# Managerial Quality and Productivity Dynamics*

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**Abstract**

What combination of skills and traits makes a good manager? We study this question by matching two years of daily, line-level production data from six garment factories in India to rich survey data on the managerial practices of line supervisors. We structurally estimate a non-linear latent factor model that: 1) addresses the common issues of noise and redundancy in comprehensive management survey data and 2) flexibly identifies the contributions of different aspects of managerial quality to the various productivity dynamics observed over line-product runs. We measure the contributions of 7 distinct dimensions of managerial quality motivated by previous literature: tenure, cognitive skills, autonomy, personality, control, attention, and relatability to workers. We find that while tenure and cognitive skills of a supervisor contribute to all aspects of productivity dynamics, additional dimensions of managerial quality such as attention and autonomy contribute strongly as well, particularly to the rate of learning and retention of learned productivity. Control impacts initial productivity most strongly, while other dimensions of personality and relatability to workers do not contribute to productivity. Additional results indicate that these dimensions of quality are generally undervalued in supervisor pay. More readily observed dimensions of quality (tenure and cognitive skills) and more obviously productive dimensions (autonomy), though still undervalued, are reflected in pay in closer proportions to their productivity contributions; while less easily observed or less obviously productive dimensions such as attention and control are less reflected in pay. Independence between quality dimensions implies that firms with shorter tenured or less cognitively skilled supervisors can still increase productivity most cost-effectively by screening on and/or training in attention and control.

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# 1 Introduction

Management matters for firm productivity. Both across and within countries, large productivity exist and are tightly linked to variation in management practices (Bloom and Van Reenen, 2007, 2011; McKenzie and Woodruff, 2016). Recent studies from around the world verify that this linkage is at least in part causal, by demonstrating the impacts of general management consulting interventions (Bloom et al., 2013; Karlan et al., 2015; McKenzie and Woodruff, 2013) on productivity.

These studies are useful in that they demonstrate a role for managers in determining firm productivity, and show that intervening to improve the overall quality of management practices can generate meaningful impacts in many contexts. But what dimensions of managerial quality matter the most for productivity? That is, what makes a "good" manager good? And does the market appropriately price these dimensions (i.e., are managers compensated for the features that matter)? These are largely unanswered questions, likely due to two main empirical challenges. First, to study managerial quality, one must extract signal from noisy measures of quality across many dimensions, and relate these underlying signals to productivity in a flexible way. Second, in contexts where productivity dynamics are salient – e.g., learning by doing is critically important in production in many manufacturing sectors (Arrow, 1962; Jovanovic and Nyarko, 1995; Lucas, 1988) – it is necessary to estimate the effects of managerial practices on the parameters governing these dynamics.

Overcoming these challenges is the scope of inquiry of the present study. We study the way in which managerial quality interacts with the learning by doing process, focusing on the case of ready-made garments production in India. We match granular production data from several garment factories in India to rich data from a management survey conducted on all line supervisors to answer the following research questions: Do production teams supervised by better managers start at higher productivity levels? Do they learn faster? Do they retain more learning from previous productions runs? Do they forget previous stock of learning at a lower rate? What managerial characteristics matter most for each dimension of learning (i.e., the intercept or initial productivity, slope of the learning curve, retention of past learning and rate of forgetting)?

We begin by documenting the presence and scope of learning in our empirical context. Productivity, as measured by the proportion of target production realized by a line per unit time (denoted "efficiency"), is strongly increasing in experience. Efficiency rises by roughly 50% or more over the life of a production run.[1] This pattern is identical when experience is measured as days the line has been producing the

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

current product.[2] Learning curves show 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 on a line and the depreciation of this retained stock of learning over the intervening time elapsed between runs. Experience from a previous run contributes roughly 40-50% 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 learning is depreciated by roughly 50% after three and a half production weeks away from a style).

Next, we analyze the relative contribution of various dimensions of managerial quality to the aspects of productivity dynamics seen in the data. 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 in a large set of survey measures of quality. (That is, many survey measures likely proxy for the same underlying dimension of managerial quality, but it is difficult to know which measure does so with the strongest signal.) Accordingly, 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 a learning function 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).

Our empirical analysis proceeds in three steps. We estimate a canonical production function that incorporates learning by doing, which takes a very similar form to the functions estimated in, e.g., Levitt et al. (2013), Benkard (2000), and Kellogg (2011), 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, and the learning parameters estimated in the first stage using maximum likelihood and minimum distance estimator. In our exploratory analysis, we identify seven distinct factors related to well-studied dimensions of managerial quality: Tenure, Cognitive skills, Au-

of the production run.

