firm can raise productivity measurably by training supervisors to be both more autonomous and attentive, but that training in attention could be more cost-effective.

Note that, across Tables 9 and 10, the pass-through is in general quite low with a maximum of 48% for training in autonomy and as little as roughly 20% for screening on both demographics and cognitive skills. This is consistent with the firm paying almost entirely fixed salaries with limited role for performance-contingent bonuses as indicated by the summary statistics on pay. As discussed above, some factors exhibit larger pass-through (e.g., tenure) than others (e.g., cognitive skills and personality). This is consistent with the executives of each factory, as well as competing employers, being unable to effectively measure many dimensions of managerial quality and evaluate which to reward in pay. That

Table 10: Training Experiment: Pass-through of Productivity to Pay

	Contribution to Productivity	Contribution to Pay	Pass-through
Autonomy	0.5121	0.2479	48.41%
	(0.01)	(0.0058)	
Attention	0.9724	0.2623	26.97%
	(0.0205)	(0.0057)	

Note: The contributions are the percentage change in productivity and pay of an independent increase of one standard deviation of each factor. We compute the pass-through of productivity to pay, dividing the contribution to pay by the contribution to productivity. Standard errors in parentheses are based on 100 bootstrap replications.

is, as discussed above, many dimensions of managerial quality, though they contribute to productivity, are not frequently or easily measured at the time of hiring and many important behaviors and practices are not easily monitored or even known to be productive.

7 Checks and Robustness

7.1 Tests for Sorting Bias: Monte Carlo Simulations

We present the result of the Monte Carlo experiment discussed in section 5.1.3 for the initial productivity, α_i, the rate of learning, β_i, retention, γ_i and rate of forgetting, δ_i. We compute the percentage mean bias for the estimated coefficients for the 120 lines for which we recover α_i and β_i and the 99 lines for which we recover γ_i and δ_i, and then we compute the average of the absolute value of the mean bias for each line. We conduct this simulation twice: first assuming i.i.d. errors and then assuming the errors are AR(1). The results of this experiment show that the bias is small (less than 0.7%) for both the initial productivity and the learning rate under both error structures. For the retention rate and the forgetting rate, the average of the absolute value of the mean bias for each line is slightly higher but still only 8% or less under both error structures. We interpret these results as strong evidence that the identifying assumptions underlying the first stage estimation, including the absence of sorting of styles to lines, are valid.

7.2 Deadline or Reference Point Effects: Robustness to Controlling for Days Left

We repeat our full three step estimation controlling for days left to complete the order in the first stage (equation 1), to account for any reference point effect (e.g., productivity rising as the deadline draws near). Table B1 reports the estimated measurement system (analogous to Table 4). Tables B2 and B3 report the estimates of the CES production functions for the learning parameters (analogous to Table 5) and pay (analogous to Table 8), respectively. Table B4 compares the contribution to productivity vs. supervisor pay of a simulated 1 SD increase in each of the factors on which supervisor candidates can be screened. We once again perform this pay simulation assuming increases in the factor on which candidates are being screened comes along with augmented stocks in other factors according to the measured covariance structure (analogous to Table 9). Table B5 repeats the above exercise for the simulations of training in autonomy and attention (analogous to Table 10). Note that the loadings and the signals of each measure are very similar to our previous results in Table 4, and the coefficients of the CES function for the learning parameters and pay are almost identical to the previous results. Finally, note that the pattern of contributions of each factor productivity and pay are nearly identical to our main results.

7.3 Alternate Productivity Measure: Robustness to Using log(Quantity) in Place of log(Efficiency)

Similarly, we repeat our three-step estimation procedure using log quantity produced instead of log efficiency as the outcome in the first stage and control for log of target quantity. Table C2 reports the results of the estimated measurement system, and Tables C3 and C4 report the estimates of the CES production functions for the learning parameters pay, respectively. Finally, Table C5 compares the contribution to productivity vs. supervisor pay of a simulated 1 SD increase in each of the factors on which supervisor candidates can be screened assuming candidates are being screened comes along with augmented stocks in other factors according to the measured covariance structure. Table C6 repeats the above exercise for the simulations of training in autonomy and attention. Again, the results show a qualitatively similar to the main results in Tables 4, 5 and 8, and 9, and 10.

8 Conclusion

Information frictions have wide-ranging implications for the functioning of labor markets around the world. Understanding which skills, traits, and practices of managers are important for productivity, and whether employers appropriately price the features that actually matter into their pay, is key to the understanding of the nature and extent of information frictions.

In this study, we combine granular administrative data on productivity and manager pay with extensive survey data on managerial skills, personality traits, and practices in the context of readymade garments production in India. Our goal is to flexibly and comprehensively incorporate features of managerial quality into a production process that is characterized by learning-by-doing, and recover the contributions of various dimensions of quality to productivity.[42] Next we study the way in which each of these features is incorporated in manager pay, enabling an assessment of the extent to which the dimensions of quality that matter most are priced accordingly into managers' wages. Finally, we conduct counterfactual simulations of screening and training policies.

We find that tenure, autonomy, locus of control, and attention all have substantial effects on productivity. Personality traits and demographic similarity with workers play limited independent roles, though they are correlated with dimensions of quality that do matter. Not all productive characteristics hold appropriate value in the labor market, as measured by manager pay. Consistent with the presence of information frictions in the labor market for managers, we find that easily observed characteristics like industry tenure are better rewarded, while less observable (or costly-to-screen) features, like attention, are rewarded less commensurately with their importance for productivity.

Given these facts, screening on personality traits via psychometric measurement would improve the quality of new managers, and training in poorly observed (and unrewarded) but valuable practices like managerial attention could substantially raise firm productivity at low cost. The insights gleaned here pave the way for future prospective trials in which the implications of our policy simulations may be tested rigorously and refined. Our specific focus on managers is especially important given that low managerial quality in many low-income country contexts has been singled out as a driver of low productivity and a barrier to firm growth. To improve the quality of managers, firms and government policymakers need first to understand which managerial skills, practices, and traits best predict productivity in low-income contexts, and assess the extent to which these characteristics are valued in the labor market.

[42]This study answers a pointed call made in Levitt et al. (2013) to conduct "research on the complementarities between the learning process and managerial practices."

Bibliography

Abowd, J. M., Creecy, R. H., and Kramarz, F. (2002). Computing person and firm effects using linked longitudinal employer-employee data. Technical report.

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–334.

Abowd, J. M., Lengermann, P., and Prez-Duarte, S. (2004). Are good workers employed by good firms? a simple test of positive assortative matching models. Technical report.

Acemoglu, D. and Pischke, J.-S. (1998). Why do firms train? theory and evidence. *The Quarterly Journal of Economics*, 113(1):79–119.

Acemoglu, D. and Pischke, J.-S. (1999). Beyond becker: training in imperfect labour markets. *The Economic Journal*, 109(453):112–142.

Adhvaryu, A. (2018). Managerial quality and worker productivity in developing countries. *IZA World of Labor*.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2018a). Management and shocks to worker productivity. *working paper*.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2018b). The skills to pay the bills: Returns to on-the-job soft skills training. Technical report, National Bureau of Economic Research.

Aghion, P., Bloom, N., Lucking, B., Sadun, R., and Van Reenen, J. (2017). Turbulence, firm decentralization and growth in bad times. *working paper*.

Alfonsi, L., Bandiera, O., Bassi, V., Burgess, R., Rasul, I., Sulaiman, M., Vitali, A., et al. (2017). Tackling youth unemployment: Evidence from a labor market experiment in uganda. *STICERD-Development Economics Papers*.

Altonji, J. G. and Pierret, C. R. (2001). Employer learning and statistical discrimination. *The Quarterly Journal of Economics*, 116(1):313–350.

Arrow, K. J. (1962). The economic implications of learning by doing. *The Review of Economic Studies*, 29(3):155–173.

Attanasio, O., Cattan, S., Fitzsimons, E., Meghir, C., and Rubio-Codina, M. (2015a). Estimating the production function for human capital: Results from a randomized control trial in colombia. Technical report, National Bureau of Economic Research.

Attanasio, O., Meghir, C., and Nix, E. (2015b). Human capital development and parental investment in india. Technical report, National Bureau of Economic Research.

Bandiera, O., Hansen, S., Prat, A., and Sadun, R. (2017). Ceo behavior and firm performance. Technical report, National Bureau of Economic Research.

Bassi, V. and Nansamba, A. (2017). Information frictions in the labor market: Evidence from a field experiment in uganda.

Benkard, C. L. (2000). Learning and forgetting: The dynamics of aircraft production. *The American Economic Review*, 90(4):1034–1054.

Bertrand, M. and Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, 118(4):1169–1208.

Blattman, C. and Dercon, S. (2016). Occupational choice in early industrializing societies: Experimental evidence on the income and health effects of industrial and entrepreneurial work. Technical report, National Bureau of Economic Research.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R., Patnaik, M., Saporta-Eksten, I., and Van Reenen, J. (2018a). What drives differences in management practices? Technical report, Working Paper, Stanford University.

Bloom, N., Brynjolfsson, E., Foster, L., Jarmin, R. S., Patnaik, M., Saporta-Eksten, I., and Van Reenen, J. (2017a). What drives differences in management? Technical report, National Bureau of Economic Research.

Bloom, N., Eifert, B., Mahajan, A., McKenzie, D., and Roberts, J. (2013). Does management matter? evidence from india. *The Quarterly Journal of Economics*, 1(51):51.