[2] 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 both time and quantity measures of accrued experience and documenting qualitatively identical patterns, we circumvent this issue. That is, if production is mean 0 conditional on past productivity and i.i.d. from a stationary distribution each day of the production run, then this sort of endogeneity is not an issue. The equivalence across time and quantity experience results, as well as additional robustness to controlling for days/quantity left to complete the order, strongly supports this assumption.

tonomy, Personality, Control, Attention, and Relatability to workers. We then draw a synthetic dataset from this joint distribution and estimate, using nonlinear least squares, a CES function for each learning parameter with the 6 factors for managerial quality as arguments.

We find that Tenure, Attention, and Autonomy impact all elements of the learning curve strongly. Personality contributes most substantially to initial productivity, while the contribution of Cognitive skills is strongest for learning and retention. Relatability does not contribute meaningfully to productivity dynamics. Additional results indicate that these dimensions of quality are imperfectly substitutable. That is, managers with short tenures or low cognitive skills can achieve the productivity of their more experienced or more cognitively skilled counterparts if they exhibit enough attentiveness and autonomy. This implies that screening on or training in these skills may be quite effective in raising productivity.

Complementary analysis on manager pay indicates that some dimensions of managerial quality are also more cost-effective in raising productivity than others. More easily measured dimensions of quality like Tenure, Attention, and Cognitive skills, though still undervalued, contribute to wages in closer proportions to their impacts on productivity. Less easily observed or less obviously productive dimensions such as Autonomy and Personality are less rewarded. Estimates of pass-through of productivity increases as a result of simulated managerial quality increases to managers' pay are quite small, ranging from 11% for Autonomy to 35% for Cognitive skills. In sum, firms could employ more productive line supervisors and more quickly and consistently achieve peak production by better measuring, screening for, training in, and rewarding dimensions of managerial quality, particularly less traditionally valued dimensions like Autonomy and Personality.

Our study contributes to fast-growing literature in economics on the importance of good management in organizations across the world (Adhvaryu et al., 2016; 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). We add to this work by evaluating the relative importance of many (error-ridden) measures of managerial quality simultaneously in one holistic structural analysis, and by calculating the pass-through of managerial quality to pay.

Our study is also related to the rich body of work on the role of learning by doing in determining firm productivity dynamics (Atkin et al., 2016; Benkard, 2000; Kellogg, 2011; Levitt et al., 2013). In particular, we answer a pointed call made in Levitt et al. (2013) to conduct "more research on the complementarities between the learning process and managerial practices." The crucial heterogeneity in learning along the distribution of managerial quality is implicit in much of the earlier work on learning but until the present study has not been directly estimated.

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.[3] If the line produces 600 garments by the end of the day its efficiency would be $600/960 = .625$ for that day. We

[3] 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.

use daily line-level efficiency as the key dependent variable of interest.[4]

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 both time and quantity measures of accrued experience and documenting qualitatively identical patterns, 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.[5] We show quantity-based experience to conform to convention from previous studies, but use time-based experience as our preferred measure as it is more robust to endogeneity concerns.[6] Both these variables are for the current production run of that style, ignoring any prior experience.

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 96 production lines with a total of 166 supervisors.[7] Our sample comprises over 37,000 production line-date observations, and we observe nearly 1,200 line-style pairings with 86% 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 23 days and produce on average 10,000 total pieces. Prior experience values are very similar to the length of time and total quantity of an average order, removing any concern that lines and styles making up subsequent runs are somehow different from unique first

[4]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).

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

[6]In additional robustness results, we also include days/quantity 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.

[7]We restrict our analysis to the largest connected set of styles-lines, which includes 96 of the 100 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.

runs. 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 | 37,192 | |
| Number of lines | 96 | |
| Number of line-style matchings observed | 1,198 | |
| Percent of lines producing same style more than once | 86% | |
| Number of supervisors | 166 | |
| | **Mean** | **SD** |
| ***Production*** | | |
| Efficiency | 0.514 | 0.167 |
| Initial Efficiency (first day of production run) | 0.408 | 0.214 |
| ***Current Experience*** | | |
| Total length of production run in days | 23.253 | 11.879 |
| Total quantity produced in a line-style run | 9978.7 | 6894.0 |
| ***Experience from Prior Production Runs*** | | |
| Total days of prior experience on a given style | 19.159 | 25.316 |
| Total quantity produced on previous runs of the same style | 8582.2 | 7328.3 |
| Intervening days between runs of the same style | 18.119 | 14.255 |

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 between 1-3 supervisors depending on the length of the line, 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.