Bloom, N., Mahajan, A., McKenzie, D., and Roberts, J. (2017b). Do management interventions last? evidence from india.

Bloom, N., Mahajan, A., McKenzie, D., and Roberts, J. (2018b). *Do management interventions last? evidence from India*. The World Bank.

Bloom, N., Sadun, R., and Van Reenen, J. (2016). Management as a technology? Technical report, National Bureau of Economic Research.

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

Bloom, N. and Van Reenen, J. (2010). Why do management practices differ across firms and countries? *The Journal of Economic Perspectives*, pages 203–224.

Bloom, N. and Van Reenen, J. (2011). Human resource management and productivity. *Handbook of labor economics*, 4:1697–1767.

Boissiere, M., Knight, J. B., and Sabot, R. H. (1985). Earnings, schooling, ability, and cognitive skills. *The American Economic Review*, 75(5):1016–1030.

Borghans, L., Duckworth, A. L., Heckman, J. J., and Ter Weel, B. (2008). The economics and psychology of personality traits. *Journal of human Resources*, 43(4):972–1059.

Bowen, D. E. and Ostroff, C. (2004). Understanding hrm–firm performance linkages: The role of the ?strength? of the hrm system. *Academy of management review*, 29(2):203–221.

Bowles, S., Gintis, H., and Osborne, M. (2001). The determinants of earnings: A behavioral approach. *Journal of economic literature*, 39(4):1137–1176.

Bresnahan, T. F., Brynjolfsson, E., and Hitt, L. M. (2002). Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence. *The Quarterly Journal of Economics*, 117(1):339–376.

Cappelli, P. and Neumark, D. (2001). Do "high-performance" work practices improve establishment-level outcomes? *ILR Review*, 54(4):737–775.

Caselli, F. (2005). Accounting for cross-country income differences. *Handbook of economic growth*, 1:679–741.

Collins, C. J. and Clark, K. D. (2003). Strategic human resource practices, top management team social networks, and firm performance: The role of human resource practices in creating organizational competitive advantage. *Academy of management Journal*, 46(6):740–751.

Collins, C. J. and Smith, K. G. (2006). Knowledge exchange and combination: The role of human resource practices in the performance of high-technology firms. *Academy of management journal*, 49(3):544–560.

Combs, J., Liu, Y., Hall, A., and Ketchen, D. (2006). How much do high-performance work practices matter? a meta-analysis of their effects on organizational performance. *Personnel psychology*, 59(3):501–528.

Cunha, F., Heckman, J. J., and Schennach, S. M. (2010). Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931.

Delaney, J. T. and Huselid, M. A. (1996). The impact of human resource management practices on perceptions of organizational performance. *Academy of Management journal*, 39(4):949–969.

Ellison, S. F. and Snyder, C. M. (2014). An empirical study of pricing strategies in an online market with high-frequency price information.

Farber, H. S. and Gibbons, R. (1996). Learning and wage dynamics. *The Quarterly Journal of Economics*, 111(4):1007–1047.

Gibbons, R. and Waldman, M. (2004). Task-specific human capital. *The American Economic Review*, 94(2):203–207.

Groves, T., Hong, Y., McMillan, J., and Naughton, B. (1994). Autonomy and incentives in chinese state enterprises. *The Quarterly Journal of Economics*, 109(1):183–209.

Hall, R. E. and Jones, C. I. (1999). Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics*, 114(1):83–116.

Hansen, G. S. and Wernerfelt, B. (1989). Determinants of firm performance: The relative importance of economic and organizational factors. *Strategic management journal*, 10(5):399–411.

Heckman, J. J. and Kautz, T. (2012). Hard evidence on soft skills. *Labour economics*, 19(4):451–464.

Heckman, J. J., Stixrud, J., and Urzua, S. (2006). The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior. *Journal of Labor economics*, 24(3):411–482.

Hjort, J. (2014). Ethnic divisions and production in firms. *The Quarterly Journal of Economics*, 129(4):1899–1946.

Huselid, M. A. (1995). The impact of human resource management practices on turnover, productivity, and corporate financial performance. *Academy of management journal*, 38(3):635–672.

Jovanovic, B. (1979). Firm-specific capital and turnover. *Journal of political economy*, 87(6):1246–1260.

Jovanovic, B. and Nyarko, Y. (1995). A bayesian learning model fitted to a variety of empirical learning curves. *Brookings Papers on Economic Activity. Microeconomics*, 1995:247–305.

Judge, T. A., Piccolo, R. F., and Ilies, R. (2004). The forgotten ones? the validity of consideration and initiating structure in leadership research. *Journal of applied psychology*, 89(1):36.

Kahn, L. B. (2013). Asymmetric information between employers. *American Economic Journal: Applied Economics*, 5(4):165–205.

Kahn, L. B. and Lange, F. (2014). Employer learning, productivity, and the earnings distribution: Evidence from performance measures. *The Review of Economic Studies*, 81(4):1575–1613.

Karlan, D., Knight, R., and Udry, C. (2015). Consulting and capital experiments with microenterprise tailors in ghana. *Journal of Economic Behavior & Organization*, 118:281–302.

Kellogg, R. (2011). Learning by drilling: Interfirm learning and relationship persistence in the texas oilpatch. *The Quarterly Journal of Economics*, 126(4):1961–2004.

Korman, A. K. (1966). "consideration","initiating structure", and organizational criteria-a review. *Personnel Psychology*, 19(4):349–361.

Lange, F. (2007). The speed of employer learning. *Journal of Labor Economics*, 25(1):1–35.

Lazear, E. P., Shaw, K. L., and Stanton, C. T. (2015). The value of bosses. *Journal of Labor Economics*, 33(4):823–861.

Levitt, S. D., List, J. A., and Syverson, C. (2013). Toward an understanding of learning by doing: Evidence from an automobile assembly plant. *Journal of Political Economy*, 121(4):643–681.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of monetary economics*, 22(1):3–42.

Macchiavello, R., Menzel, A., Rabbani, A., and Woodruff, C. (2015). Challenges of change: An experiment training women to manage in the bangladeshi garment sector. Technical report.

McKenzie, D. and Woodruff, C. (2013). What are we learning from business training and entrepreneurship evaluations around the developing world? *The World Bank Research Observer*, 29(1):48–82.

McKenzie, D. and Woodruff, C. (2016). Business practices in small firms in developing countries. *Management Science*.

Mincer, J. and Ofek, H. (1982). Interrupted work careers: Depreciation and restoration of human capital. *Journal of human resources*, pages 3–24.

Mincer, J. A. et al. (1974). Schooling, experience, and earnings. *NBER Books*.

Neal, D. (1995). Industry-specific human capital: Evidence from displaced workers. *Journal of labor Economics*, 13(4):653–677.

Pesaran, M. H. (2015). *Time Series and Panel Data Econometrics*. Oxford University Press.

Pesaran, M. H. and Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, 58(1):17–29.

Reis, R. (2006). Inattentive producers. *The Review of Economic Studies*, 73(3):793–821.

Schoar, A. (2011). The importance of being nice: Evidence from a supervisory training program in cambodia. Technical report, mimeo, MIT.

Schoar, A. (2014). The importance of being nice: Supervisory skill training in the cambodian garment industry. *working paper*.

Stogdill, R. M. and Coons, A. E. (1957). Leader behavior: Its description and measurement.

Syverson, C. (2011). What determines productivity? *Journal of Economic Literature*, 49(2):326–365.

Thompson, P. (2001). How much did the liberty shipbuilders learn? new evidence for an old case study. *Journal of Political Economy*, 109(1):103–137.

Thompson, P. (2012). The relationship between unit cost and cumulative quantity and the evidence for organizational learning-by-doing. *Journal of Economic Perspectives*, 26(3):203–224.

Topel, R. (1991). Specific capital, mobility, and wages: Wages rise with job seniority. *Journal of political Economy*, 99(1):145–176.