We attempted to comprehensively utilize the entirety of the survey in constructing measures to include in the non-linear factor system.[8] 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.[9] We follow Cunha et al. (2010),Attanasio et al. (2015b),Attanasio et al. (2015a) in conducting this exploratory analysis to define factors and determine the mapping of measures to factors. Like them, we use orthogonal rotations of the factor loadings to confirm that factors are distinct and to check that the mappings are correct.

We first construct factors that capture the traditional dimensions of skill emphasized in the literature. 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 Cognitive Skills factor from direct measures of memory and arithmetic.

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 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 per-

[8]In the end, we include all measures from the survey except for: a measure of mental distress which showed little variation and low correlation with productivity; a coarse self-assessment ladder measure of managerial quality which proved noisy and uninformative as compared to the more granular, specific measures of quality we collected from validated modules; a measure for the incidence of interpersonal conflicts with workers which proved noisy and uncorrelated with more detailed measures from validated modules on leadership style and managerial attention; and 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.

[9]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.

sistently 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 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.

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.[10] 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). Once again, as has been emphasized in recent studies of the returns to cognitive and non-cognitive 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.

We next construct two factors meant to capture non-cognitive skills or personality dimensions and attitudes not readily captured by traditional measures of cognitive skills and tenure. The survey included a standard module for conscientiousness meant to capture commonly measured personality psychometrics.[11] In addition, we collected measures of perseverance, self-esteem, and internal locus of control as well as risk aversion and patience.[12]

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, self-esteem, and internal locus of control) revealed two distinct factors. Conscientiousness,

[10]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.

[11]Piloting showed that the other Big 5 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.

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

perseverance and self-esteem are highly correlated and load onto a single factor, while internal locus of control is orthogonal to this 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. Once again additional factor analyses alternately pooling these measures with other modules of the survey confirm that these two factors are distinct and that these measures load more strongly onto these factors than any others. Recent empirical studies have begun to document the importance of personality psychometrics for earnings and productivity (Borghans et al., 2008; Heckman and Kautz, 2012).

Finally, 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. 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 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. 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 in production 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 four managerial practice measures: efforts to achieve production targets, production monitoring frequency, active personnel management, and communication. Each of these is meant to measure effort and attention on the part of the supervisor in accomplishing supervisor 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. 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. (2016) find that more attentive managers are better able to diagnose and relieve bottlenecks that arise from shocks to worker productivity.

The last two measures we analyze are 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. 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, but appear only weakly positively correlated with each other. Indeed, 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).

Summary statistics for these measures across all 166 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.

Table 2: Managerial Quality Measures

| | Mean | SD |
|---|---|---|
| ***Tenure*** | | |
| Total Years Working | 12.378 | 5.220 |
| Tenure in Garment Industry | 10.173 | 4.442 |
| Tenure as Supervisor | 4.827 | 3.130 |
| Tenure Supervising Current Line | 1.992 | 2.002 |
| ***Cognitive Skills*** | | |
| Digit Span Recall | 6.283 | 1.847 |
| Arithmetic (Number Correct) | 11.583 | 3.706 |
| Arithmetic (% Correct of Attempted) | 0.810 | 0.181 |
| ***Autonomy*** | | |
| Initiating Structure | 41.850 | 5.479 |
| Consideration | 44.071 | 5.196 |
| Autonomous Problem-Solving | -0.260 | 1.128 |
| Problem Identification | 3.921 | 1.232 |
| **Personality** | | |
| Perseverance | 17.622 | 3.338 |
| Conscientiousness | 12.937 | 4.017 |
| Self-Esteem | 8.488 | 3.418 |
| ***Control*** | | |
| Internal Locus of Control | -4.661 | 3.928 |
| Risk Aversion | 3.142 | 1.462 |
| Patience | 2.063 | 1.289 |
| ***Attention*** | | |
| Efforts to Meet Targets | 2.850 | 0.926 |
| Monitoring Frequency | 4.850 | 0.419 |
| Active Personnel Management | 8.465 | 2.058 |
| Communication | 8.079 | 2.496 |
| ***Relatability*** | | |
| Demographic Similarity | 4.811 | 2.315 |
| Egalitarianism | 1.843 | 0.821 |
| ***Pay*** | | |
| Gross Salary (monthly) | 14831.5 | 1959.7 |
| Gross Pay with production bonus (monthly) | 15006.5 | 1969.0 |

Note: Tenure variables are measure in years. Digit span recall measures the number of correct digits a manager remember from a list of 12 numbers; 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; arithmetic (number correct) counts the number of correct answers in a math test with 16 questions; autonomous management style is associated with the capacity of the manager to "act without consulting others," (range -8 to 1) and autonomous problem solving measures the ability of the managers to identify and solve production problems alone (range -3 to 2); risk averse and patience are index from 0 to 4; locus of controls is an index from -15 to 1; production monitoring frequency is the number of rounds of the line to monitor production (range 2 to 5); effort to achieve 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); 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).