APPENDIX

A Tests for Sorting Bias: Balance Checks and Monte Carlo Simulations

Table A1: Sorting of Workers' and Managers Characteristics

Characteristic Supervisor	*Efficiency**				*Grade workers*			
	Full Sample	*High*	*Low*	*Difference*	*Full Sample*	*High*	*Low*	*Difference*
Total Years Working	0.006	0.004	0.008	-0.003	6.003	6.010	5.997	0.014
	(0.006)	(0.008)	(0.008)	(0.011)	(0.077)	(0.117)	(0.104)	(0.156)
Tenure in Garment Industry	0.006	0.012	0.001	0.012	6.003	6.140	5.880	0.260**
	(0.006)	(0.008)	(0.008)	(0.011)	(0.077)	(0.116)	(0.101)	(0.154)
Tenure as Supervisor	0.006	0.011	0.002	0.009	6.003	6.121	5.898	0.223*
	(0.006)	(0.009)	(0.006)	(0.011)	(0.077)	(0.114)	(0.105)	(0.154)
Tenure Supervising Current Line	0.006	0.011	0.004	0.007	6.003	6.123	5.933	0.190
	(0.006)	(0.010)	(0.007)	(0.011)	(0.077)	(0.132)	(0.095)	(0.160)
Digit Span Recall	0.006	0.002	0.010	-0.008	6.003	5.903	6.102	-0.199
	(0.006)	(0.006)	(0.009)	(0.011)	(0.077)	(0.124)	(0.093)	(0.154)
Arithmetic	0.006	-0.001	0.010	-0.011	6.003	6.012	5.999	0.013
	(0.006)	(0.010)	(0.007)	(0.011)	(0.077)	(0.143)	(0.092)	(0.162)
Arithmetic Correct (%)	0.006	0.007	0.005	0.002	6.003	5.880	6.109	-0.229
	(0.006)	(0.007)	(0.009)	(0.011)	(0.077)	(0.125)	(0.095)	(0.154)
Initiating Structure	0.006	0.012	0.001	0.011	6.003	5.745	6.217	-0.472
	(0.006)	(0.008)	(0.007)	(0.011)	(0.077)	(0.120)	(0.092)	(0.149)
Consideration	0.006	0.013	0.000	0.013	6.003	5.793	6.201	-0.408
	(0.006)	(0.008)	(0.007)	(0.011)	(0.077)	(0.120)	(0.092)	(0.150)
Autonomous Problem-Solving	0.006	-0.008	0.014	-0.022	6.003	5.926	6.046	-0.120
	(0.006)	(0.009)	(0.007)	(0.011)	(0.077)	(0.124)	(0.099)	(0.162)
Identifying Production Problems	0.006	0.016	0.000	0.016*	6.003	5.861	6.094	-0.233
	(0.006)	(0.008)	(0.007)	(0.011)	(0.077)	(0.153)	(0.080)	(0.158)
Self-Assessment	0.006	0.004	0.008	-0.003	6.003	5.844	6.105	-0.260
	(0.006)	(0.010)	(0.006)	(0.011)	(0.077)	(0.126)	(0.097)	(0.157)
Conscientiousness	0.006	0.002	0.009	-0.007	6.003	5.777	6.191	-0.414
	(0.006)	(0.009)	(0.007)	(0.011)	(0.077)	(0.126)	(0.089)	(0.150)
Perseverance	0.006	0.015	-0.001	0.017*	6.003	5.828	6.148	-0.320
	(0.006)	(0.008)	(0.007)	(0.011)	(0.077)	(0.127)	(0.091)	(0.153)
Self-Esteem	0.006	0.010	0.003	0.007	6.003	5.984	6.019	-0.036
	(0.006)	(0.009)	(0.007)	(0.011)	(0.077)	(0.122)	(0.100)	(0.156)
Psychological Distress	0.006	0.015	0.000	0.015*	6.003	6.102	5.937	0.165
	(0.006)	(0.009)	(0.007)	(0.011)	(0.077)	(0.125)	(0.098)	(0.158)
Internal Locus of Control	0.006	0.007	0.005	0.002	6.003	5.979	6.025	-0.046
	(0.006)	(0.007)	(0.008)	(0.011)	(0.077)	(0.124)	(0.098)	(0.156)
Risk Aversion	0.006	0.002	0.008	-0.006	6.003	5.850	6.081	-0.230
	(0.006)	(0.011)	(0.006)	(0.012)	(0.077)	(0.151)	(0.088)	(0.163)
Patience	0.006	-0.009	0.012	-0.021	6.003	5.916	6.038	-0.123
	(0.006)	(0.012)	(0.006)	(0.012)	(0.077)	(0.126)	(0.096)	(0.172)
Monitoring Frequency	0.006	0.003	0.007	-0.004	6.003	5.927	6.022	-0.095
	(0.006)	(0.013)	(0.006)	(0.014)	(0.077)	(0.181)	(0.086)	(0.194)
Efforts to Meet Targets	0.006	0.013	0.003	0.010	6.003	5.649	6.159	-0.509
	(0.006)	(0.007)	(0.007)	(0.012)	(0.077)	(0.160)	(0.080)	(0.161)
Active Personnel Management	0.006	0.007	0.006	0.002	6.003	5.724	6.120	-0.397
	(0.006)	(0.010)	(0.007)	(0.012)	(0.077)	(0.158)	(0.084)	(0.166)
Lack of Communication	0.006	-0.001	0.013	-0.014	6.003	6.138	5.882	0.255*
	(0.006)	(0.009)	(0.007)	(0.011)	(0.077)	(0.106)	(0.110)	(0.154)
Issues Motivating Workers, Resistance	0.006	-0.008	0.020	-0.027	6.003	6.103	5.902	0.201*
	(0.006)	(0.008)	(0.007)	(0.011)	(0.077)	(0.099)	(0.119)	(0.154)
Demographic Similarity	0.006	-0.002	0.014	-0.016	6.003	5.745	6.236	-0.491
	(0.006)	(0.008)	(0.007)	(0.011)	(0.077)	(0.115)	(0.094)	(0.147)
Egalitarianism	0.006	0.012	0.002	0.010	6.003	5.866	6.091	-0.226
	(0.006)	(0.010)	(0.006)	(0.011)	(0.077)	(0.136)	(0.092)	(0.158)

Table A2: Sorting of Workers' and Managers Characteristics

Characteristic Supervisor	*Highest-Skill workers*				*Pay*			
	Full Sample	*High*	*Low*	*Difference*	*Full Sample*	*High*	*Low*	*Difference*
Total Years Working	0.173	0.163	0.182	-0.019	6,691.604	6,637.432	6,741.442	-104.010
	(0.009)	(0.011)	(0.013)	(0.018)	(31.689)	(45.576)	(43.327)	(62.860)
Tenure in Garment Industry	0.173	0.198	0.150	0.048***	6,691.604	6,699.192	6,684.623	14.570
	(0.009)	(0.014)	(0.011)	(0.017)	(31.689)	(50.826)	(39.412)	(63.752)
Tenure as Supervisor	0.173	0.194	0.154	0.040**	6,691.604	6,696.930	6,686.704	10.226
	(0.009)	(0.014)	(0.011)	(0.017)	(31.689)	(51.091)	(39.136)	(63.761)
Tenure Supervising Current Line	0.173	0.175	0.172	0.002	6,691.604	6,627.934	6,729.806	-101.872
	(0.009)	(0.015)	(0.011)	(0.018)	(31.689)	(52.305)	(39.336)	(64.959)
Digit Span Recall	0.173	0.172	0.174	-0.002	6,691.604	6,716.739	6,667.495	49.244
	(0.009)	(0.014)	(0.011)	(0.018)	(31.689)	(37.915)	(50.474)	(63.525)
Arithmetic	0.173	0.170	0.175	-0.004	6,691.604	6,704.119	6,684.423	19.696
	(0.009)	(0.013)	(0.012)	(0.018)	(31.689)	(43.588)	(43.384)	(66.156)
Arithmetic Correct (%)	0.173	0.162	0.182	-0.020	6,691.604	6,655.145	6,722.454	-67.309
	(0.009)	(0.014)	(0.011)	(0.018)	(31.689)	(47.390)	(42.549)	(63.558)
Initiating Structure	0.173	0.149	0.193	-0.043	6,691.604	6,702.096	6,682.726	19.370
	(0.009)	(0.013)	(0.011)	(0.017)	(31.689)	(49.471)	(41.278)	(63.905)
Consideration	0.173	0.153	0.192	-0.039	6,691.604	6,667.810	6,714.427	-46.616
	(0.009)	(0.014)	(0.010)	(0.017)	(31.689)	(47.757)	(42.132)	(63.546)
Autonomous Problem-Solving	0.173	0.160	0.180	-0.020	6,691.604	6,670.296	6,703.289	-32.993
	(0.009)	(0.013)	(0.012)	(0.018)	(31.689)	(46.213)	(42.209)	(66.523)
Identifying Production Problems	0.173	0.160	0.181	-0.021	6,691.604	6,660.086	6,712.254	-52.167
	(0.009)	(0.017)	(0.009)	(0.018)	(31.689)	(51.839)	(40.105)	(64.921)
Self-Assessment	0.173	0.151	0.187	-0.036	6,691.604	6,580.871	6,764.153	-183.282
	(0.009)	(0.014)	(0.011)	(0.018)	(31.689)	(52.244)	(37.095)	(62.340)
Conscientiousness	0.173	0.155	0.188	-0.033	6,691.604	6,685.922	6,696.412	-10.490
	(0.009)	(0.015)	(0.010)	(0.017)	(31.689)	(47.050)	(43.278)	(63.927)
Perseverance	0.173	0.150	0.192	-0.042	6,691.604	6,678.787	6,702.449	-23.661
	(0.009)	(0.014)	(0.011)	(0.017)	(31.689)	(49.351)	(41.361)	(63.890)
Self-Esteem	0.173	0.171	0.175	-0.004	6,691.604	6,695.414	6,688.381	7.033
	(0.009)	(0.016)	(0.009)	(0.018)	(31.689)	(49.464)	(41.320)	(63.932)
Psychological Distress	0.173	0.180	0.169	0.011	6,691.604	6,678.247	6,700.743	-22.496
	(0.009)	(0.014)	(0.011)	(0.018)	(31.689)	(54.022)	(38.865)	(64.823)
Internal Locus of Control	0.173	0.163	0.182	-0.019	6,691.604	6,653.989	6,723.433	-69.444
	(0.009)	(0.014)	(0.011)	(0.018)	(31.689)	(46.402)	(43.288)	(63.534)
Risk Aversion	0.173	0.150	0.185	-0.035	6,691.604	6,677.685	6,698.564	-20.879
	(0.009)	(0.015)	(0.010)	(0.018)	(31.689)	(53.222)	(39.651)	(67.544)
Patience	0.173	0.178	0.171	0.007	6,691.604	6,776.983	6,658.195	118.788**
	(0.009)	(0.015)	(0.011)	(0.020)	(31.689)	(49.828)	(39.013)	(69.787)
Monitoring Frequency	0.173	0.166	0.175	-0.009	6,691.604	6,729.050	6,682.364	46.686
	(0.009)	(0.019)	(0.010)	(0.022)	(31.689)	(36.645)	(38.481)	(79.811)
Efforts to Meet Targets	0.173	0.115	0.199	-0.084	6,691.604	6,578.119	6,743.188	-165.069
	(0.009)	(0.015)	(0.009)	(0.017)	(31.689)	(62.824)	(34.689)	(66.587)
Active Personnel Management	0.173	0.130	0.191	-0.061	6,691.604	6,549.797	6,752.983	-203.186
	(0.009)	(0.018)	(0.009)	(0.018)	(31.689)	(61.850)	(34.346)	(66.140)
Lack of Communication	0.173	0.187	0.161	0.026*	6,691.604	6,744.139	6,645.250	98.888*
	(0.009)	(0.012)	(0.012)	(0.018)	(31.689)	(42.914)	(45.495)	(63.019)
Issues Motivating Workers, Resistance	0.173	0.184	0.162	0.022	6,691.604	6,720.307	6,662.901	57.406
	(0.009)	(0.011)	(0.014)	(0.018)	(31.689)	(43.468)	(46.205)	(63.438)
Demographic Similarity	0.173	0.146	0.198	-0.052	6,691.604	6,677.864	6,704.245	-26.382
	(0.009)	(0.013)	(0.011)	(0.017)	(31.689)	(46.246)	(43.866)	(63.711)
Egalitarianism	0.173	0.163	0.179	-0.016	6,691.604	6,727.805	6,668.902	58.903
	(0.009)	(0.014)	(0.011)	(0.018)	(31.689)	(40.217)	(44.985)	(65.173)

Table A3: Sorting of Workers' and Managers Characteristics

Characteristic Supervisor	*Age*				*Tenure*			
	Full Sample	*High*	*Low*	*Difference*	*Full Sample*	*High*	*Low*	*Difference*
Total Years Working	29.145	29.171	29.120	0.051	2.517	2.481	2.551	-0.070
	(0.182)	(0.327)	(0.183)	(0.367)	(0.042)	(0.065)	(0.055)	(0.085)
Tenure in Garment Industry	29.145	29.054	29.228	-0.175	2.517	2.533	2.502	0.031
	(0.182)	(0.292)	(0.226)	(0.367)	(0.042)	(0.065)	(0.055)	(0.085)
Tenure as Supervisor	29.145	28.945	29.328	-0.383	2.517	2.557	2.481	0.076
	(0.182)	(0.281)	(0.236)	(0.365)	(0.042)	(0.067)	(0.052)	(0.084)
Tenure Supervising Current Line	29.145	29.073	29.188	-0.116	2.517	2.531	2.509	0.022
	(0.182)	(0.328)	(0.218)	(0.379)	(0.042)	(0.074)	(0.051)	(0.088)
Digit Span Recall	29.145	28.889	29.390	-0.501	2.517	2.408	2.622	-0.213
	(0.182)	(0.255)	(0.258)	(0.363)	(0.042)	(0.058)	(0.057)	(0.082)
Arithmetic	29.145	28.497	29.516	-1.020	2.517	2.397	2.586	-0.189
	(0.182)	(0.354)	(0.190)	(0.366)	(0.042)	(0.077)	(0.048)	(0.086)
Arithmetic Correct (%)	29.145	29.024	29.247	-0.224	2.517	2.427	2.593	-0.166
	(0.182)	(0.248)	(0.265)	(0.367)	(0.042)	(0.056)	(0.060)	(0.083)
Initiating Structure	29.145	28.251	29.901	-1.650	2.517	2.412	2.606	-0.195
	(0.182)	(0.240)	(0.221)	(0.326)	(0.042)	(0.058)	(0.058)	(0.083)
Consideration	29.145	28.668	29.602	-0.935	2.517	2.479	2.554	-0.075
	(0.182)	(0.247)	(0.253)	(0.354)	(0.042)	(0.059)	(0.060)	(0.084)
Autonomous Problem-Solving	29.145	29.424	28.992	0.432	2.517	2.525	2.513	0.012
	(0.182)	(0.299)	(0.229)	(0.381)	(0.042)	(0.075)	(0.051)	(0.089)
Identifying Production Problems	29.145	28.563	29.526	-0.962	2.517	2.394	2.598	-0.203
	(0.182)	(0.306)	(0.214)	(0.362)	(0.042)	(0.064)	(0.054)	(0.084)
Self-Assessment	29.145	29.237	29.084	0.153	2.517	2.517	2.518	-0.001
	(0.182)	(0.306)	(0.228)	(0.375)	(0.042)	(0.072)	(0.052)	(0.087)
Conscientiousness	29.145	28.320	29.843	-1.523	2.517	2.405	2.612	-0.208
	(0.182)	(0.246)	(0.225)	(0.333)	(0.042)	(0.062)	(0.054)	(0.082)
Perseverance	29.145	28.569	29.632	-1.064	2.517	2.422	2.598	-0.175
	(0.182)	(0.242)	(0.250)	(0.351)	(0.042)	(0.058)	(0.059)	(0.083)
Self-Esteem	29.145	28.595	29.610	-1.014	2.517	2.501	2.531	-0.030
	(0.182)	(0.245)	(0.250)	(0.353)	(0.042)	(0.057)	(0.062)	(0.085)
Psychological Distress	29.145	29.068	29.197	-0.129	2.517	2.545	2.498	0.047
	(0.182)	(0.332)	(0.209)	(0.373)	(0.042)	(0.071)	(0.052)	(0.086)
Internal Locus of Control	29.145	29.367	28.957	0.410	2.517	2.518	2.516	0.002
	(0.182)	(0.236)	(0.270)	(0.366)	(0.042)	(0.066)	(0.055)	(0.085)
Risk Aversion	29.145	28.894	29.270	-0.375	2.517	2.445	2.553	-0.108
	(0.182)	(0.336)	(0.216)	(0.387)	(0.042)	(0.080)	(0.049)	(0.089)
Patience	29.145	28.997	29.203	-0.206	2.517	2.482	2.531	-0.049
	(0.182)	(0.297)	(0.227)	(0.407)	(0.042)	(0.082)	(0.049)	(0.094)
Monitoring Frequency	29.145	29.430	29.074	0.356	2.517	2.661	2.482	0.179**
	(0.182)	(0.351)	(0.211)	(0.459)	(0.042)	(0.102)	(0.046)	(0.105)
Efforts to Meet Targets	29.145	28.413	29.477	-1.064	2.517	2.348	2.594	-0.247
	(0.182)	(0.323)	(0.210)	(0.380)	(0.042)	(0.066)	(0.051)	(0.088)
Active Personnel Management	29.145	28.718	29.329	-0.611	2.517	2.444	2.549	-0.105
	(0.182)	(0.364)	(0.206)	(0.394)	(0.042)	(0.076)	(0.050)	(0.092)
Lack of Communication	29.145	29.575	28.765	0.810**	2.517	2.623	2.424	0.199***
	(0.182)	(0.232)	(0.266)	(0.358)	(0.042)	(0.057)	(0.059)	(0.082)
Issues Motivating Workers, Resistance	29.145	29.525	28.764	0.761**	2.517	2.582	2.452	0.129*
	(0.182)	(0.263)	(0.243)	(0.358)	(0.042)	(0.059)	(0.059)	(0.084)
Demographic Similarity	29.145	28.488	29.749	-1.261	2.517	2.371	2.651	-0.280
	(0.182)	(0.268)	(0.218)	(0.343)	(0.042)	(0.055)	(0.057)	(0.080)
Egalitarianism	29.145	28.941	29.272	-0.331	2.517	2.471	2.546	-0.075
	(0.182)	(0.279)	(0.240)	(0.375)	(0.042)	(0.073)	(0.051)	(0.087)