### 2.3 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. As noted each production line is managed by between 1 and 3 supervisors. 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.

## 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.[13] 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

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

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.[14] 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.[15]

Figure 1A: Efficiency by Days Running

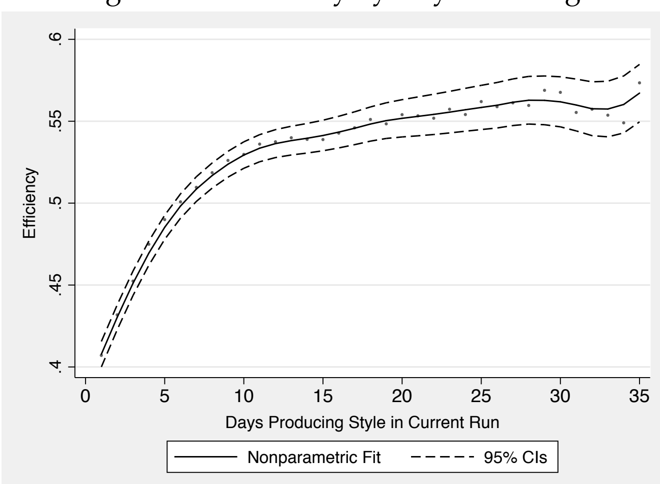
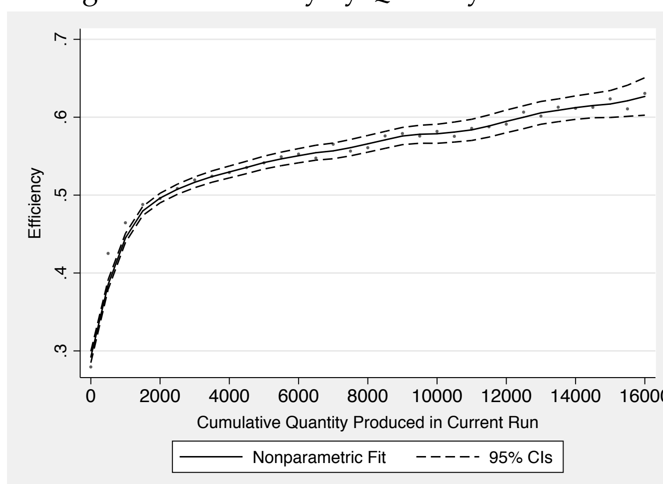



Figure 1B: Efficiency by Quantity Produced




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.

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 3-4000 units produced of a

[14]We also control for days left to complete production in the current order as an additional check of this possible endogeneity. The results are presented Appendix B. The additional control does not impact the results and so is not included in the preferred specification.

[15]We report the full set of results using the quantity-based measure in Appendix D. As expected given the similarity between

given style.[16]

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.

Figure 2A: Retention (Prior Days)

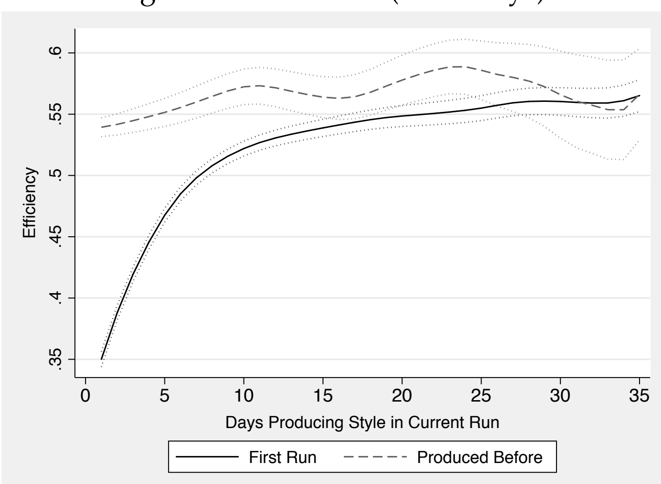
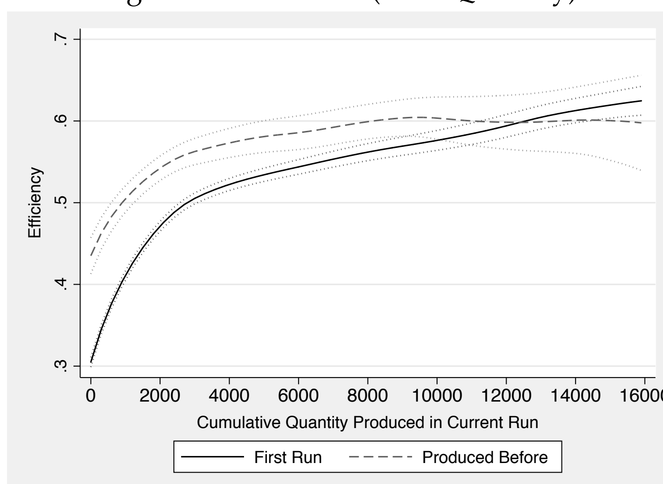