Table A4: Sorting of Workers' and Managers Characteristics

Characteristic Supervisor	*Gender (1[Female])*				*Language (1[Kannada])*			
	Full Sample	*High*	*Low*	*Difference*	*Full Sample*	*High*	*Low*	*Difference*
Total Years Working	0.895	0.894	0.896	-0.002	0.652	0.735	0.576	0.159***
	(0.011)	(0.021)	(0.007)	(0.021)	(0.028)	(0.043)	(0.034)	(0.055)
Tenure in Garment Industry	0.895	0.886	0.903	-0.017	0.652	0.655	0.650	0.005
	(0.011)	(0.021)	(0.007)	(0.021)	(0.028)	(0.043)	(0.038)	(0.057)
Tenure as Supervisor	0.895	0.874	0.914	-0.040	0.652	0.587	0.712	-0.125
	(0.011)	(0.021)	(0.006)	(0.021)	(0.028)	(0.041)	(0.038)	(0.055)
Tenure Supervising Current Line	0.895	0.881	0.903	-0.022	0.652	0.665	0.645	0.020
	(0.011)	(0.026)	(0.006)	(0.022)	(0.028)	(0.048)	(0.035)	(0.059)
Digit Span Recall	0.895	0.903	0.887	0.016	0.652	0.636	0.668	-0.031
	(0.011)	(0.007)	(0.020)	(0.021)	(0.028)	(0.038)	(0.042)	(0.057)
Arithmetic	0.895	0.874	0.907	-0.033	0.652	0.642	0.658	-0.017
	(0.011)	(0.027)	(0.007)	(0.022)	(0.028)	(0.046)	(0.036)	(0.059)
Arithmetic Correct (%)	0.895	0.903	0.889	0.014	0.652	0.632	0.670	-0.038
	(0.011)	(0.007)	(0.019)	(0.021)	(0.028)	(0.038)	(0.041)	(0.057)
Initiating Structure	0.895	0.864	0.921	-0.057	0.652	0.494	0.786	-0.292
	(0.011)	(0.021)	(0.007)	(0.021)	(0.028)	(0.029)	(0.037)	(0.049)
Consideration	0.895	0.874	0.915	-0.041	0.652	0.546	0.754	-0.207
	(0.011)	(0.020)	(0.008)	(0.021)	(0.028)	(0.033)	(0.040)	(0.053)
Autonomous Problem-Solving	0.895	0.911	0.886	0.025	0.652	0.711	0.620	0.091*
	(0.011)	(0.009)	(0.016)	(0.022)	(0.028)	(0.048)	(0.035)	(0.059)
Identifying Production Problems	0.895	0.870	0.912	-0.042	0.652	0.616	0.676	-0.059
	(0.011)	(0.024)	(0.007)	(0.021)	(0.028)	(0.041)	(0.038)	(0.058)
Self-Assessment	0.895	0.878	0.907	-0.029	0.652	0.627	0.669	-0.041
	(0.011)	(0.025)	(0.006)	(0.022)	(0.028)	(0.046)	(0.036)	(0.058)
Conscientiousness	0.895	0.866	0.919	-0.053	0.652	0.487	0.792	-0.306
	(0.011)	(0.021)	(0.007)	(0.021)	(0.028)	(0.029)	(0.036)	(0.048)
Perseverance	0.895	0.867	0.919	-0.052	0.652	0.519	0.765	-0.247
	(0.011)	(0.021)	(0.007)	(0.021)	(0.028)	(0.031)	(0.039)	(0.051)
Self-Esteem	0.895	0.870	0.916	-0.046	0.652	0.504	0.777	-0.273
	(0.011)	(0.021)	(0.007)	(0.021)	(0.028)	(0.030)	(0.038)	(0.050)
Psychological Distress	0.895	0.897	0.894	0.004	0.652	0.710	0.612	0.098**
	(0.011)	(0.025)	(0.006)	(0.022)	(0.028)	(0.049)	(0.033)	(0.057)
Internal Locus of Control	0.895	0.914	0.879	0.034*	0.652	0.699	0.612	0.087*
	(0.011)	(0.007)	(0.019)	(0.021)	(0.028)	(0.040)	(0.039)	(0.056)
Risk Aversion	0.895	0.907	0.889	0.018	0.652	0.658	0.649	0.009
	(0.011)	(0.008)	(0.015)	(0.023)	(0.028)	(0.047)	(0.036)	(0.060)
Patience	0.895	0.887	0.898	-0.012	0.652	0.562	0.688	-0.126
	(0.011)	(0.009)	(0.014)	(0.024)	(0.028)	(0.049)	(0.034)	(0.062)
Monitoring Frequency	0.895	0.910	0.891	0.019	0.652	0.643	0.654	-0.011
	(0.011)	(0.010)	(0.013)	(0.027)	(0.028)	(0.063)	(0.032)	(0.071)
Efforts to Meet Targets	0.895	0.869	0.907	-0.038	0.652	0.630	0.662	-0.032
	(0.011)	(0.031)	(0.006)	(0.023)	(0.028)	(0.046)	(0.036)	(0.061)
Active Personnel Management	0.895	0.876	0.903	-0.027	0.652	0.659	0.649	0.009
	(0.011)	(0.032)	(0.006)	(0.023)	(0.028)	(0.050)	(0.034)	(0.062)
Lack of Communication	0.895	0.910	0.882	0.029*	0.652	0.660	0.645	0.015
	(0.011)	(0.007)	(0.019)	(0.021)	(0.028)	(0.042)	(0.038)	(0.057)
Issues Motivating Workers, Resistance	0.895	0.917	0.873	0.044**	0.652	0.725	0.579	0.146***
	(0.011)	(0.007)	(0.019)	(0.021)	(0.028)	(0.042)	(0.036)	(0.055)
Demographic Similarity	0.895	0.877	0.912	-0.034	0.652	0.610	0.691	-0.081
	(0.011)	(0.021)	(0.007)	(0.021)	(0.028)	(0.039)	(0.041)	(0.056)
Egalitarianism	0.895	0.906	0.889	0.017	0.652	0.607	0.681	-0.074
	(0.011)	(0.007)	(0.017)	(0.022)	(0.028)	(0.044)	(0.037)	(0.058)

Table A5: Sorting of Workers' and Managers Characteristics

Characteristic Supervisor	*City (1[Bengaluru])*				*Principal Component*			
	Full Sample	*High*	*Low*	*Difference*	*Full Sample*	*High*	*Low*	*Difference*
Total Years Working	0.808	0.822	0.796	0.026*	0.000	0.302	-0.272	0.573*
	(0.008)	(0.013)	(0.011)	(0.016)	(0.191)	(0.321)	(0.217)	(0.381)
Tenure in Garment Industry	0.808	0.810	0.807	0.003	0.000	0.130	-0.117	0.247
	(0.008)	(0.012)	(0.012)	(0.017)	(0.191)	(0.303)	(0.243)	(0.385)
Tenure as Supervisor	0.808	0.803	0.813	-0.010	0.000	-0.167	0.150	-0.317
	(0.008)	(0.012)	(0.012)	(0.017)	(0.191)	(0.295)	(0.250)	(0.384)
Tenure Supervising Current Line	0.808	0.804	0.811	-0.007	0.000	0.112	-0.066	0.178
	(0.008)	(0.016)	(0.009)	(0.017)	(0.191)	(0.336)	(0.233)	(0.399)
Digit Span Recall	0.808	0.821	0.797	0.024*	0.000	-0.280	0.274	-0.555
	(0.008)	(0.011)	(0.012)	(0.016)	(0.191)	(0.264)	(0.274)	(0.381)
Arithmetic	0.808	0.828	0.797	0.031**	0.000	-0.360	0.201	-0.561
	(0.008)	(0.015)	(0.010)	(0.017)	(0.191)	(0.341)	(0.228)	(0.397)
Arithmetic Correct (%)	0.808	0.807	0.810	-0.003	0.000	-0.209	0.180	-0.389
	(0.008)	(0.013)	(0.011)	(0.017)	(0.191)	(0.253)	(0.282)	(0.384)
Initiating Structure	0.808	0.813	0.805	0.008	0.000	-0.950	0.785	-1.735
	(0.008)	(0.016)	(0.008)	(0.017)	(0.191)	(0.214)	(0.256)	(0.342)
Consideration	0.808	0.803	0.814	-0.010	0.000	-0.520	0.488	-1.009
	(0.008)	(0.014)	(0.009)	(0.017)	(0.191)	(0.243)	(0.277)	(0.371)
Autonomous Problem-Solving	0.808	0.816	0.804	0.012	0.000	0.174	-0.097	0.271
	(0.008)	(0.016)	(0.010)	(0.017)	(0.191)	(0.335)	(0.234)	(0.401)
Identifying Production Problems	0.808	0.825	0.798	0.027*	0.000	-0.389	0.248	-0.637
	(0.008)	(0.016)	(0.009)	(0.017)	(0.191)	(0.293)	(0.248)	(0.389)
Self-Assessment	0.808	0.794	0.818	-0.023	0.000	-0.027	0.017	-0.043
	(0.008)	(0.015)	(0.010)	(0.017)	(0.191)	(0.286)	(0.257)	(0.395)
Conscientiousness	0.808	0.792	0.822	-0.030	0.000	-0.993	0.822	-1.815
	(0.008)	(0.014)	(0.009)	(0.016)	(0.191)	(0.223)	(0.246)	(0.338)
Perseverance	0.808	0.803	0.813	-0.010	0.000	-0.713	0.589	-1.302
	(0.008)	(0.015)	(0.009)	(0.017)	(0.191)	(0.222)	(0.274)	(0.362)
Self-Esteem	0.808	0.793	0.822	-0.029	0.000	-0.606	0.501	-1.108
	(0.008)	(0.014)	(0.009)	(0.016)	(0.191)	(0.219)	(0.283)	(0.369)
Psychological Distress	0.808	0.831	0.793	0.038**	0.000	0.444	-0.296	0.740**
	(0.008)	(0.011)	(0.011)	(0.017)	(0.191)	(0.326)	(0.228)	(0.385)
Internal Locus of Control	0.808	0.814	0.804	0.009	0.000	0.219	-0.189	0.408
	(0.008)	(0.012)	(0.011)	(0.017)	(0.191)	(0.270)	(0.270)	(0.384)
Risk Aversion	0.808	0.807	0.809	-0.003	0.000	-0.189	0.096	-0.285
	(0.008)	(0.016)	(0.010)	(0.018)	(0.191)	(0.377)	(0.217)	(0.406)
Patience	0.808	0.798	0.813	-0.015	0.000	-0.553	0.220	-0.773
	(0.008)	(0.016)	(0.010)	(0.018)	(0.191)	(0.336)	(0.228)	(0.419)
Monitoring Frequency	0.808	0.828	0.804	0.025	0.000	0.225	-0.056	0.281
	(0.008)	(0.013)	(0.010)	(0.021)	(0.191)	(0.395)	(0.219)	(0.480)
Efforts to Meet Targets	0.808	0.816	0.805	0.011	0.000	-0.463	0.203	-0.666
	(0.008)	(0.021)	(0.008)	(0.018)	(0.191)	(0.297)	(0.240)	(0.412)
Active Personnel Management	0.808	0.802	0.811	-0.009	0.000	-0.123	0.051	-0.174
	(0.008)	(0.019)	(0.009)	(0.018)	(0.191)	(0.325)	(0.236)	(0.422)
Lack of Communication	0.808	0.806	0.810	-0.004	0.000	0.297	-0.267	0.564*
	(0.008)	(0.012)	(0.012)	(0.017)	(0.191)	(0.272)	(0.266)	(0.381)
Issues Motivating Workers, Resistance	0.808	0.811	0.806	0.004	0.000	0.428	-0.437	0.865**
	(0.008)	(0.010)	(0.013)	(0.017)	(0.191)	(0.289)	(0.237)	(0.374)
Demographic Similarity	0.808	0.812	0.805	0.006	0.000	-0.588	0.529	-1.117
	(0.008)	(0.013)	(0.010)	(0.017)	(0.191)	(0.244)	(0.271)	(0.368)
Egalitarianism	0.808	0.814	0.805	0.010	0.000	-0.276	0.176	-0.453
	(0.008)	(0.014)	(0.010)	(0.017)	(0.191)	(0.297)	(0.249)	(0.392)

Table A6: Sorting of Styles and Managers Characteristics

Characteristic Supervisor	*Target Quantity*				*Scheduled Quantity*			
	Full Sample	*High*	*Low*	*Difference*	*Full Sample*	*High*	*Low*	*Difference*
Total Years Working	862.977	843.453	880.938	-37.486	627,209.200	568,114.100	681,576.600	-113,462.500
	(9.707)	(13.834)	(13.241)	(19.148)	(36,391.580)	(50,399.790)	(51,553.520)	(72,291.770)
Tenure in Garment Industry	862.977	874.893	852.013	22.880	627,209.200	622,134.400	631,878.000	-9,743.613
	(9.707)	(15.391)	(12.062)	(19.391)	(36,391.580)	(60,060.030)	(43,372.390)	(73,225.980)
Tenure as Supervisor	862.977	880.502	846.853	33.649**	627,209.200	688,952.700	570,405.200	118,547.500*
	(9.707)	(15.204)	(12.016)	(19.224)	(36,391.580)	(58,784.140)	(43,275.610)	(72,204.910)
Tenure Supervising Current Line	862.977	869.779	858.895	10.884	627,209.200	615,282.300	634,365.300	-19,083.060
	(9.707)	(18.146)	(11.172)	(20.126)	(36,391.580)	(74,028.460)	(38,196.580)	(75,543.270)
Digit Span Recall	862.977	862.228	863.695	-1.467	627,209.200	632,150.800	622,469.300	9,681.510
	(9.707)	(14.437)	(13.182)	(19.521)	(36,391.580)	(49,778.230)	(53,446.830)	(73,178.350)
Arithmetic	862.977	881.482	852.359	29.123*	627,209.200	590,357.300	648,353.700	-57,996.430
	(9.707)	(13.811)	(12.947)	(20.051)	(36,391.580)	(65,326.470)	(43,497.570)	(75,774.320)
Arithmetic Correct (%)	862.977	848.118	875.549	-27.432	627,209.200	579,045.200	667,963.300	-88,918.090
	(9.707)	(14.246)	(13.134)	(19.380)	(36,391.580)	(48,918.950)	(52,687.690)	(72,849.650)
Initiating Structure	862.977	875.609	852.288	23.321	627,209.200	676,495.900	585,505.000	90,990.910
	(9.707)	(13.803)	(13.536)	(19.437)	(36,391.580)	(55,313.310)	(47,928.550)	(72,822.420)
Consideration	862.977	857.150	868.565	-11.415	627,209.200	668,030.800	588,053.800	79,976.960
	(9.707)	(13.140)	(14.330)	(19.486)	(36,391.580)	(54,893.530)	(47,959.420)	(72,718.790)
Autonomous Problem-Solving	862.977	842.373	874.275	-31.902	627,209.200	675,574.300	600,686.400	74,887.930
	(9.707)	(13.245)	(13.011)	(20.138)	(36,391.580)	(65,319.400)	(43,534.200)	(76,104.330)
Identifying Production Problems	862.977	854.381	868.608	-14.227	627,209.200	509,817.600	704,120.900	-194,303.400
	(9.707)	(14.981)	(12.771)	(19.901)	(36,391.580)	(58,197.470)	(44,167.490)	(72,076.470)
Self-Assessment	862.977	838.668	878.903	-40.235	627,209.200	648,502.500	613,258.400	35,244.120
	(9.707)	(12.926)	(13.328)	(19.519)	(36,391.580)	(68,116.260)	(40,883.820)	(74,722.420)
Conscientiousness	862.977	888.154	841.673	46.481***	627,209.200	684,328.700	578,877.300	105,451.500*
	(9.707)	(15.554)	(11.491)	(18.990)	(36,391.580)	(58,014.640)	(45,312.380)	(72,614.630)
Perseverance	862.977	870.315	856.767	13.547	627,209.200	657,954.100	601,194.300	56,759.810
	(9.707)	(14.363)	(13.237)	(19.536)	(36,391.580)	(57,667.210)	(46,399.000)	(73,190.910)
Self-Esteem	862.977	878.106	850.175	27.931*	627,209.200	692,239.200	572,183.800	120,055.500*
	(9.707)	(14.867)	(12.623)	(19.372)	(36,391.580)	(53,087.960)	(49,133.690)	(72,372.990)
Psychological Distress	862.977	851.321	870.952	-19.631	627,209.200	577,706.200	661,079.600	-83,373.460
	(9.707)	(16.447)	(11.868)	(19.766)	(36,391.580)	(49,946.230)	(50,746.460)	(73,992.370)
Internal Locus of Control	862.977	849.882	874.056	-24.174	627,209.200	541,688.500	699,572.800	-157,884.400
	(9.707)	(14.644)	(12.877)	(19.426)	(36,391.580)	(49,522.400)	(50,800.050)	(71,596.070)
Risk Aversion	862.977	848.719	870.105	-21.386	627,209.200	527,725.300	676,951.100	-149,225.800
	(9.707)	(14.777)	(12.530)	(20.583)	(36,391.580)	(63,092.240)	(43,570.220)	(76,066.190)
Patience	862.977	879.868	856.367	23.501	627,209.200	721,508.200	590,309.600	131,198.600*
	(9.707)	(16.332)	(11.873)	(21.569)	(36,391.580)	(57,091.550)	(44,892.300)	(80,236.760)
Monitoring Frequency	862.977	851.844	865.724	-13.880	627,209.200	667,524.100	617,261.300	50,262.800
	(9.707)	(20.462)	(11.040)	(24.451)	(36,391.580)	(100,210.200)	(38,346.620)	(91,675.770)
Efforts to Meet Targets	862.977	830.870	877.571	-46.701	627,209.200	422,761.600	720,139.900	-297,378.300
	(9.707)	(12.422)	(12.591)	(20.495)	(36,391.580)	(60,194.200)	(40,686.960)	(72,725.690)
Active Personnel Management	862.977	828.570	877.869	-49.299	627,209.200	453,933.300	702,209.200	-248,275.900
	(9.707)	(13.800)	(12.176)	(20.636)	(36,391.580)	(69,548.130)	(39,509.840)	(75,449.910)
Lack of Communication	862.977	857.603	867.718	-10.116	627,209.200	726,748.700	539,380.200	187,368.600***
	(9.707)	(13.089)	(14.249)	(19.528)	(36,391.580)	(48,328.730)	(50,929.210)	(70,719.590)
Issues Motivating Workers, Resistance	862.977	855.063	870.890	-15.827	627,209.200	614,248.100	640,170.300	-25,922.190
	(9.707)	(13.195)	(14.288)	(19.449)	(36,391.580)	(44,395.480)	(58,100.230)	(73,120.420)
Demographic Similarity	862.977	860.800	864.979	-4.180	627,209.200	592,432.600	659,203.600	-66,770.990
	(9.707)	(12.985)	(14.427)	(19.530)	(36,391.580)	(51,109.600)	(51,760.810)	(72,908.330)
Egalitarianism	862.977	865.245	861.554	3.691	627,209.200	632,292.500	624,021.400	8,271.104
	(9.707)	(16.774)	(11.896)	(20.047)	(36,391.580)	(52,523.540)	(49,550.500)	(75,164.920)

Table A7: Correlation Learning Parameters

Parameter	Initial Productivity (α)	Rate of learning (β)	Retention (γ)	Forgetting (δ)
Initial Productivity (α)	1			
Rate of learning (β)	-0.6067	1		
Retention (γ)	-0.056	-0.052	1	
Forgetting (δ)	0.0697	-0.0369	-0.0138	1