Figure 2B: Retention (Prior Quantity)




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 next pressing 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

[16]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 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)).

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 the same style again. It appears that roughly 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)

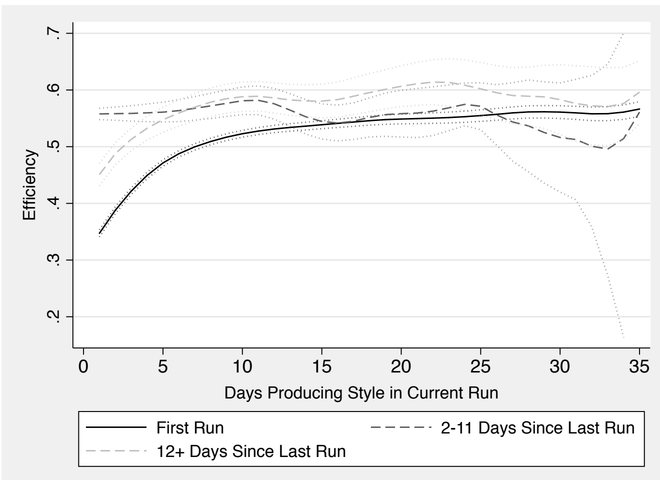
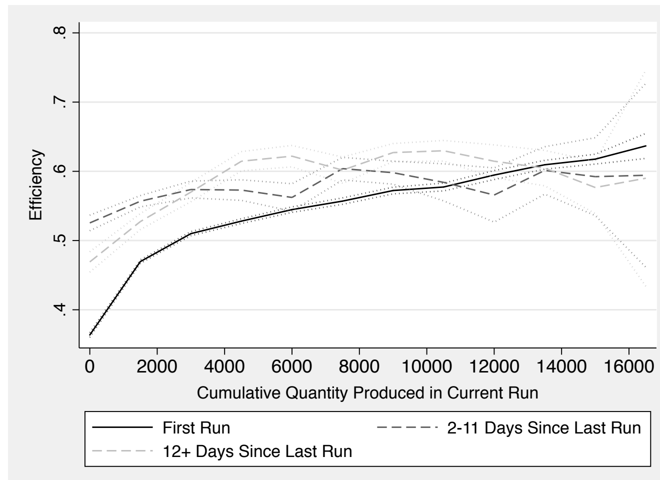



Figure 3B: Forgetting (Prior Quantity)




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 production dynamics in line-style production order 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, Autonomy, Cognition, Personality, Control, Attention and Relatability. 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 initial level of productivity, the rate of learning, and retention of learned productivity.

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.[17] 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.

Figure 4A: Tenure Supervising Current Line

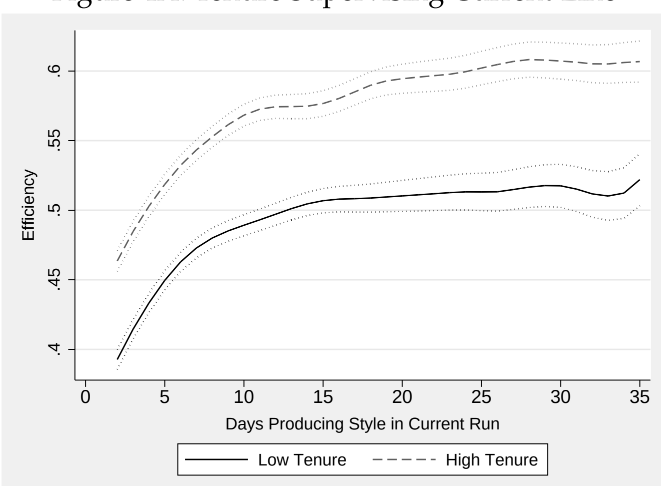
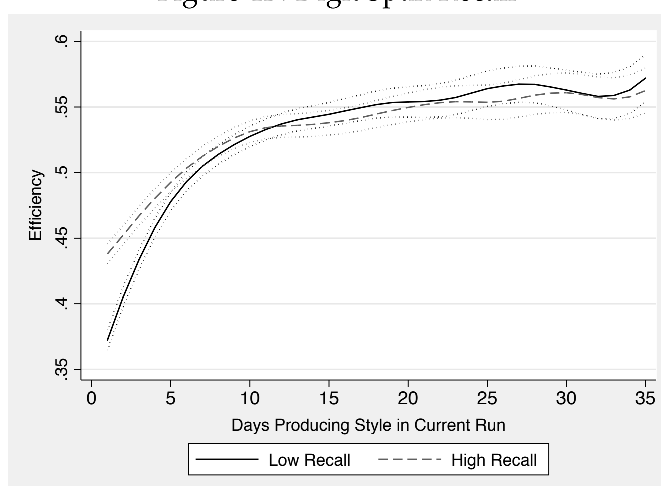