Table A8: Bias Learning Parameters

Parameter	Bias (%)	Bias (%)
Initial Productivity (α)	0.12%	0.16%
Rate of learning (β)	0.32%	0.67%
Previous Experience (γ)	5.93%	7.58%
Forgetting (δ)	6.43%	8.21%
Simulated Error	White Noise	AR(1)

Table A9: Correlation of the factors

Factor	Tenure	Cognitive Skills	Autonomy	Personality	Control	Attention	Relatability
Tenure	1						
Cognitive Skills	0.104	1					
Autonomy	-0.309	0.307	1				
Personality	-0.264	0.326	0.852	1			
Control	0.419	0.335	0.268	0.358	1		
Attention	-0.117	0.238	0.060	0.195	0.187	1	
Relatability	-0.032	0.215	0.383	0.255	0.476	0.308	1

B Reference Points: Robustness to Controlling for Days Left

Table B1: Loadings and Signals

Measures	Tenure	Demographics	Cognitive Skills	*Latent Factor* Control	Personality	Autonomy	Attention	*Signal*
Tenure Supervising Current Line	1	0	0	0	0	0	0	0.405
Tenure as Supervisor	0.6629	0	0	0	0	0	0	0.349
Tenure in Garment Industry	0.5258	0	0	0	0	0	0	0.184
Total Years Working	0.1945	0	0	0	0	0	0	0.022
Demographic Similarity	0	1	0	0	0	0	0	0.768
Egalitarianism	0	-0.0144	0	0	0	0	0	0.001
Digit Span Recall	0	0	1	0	0	0	0	0.990
Arithmetic	0	0	0.1997	0	0	0	0	0.061
Arithmetic Correct (%)	0	0	0.2453	0	0	0	0	0.346
Internal Locus of Control	0	0	0	1	0	0	0	0.442
Risk Aversion	0	0	0	0.254	0	0	0	0.024
Patience	0	0	0	0.2628	0	0	0	0.022
Conscientiousness	0	0	0	0	1	0	0	0.913
Perseverance	0	0	0	0	0.8723	0	0	0.733
Self-Esteem	0	0	0	0	0.8689	0	0	0.701
Psychological Distress	0	0	0	0	-0.1932	0	0	0.018
Initiating Structure	0	0	0	0	0	1	0	0.820
Consideration	0	0	0	0	0	0.9171	0	0.855
Autonomous Problem-Solving	0	0	0	0	0	-0.0052	0	0.000
Identifying Production Problems	0	0	0	0	0	0.0477	0	0.003
Self-Assessment	0	0	0	0	0	0.0159	0	0.000
Monitoring Frequency	0	0	0	0	0	0	1	0.647
Efforts to Meet Targets	0	0	0	0	0	0	0.2978	0.078
Active Personnel Management	0	0	0	0	0	0	0.6889	0.311
Lack of Communication	0	0	0	0	0	0	-0.3711	0.140
Issues Motivating Workers, Resistance	0	0	0	0	0	0	0.0677	0.003

Note: The first loading of each factor is normalized to 1. Signal of measure j of factor k is $s_j^k = \frac{(\lambda_{j,k})^2 Var(\ln\theta_k)}{(\lambda_{j,k})^2 Var(\ln\theta_k) + Var(\varepsilon_{j,k})}$. The measures were standardized across all supervisors who were surveyed. Learning parameters (α, β,γ, and δ) and the mean of log pay (including both monthly salary and production bonus) from November 2014 across supervisors of a line are all included in the extended system but measured with no error, i.e., the corresponding factor loadings are set equal to 1 but omitted from this table.

Table B2: Contributions of Managerial Quality to Productivity Dynamics

	Initial Productivity (α)	Rate of learning (β)	Retention (γ)	Forgetting (δ)
Tenure	0.203	0.301	0.330	0.428
	(0.033)	(0.024)	(0.026)	(0.025)
Demographics	0.002	0.000	0.001	0.033
	(0.005)	(0.000)	(0.002)	(0.011)
Cognitive Skills	0.032	0.040	0.049	0.000
	(0.017)	(0.014)	(0.014)	(0.002)
Control	0.333	0.170	0.143	0.016
	(0.058)	(0.047)	(0.049)	(0.030)
Personality	0.000	0.001	0.001	0.202
	(0.000)	(0.000)	(0.000)	(0.044)
Autonomy	0.143	0.210	0.196	0.155
	(0.025)	(0.019)	(0.020)	(0.042)
Attention	0.288	0.280	0.281	0.166
	(0.024)	(0.016)	(0.017)	(0.025)
Productivity Parameter	1.011	1.028	1.023	1.058
	(0.030)	(0.019)	(0.022)	(0.036)
Complementarity Parameter	-0.105	0.147	0.130	-0.012
	(0.140)	(0.064)	(0.067)	(0.083)
Elasticity of substitution	0.905	1.172	1.149	0.988
Std. Dev. of Dep. Variable	0.2982	0.1055	0.8461	0.1623
First Stage	log(Eff)	log(Eff)	log(Eff)	log(Eff)

Note: Standard errors in parentheses based on 100 bootstrap replications.

Table B3: CES Function *Pay*

	Pay
Tenure	0.351
	(0.020)
Cognitive Skills	0.031
	(0.012)
Personality	0.000
	(0.002)
Control	0.076
	(0.036)
Relatability	0.000
	(0.000)
Autonomy	0.250
	(0.016)
Attention	0.292
	(0.012)
Productivity Parameter	1.031
	(0.015)
Complementarity Parameter	0.083
	(0.044)
Elasticity of substitution	1.091
Std. Dev. of Dep. Variable	0.1011
First Stage	log(Eff)

Note: Standard errors in parentheses based on 100 bootstrap replications.

B.1 Screening Experiment

Table B4: Screening Experiment: Contribution to Productivity and Pay

Factor	Contribution to Productivity	Contribution to Pay
	Easily Screened	
Tenure	0.6275	0.2023
	(0.0513)	(0.011)
Demographics	0.5444	0.1064
	(0.0442)	(0.012)
	Costly to Screen	
Cognitive Skills	0.5434	0.1335
	(0.048)	(0.0121)
Control	1.2093	0.250
	(0.0413)	(0.0117)
Personality	0.6581	0.1806
	(0.0458)	(0.0118)

Note: The contributions are the percentage change in productivity and pay of an increase of one standard deviation of each factor, and associated changes in all other factors as given by the covariance structure among factors. Standard errors in parentheses are based on 100 bootstrap replications.

B.2 Training Experiment

Table B5: Training Experiment: Contributions to Productivity and Pay

Factor	Contribution to Productivity	Contribution to Pay
Autonomy	0.5280	0.2522
	(0.0114)	(0.0063)
Attention	0.850	0.2375
	(0.0216)	(0.0064)

Note: The contributions are the percentage change in productivity and pay of an independent increase of one standard deviation of each factor. Standard errors in parentheses are based on 100 bootstrap replications.

C Alternate Productivity Measure: Robustness to Using log(Quantity) in Place of log(Efficiency)

Table C1: log(Units Produced)

	Log(Units Produced)		
Log(Number of Days)	0.143	0.144	0.146
	(0.00944)	(0.00925)	(0.0102)
Log(Total Days in Prior Production Runs)	0.0761	0.0781	0.0798
	(0.0172)	(0.0174)	(0.0175)
Log(Prior Days) X Log(Days Since Prior Run)	-0.0137	-0.0143	-0.0150
	(0.00551)	(0.00565)	(0.00563)
Log(Target Quantity)	1.016	1.018	1.017
	(0.0140)	(0.0141)	(0.0142)
Observations	49,938	49,938	49,938
Additional Time Controls	Trend	Trend, Year and Month, and DOW FE	Trend, Year and Month, and DOW FE
Additional Controls	Style FE and Worker Characteristics	Style FE and Worker Characteristics	Style FE, Worker Characteristics and Days left

Note: robust standard errors in parentheses. Standard errors are clustered at the line level.

Table C2: Contribution to Efficiency and Wages of Each Factor (%)

Measures	Tenure	Demographics	Cognitive Skills	*Latent Factor* Control	Personality	Autonomy	Attention	*Signal*
Tenure Supervising Current Line	1	0	0	0	0	0	0	0.390
Tenure as Supervisor	0.716	0	0	0	0	0	0	0.371
Tenure in Garment Industry	0.547	0	0	0	0	0	0	0.197
Total Years Working	0.262	0	0	0	0	0	0	0.039
Demographic Similarity	0	1	0	0	0	0	0	0.998
Egalitarianism	0	-0.011	0	0	0	0	0	0.001
Digit Span Recall	0	0	1	0	0	0	0	0.530
Arithmetic	0	0	0.608	0	0	0	0	0.271
Arithmetic Correct (%)	0	0	0.348	0	0	0	0	0.362
Internal Locus of Control	0	0	0	1	0	0	0	0.467
Risk Aversion	0	0	0	0.198	0	0	0	0.015
Patience	0	0	0	0.266	0	0	0	0.023
Conscientiousness	0	0	0	0	1	0	0	0.849
Perseverance	0	0	0	0	0.965	0	0	0.795
Self-Esteem	0	0	0	0	0.896	0	0	0.701
Psychological Distress	0	0	0	0	-0.327	0	0	0.050
Initiating Structure	0	0	0	0	0	1	0	0.825
Consideration	0	0	0	0	0	0.927	0	0.850
Autonomous Problem-Solving	0	0	0	0	0	0.072	0	0.005
Identifying Production Problems	0	0	0	0	0	0.032	0	0.001
Self-Assessment	0	0	0	0	0	0.058	0	0.005
Monitoring Frequency	0	0	0	0	0	0	1	0.562
Efforts to Meet Targets	0	0	0	0	0	0	0.241	0.040
Active Personnel Management	0	0	0	0	0	0	0.776	0.303
Lack of Communication	0	0	0	0	0	0	-0.310	0.079
Issues Motivating Workers, Resistance	0	0	0	0	0	0	0.159	0.012

Note: The first loading of each factor is normalized to 1. Signal of measure j of factor k is $s_j^k = \frac{(\lambda_{j,k})^2 Var(\ln\theta_k)}{(\lambda_{j,k})^2 Var(\ln\theta_k) + Var(\varepsilon_{j,k})}$. The measures were standardized across all supervisors who were surveyed. Learning parameters (α, β,γ, and δ) and the mean of log pay (including both monthly salary and production bonus) from November 2014 across supervisors of a line are all included in the extended system but measured with no error, i.e., the corresponding factor loadings are set equal to 1 but omitted from this table.