Figure 4B: Digit Span Recall



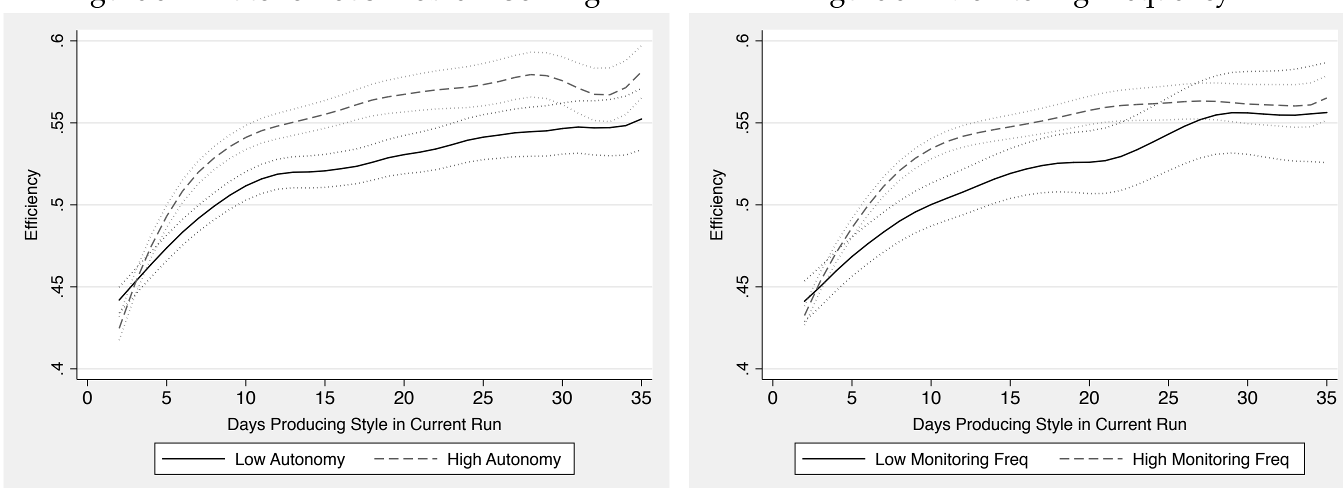

Note: Figures 4A and 4B depict learning curves of efficiency by current-style experience defined by consecutive number of days a style has been running on the production line. We split the sample into lines managed by supervisors with above and below median tenure defined by years supervising current 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.

[17]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. In Appendix D, we present results for the cumulative quantity as a measure of current experience, instead. Results using cumulative quantity to define all measures of experience are qualitatively identical and the time-based experience measures are preferred given the endogeneity concerns discussed in section 2.1 above.

Figures 5A and 5B depict analogous comparisons across lines managed by supervisors with above and below median autonomy and attention, respectively. In Figure 5A, we use an index of autonomous problem-solving measuring the degree to which managers identify and solve production problems on their own. In Figure 5B, we use the manager's reported number of rounds of the line made 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.

Figure 5A: Autonomous Problem-Solving

Figure 5B: Monitoring Frequency




Note: Figures 5A and 5B 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 5A we use an index of autonomous problem-solving related to the ability of the managers to identify and solve production problems alone. In figure 5B, 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.

We next repeat the exercise using two measures of supervisor personality: internal locus of control (Figure 6A) and conscientiousness (Figure 6B). Figure 6Ashows a higher initial productivity at the start of new production runs for lines managed by supervisors with higher internal locus of control, but subsequent slopes appear indistinguishable. Figure 6B shows a counter intuitive result; production lines managed by less conscientious supervisors learn faster. This figure highlights the primary short-coming of these preliminary graphical explorations: we cannot account for correlations with and contributions of the many other dimensions of managerial quality when studying each of these graphs. That is, we

Figure 6A: Internal Locus of Control

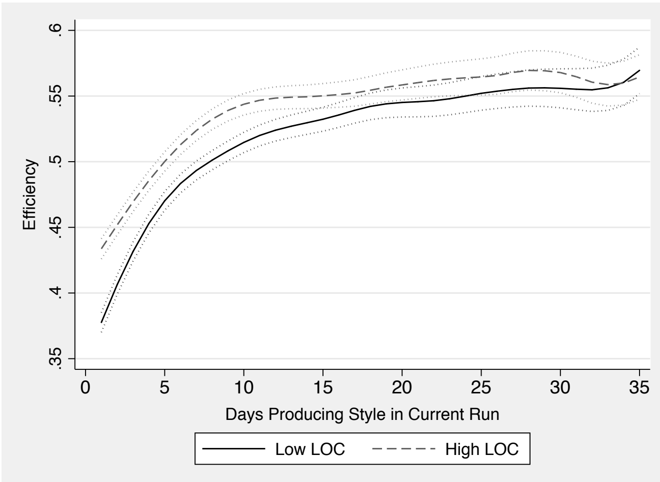
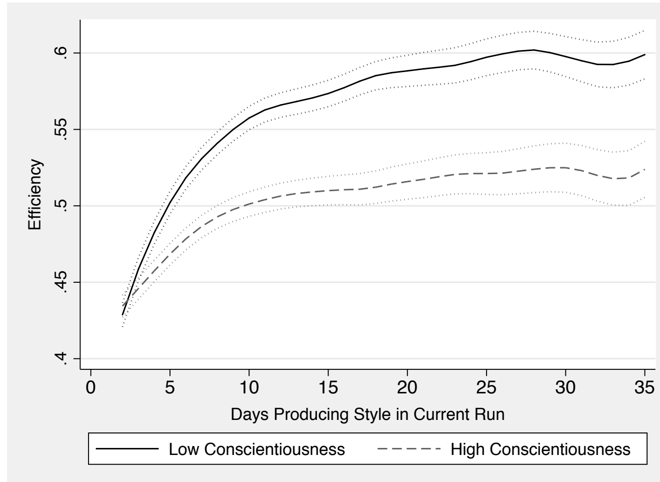



Figure 6B: Conscientiousness




Note: Figures 6A and 6B 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 conscientiousness, 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.

cannot say if indeed conscientiousness is negatively correlated with rate of learning or if it is negatively correlated with some other important dimension of managerial quality that is driving this relationship with productivity.

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 related to both the initial productivity and the rate of learning (e.g., tenure); others seem to be related mainly to the initial productivity (e.g., cognition and control) or rate of learning (e.g., autonomy and attention). On the other hand, personality measures show a counter intuitive relationship. However, this preliminary evidence 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 $t \in \{1, ..., T\}$.[18] $E_{ijt}$ 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.[19] $\alpha_i$ measures the initial level of productivity and $\beta_i$ 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).[20] $D_{ij}$ is the measure of forgetting, which is defined as the number of days since line $i$ last produced style $j$. $\gamma_i$ measures the contribution of previous stock learning (retention) and $\delta_i$ is the depreciation rate of previous stock learning (rate of forgetting) of line $i$. $\psi_t$ is a time trend that is included in all specifications.[21] Finally, $\varepsilon_{ijt}$, is an idiosyncratic error term.[22]

Note that the dynamic log production function in equation (1) differs primarily from those consid-

[18] 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 level 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).

[19] As discussed above, we estimate alternate specifications in which experience is measured as the cumulative quantity of that style produced to date. These results are reported in Appendix D and appear qualitatively identical. As noted earlier, we use experience in days as the preferred measure in our main results to circumvent the endogeneity issues discussed in Thompson (2001).

[20] In the alternative specifications presented in Appendix D using quantity-based measures of experience, we also measure previous experience as the total quantity produced in the prior production run.

[21] 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.

[22] 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.

ered 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 ($\alpha_i$, $\beta_i$, $\gamma_i$ and $\delta_i$) 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 ($\alpha_i$, $\beta_i$, $\gamma_i$ and $\delta_i$) 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.,

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

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 ($f_\alpha$), rate of learning ($f_\beta$), degree of retention ($f_\gamma$) and rate of forgetting ($f_\delta$) 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 $f_\iota$ 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 $f_\iota$ 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 be irrelevant in any of these functions when $\lambda_{\iota,k} = 0$. $\rho_\iota$ determines the elasticity of substitution between the latent factors, which is defined by $\frac{1}{1-\rho_\iota}$, and $A_\iota$ is a factor-neutral productivity parameter. Under this technology, $\rho_\iota \in [-\infty, 1]$; as $\rho_\iota$ approaches 1, the latent factors become perfect substitutes, and as $\rho_\iota$ 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 ($\rho_\iota$) to differ across learning parameters.