Table C3: CES Production of the Learning Parameters

	Initial Productivity (α)	Rate of learning (β)	Retention (γ)	Forgetting (δ)
Tenure	0.144	0.290	0.323	0.310
	(0.037)	(0.019)	(0.023)	(0.033)
Demographics	0.002	0.000	0.000	0.003
	(0.004)	(0.000)	(0.002)	(0.006)
Cognitive Skills	0.043	0.026	0.046	0.000
	(0.025)	(0.018)	(0.020)	(0.000)
Control	0.409	0.160	0.126	0.094
	(0.070)	(0.039)	(0.046)	(0.060)
Personality	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Autonomy	0.079	0.180	0.162	0.253
	(0.029)	(0.017)	(0.020)	(0.029)
Attention	0.323	0.345	0.343	0.340
	(0.029)	(0.015)	(0.016)	(0.027)
Productivity Parameter	0.997	1.027	1.022	1.034
	(0.032)	(0.017)	(0.019)	(0.035)
Complementarity Parameter	-0.102	0.155	0.141	0.050
	(0.198)	(0.053)	(0.060)	(0.091)
Elasticity of substitution	0.907	1.183	1.164	1.053
Std. Dev. of Dep. Variable	0.298	0.106	0.846	0.162
First Stage	log(Quantity)	log(Quantity)	log(Quantity)	log(Quantity)

Note: Standard errors in parentheses based on 100 bootstrap replications.

Table C4: CES Function *Pay*

	Pay
Tenure	0.345
	(0.015)
Demographics	0.000
	(0.000)
Cognitive Skills	0.009
	(0.011)
Control	0.068
	(0.029)
Personality	0.000
	(0.000)
Autonomy	0.225
	(0.013)
Attention	0.354
	(0.013)
Productivity Parameter	1.030
	(0.013)
Complementarity Parameter	0.088
	(0.036)
Elasticity of substitution	1.096
Std. Dev. of Dep. Variable	0.1011

Note: Standard errors in parentheses based on 100 bootstrap replications.

C.1 Screening Experiment

Table C5: Screening Experiment: Contribution to Productivity and Pay

Factor	Contribution to Productivity	Contribution to Pay
	Easily Screened	
Tenure	0.5577	0.1848
	(0.0596)	(0.0105)
Demographics	0.5282	0.0873
	(0.0534)	(0.0117)
	Costly to Screen	
Cognitive Skills	0.771	0.1547
	(0.0354)	(0.009)
Control	1.2401	0.210
	(0.0455)	(0.0098)
Personality	0.6555	0.165
	(0.0453)	(0.0095)

Note: The contributions are the percentage change in productivity and pay of an increase of one standard deviation of each factor, and associated changes in all other factors as given by the covariance structure among factors. Standard errors in parentheses are based on 100 bootstrap replications.

C.2 Training Experiment

Table C6: Training Experiment: Contributions to Productivity and Pay

Factor	Contribution to Productivity	Contribution to Pay
Autonomy	0.3346	0.2323
	(0.0074)	(0.0059)
Attention	0.899	0.2521
	(0.0232)	(0.0069)

Note: The contributions are the percentage change in productivity and pay of an independent increase of one standard deviation of each factor. Standard errors in parentheses are based on 100 bootstrap replications.

D Data Appendix

The survey can be obtained at the following link: **SUPERVISOR SURVEY**

- Tenure:
  - Tenure Supervising Current Line: s3q7a + s3q7b/12
  - Tenure as Supervisor : s3q3a + s3q3b/12
  - Tenure in Garment Industry: s3q2a + s3q2b/12
  - Total Years Working: s3q1
- Demograhpics:
  - Demographic Similarity: s2q3 + s2q10a + s2q1 + 1[s2q2 =Female] + 1[s2q6=s2q8] + 1[s2q9=s2q9a]
  - Egalitarianism: s8q8a + s8q8b + s8q8c + s8q8d + s8q8e + s8q8f + s8q8g + s8q8h + s8q8i
- Cognitive Skills:
  - Digit Span Recall: s5q1-s5q9
  - Arithmetic: s5q10c
  - Arithmetic Correct (%): s5q10c/(s5q10c+s5q10d)
- Control:
  - Locus of Control: s4q2a - (s4q2b + s4q2c + s4q2d + s4q2e)
  - Risk Aversion: 4 - *risk index*. Where *risk index* is equal to 1 if $minriskprem = 0.5$, 2 if $minriskprem = 0.375$, 3 if $minriskprem = 0.35$, and 4 if $minriskprem = 0.125$ and

$$minriskprem \equiv \min_{i \in \{1,\ldots,6\}} \{RP_i\},$$

    where $RP_1 \equiv (10000 * .5 + 2500 * .5 - 5000)/5000$ if s6q2= 2, $RP_2 \equiv (10000 * .5 + 3750 * .5 - 5000)/5000$ if s6q3= 2, $RP_3 \equiv (10000 * .5 + 1250 * .5 - 5000)/5000$ if s6q4= 2, $RP_4 \equiv (75000 * .5 + 0 * .5 - 25000)/25000$ if s6q6= 2, $RP_5 \equiv (50000 * .5 + 12500 * .5 - 25000)/25000$ if s6q7= 2, and $RP_6 \equiv (50000 * .5 + 12500 * .5 - 25000)/25000$ if s6q8= 2.

- Patience: is equal to 1 if $mindiscrate \geq 1$, 2 if $mindiscrate \in [0.5, 1)$, 3 if $mindiscrate \in [0.25, 0.5)$ and 4 if $mindiscrate \in [0, 0.25)$, where

$$mindiscrate \equiv \min_{i \in \{1,\ldots,6\}} \{DR_i\},$$

where $DR_1 \equiv (30000/10000) - 1$ if s6q10$=2$, $DR_2 \equiv (60000/10000) - 1$ if s6q11$=2$, $DR_3 \equiv (20000/10000) - 1$ if s6q12$=2$, $DR_4 \equiv [(40000/10000)]^{(1/5)} - 1$ if s6q15$=2$, $DR_5 \equiv [(100000/10000)]^{(1/5)} - 1$ if s6q16$=2$, and $DR_6 \equiv [(20000/10000)]^{(1/5)} - 1$ if s6q17$=2$.

- Personality:
  - Conscientiousness: (s4q1a + s4q1b + s4q1c + s4q1d + s4q1e) - (s4q1f + s4q1g + s4q1h + s4q1i + s4q1j)
  - Perseverance: (s4q3a + s4q3b + s4q3c + s4q3d + s4q3e) - (s4q3f + s4q3g + s4q3h)
  - Self-Esteem: (s4q4a + s4q4c + s4q4d + s4q4g + s4q4j) - (s4q4b + s4q4e + s4q4f + s4q4h + s4q4i)
  - Psychological Distress: s7q1 + s7q2 + s7q3 + s7q4 + s7q5 + s7q6 + s7q7 + s7q8 + s7q9 + s7q10
- Autonomy:
  - Initiating Structure: s8q3a + s8q3c + s8q3d + s8q3f + s8q3m + s8q3l + s8q3r + s8q3s + s8q3t + s8q3w
  - Consideration: s8q3b + s8q3e + s8q3g + s8q3i + s8q3k + s8q3n + s8q3p + s8q3v + s8q3x
  - Autonomous Problem-Solving: s9q1b2 + s9q1c2 -(s9q1b1+s9q1c1) - (s9q1b3+s9q1c3)
  - Identifying Production Problems: s9q1a1 + s9q1a2 + s9q1a3 + s9q1a4 + s9q1a5 + s9q1a6 + s9q1a7
  - Self-Assessment: s8q5a
- Attention:
  - Monitoring Frequency: 6 - s9q2e
  - Efforts to Meet Targets: s9q2d1 + s9q2d2 + s9q2d3 + s9q2d4 + s9q2d5
  - Active Personnel Management: s9q3a1 + s9q3a2 + s9q3a3 + s9q3a4 + s9q4a1 + s9q4a2 + s9q4a3 + s9q4a4 + s9q4a5 + s9q4j1 + s9q4j2 + s9q4j3 + s9q4j4
  - Lack of Communication: s9q2f*s9q2h + s9q2i*s9q2k + s9q2l*s9q2n

– Issues Motivating Workers, Resistance: s8q1a + s8q1b + s8q1c + s8q1d + s8q1e