# 5 Empirical Strategy

Having adapted the canonical production function exhibiting learning-by-doing 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 $\alpha_i$, $\beta_i$, $\gamma_i$ and $\delta_i$ 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 $\alpha_i$, $\beta_i$, $\gamma_i$, and $\delta_i$ for each line $i \in \{1, ..., N\}$ using ordinary least squares. Second, we follow Attanasio et al. (2015a,b); Cunha et al. (2010) 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 ($\theta_k$) underlying the multitude of noisy survey measures and the learning parameters estimated in the first stage ($\alpha_i$, $\beta_i$, $\gamma_i$, $\delta_i$) 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 $\alpha$, $\beta$, $\gamma$, and $\delta$. 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 level changes in the productivity due to complexity of the style, 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 dynamic production function from equation (1) as it is written, allowing for initial levels of productivity, learning rate, degree of retention and rate of forgetting to vary across lines. That is, we estimate $\alpha_i$, $\beta_i$, $\gamma_i$, and $\delta_i$ 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-sided fixed effect model of lines matched to styles. This two-sided fixed effect model is analogous to the worker-firm sorting model studied Abowd et al. (1999) (also known as AKM).[23] 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 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 heteroge-

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

neous 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-sided 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.

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

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 firm's Human Resources (which is above the the factory level) and these demands queue and get filled on 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-A4 compare different characteristics of the workers (efficiency, skill grade, salary, gender, tenure, and migrant status) for high and low-type managers defined by the eight characteristics for which we provide graphical evidence in Section 3 (figures 4A-6B). Note that the groups are quite balanced across high and low-type managers. Only 4 out of 56 differences are statically significant with significant differences spread across various manager characteristics.[24]

We perform similar balance checks for style to manager sorting, checking that the complexity of the style being assigned (measured by the standard allowable minute, or SAM) and the size of the order (schedule quantity) are balanced across these same managerial characteristics. We find no significant

[24]Longer tenured supervisors and those with high locus of control have slightly more females in their production lines. Supervisors reporting higher production monitoring frequency have workers with more tenure, and supervisor with reporting more autonomous problem solving have more local workers. None of these differences appear to systematically match to the pattern of findings presented and discussed below.

differences in these analogous checks reported in the Appendix. Nevertheless, to further assess if there is any bias due to endogenous sorting of styles to lines in our estimation of the two-sided 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.[25] 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.[26] We repeat the procedure 10,000 times, and compute the percentage mean bias in absolute value for the coefficients of interest ($\alpha_i$, $\beta_i$, $\gamma_i$ and $\delta_i$). 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 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,

[25] 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.

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

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 $\theta_i$. 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, Autonomy, Cognition, Personality, Control, Attention, and Relatability. As discussed in section 2.2, we use the original survey module delineations and exploratory factor analyses, following Attanasio et al. (2015a,b); Cunha et al. (2010), to map the largest possible set of survey measures to these 7 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 $l$th 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 $k \in K \equiv \{T, A, C, P, Ct, Att, R\}$ (Tenure, Autonomy, Cognition, Personality, Control, Attention, and Relatability) 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.[27]

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 $i$.[28] As we explain later in Section 6, we are able to recover $\alpha_i$ and $\beta_i$ for 96 lines, which is the largest connected set, but we are only able to recover $\gamma_i$ and $\delta_i$ for 79 lines. The 17 lines for which we cannot recover $\gamma_i$ and $\delta_i$ 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 79 lines (131 managers) for which we can estimate the full model.[29] Finally, we assume that the learning parameters from the first stage and the log of supervisor pay are measured with no error.[30] Let $\theta \equiv \left(\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, \theta_6, \hat{\alpha_i}, \hat{\beta_i}, \hat{\gamma_i}, \hat{\delta_i}, w_i\right)$, thus we can express the *extended* demeaned measurement system in vector notation as,

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

where $\Lambda$ is the matrix of factor loadings, $\varepsilon$ is a vector of measurement errors and $\Sigma_\varepsilon$ is a diagonal matrix with the standard deviation of the measurement error defined before. [31]

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, $f(\cdot)$,

[27]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.

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

[29]We use all 96 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 $\alpha$ and $\beta$ are nearly identical to those in the main results reported below, confirming that restricting attention in the main estimation to the 131 managers of the 79 lines for which we can recover the full set of learning parameters does not meaningfully impact the conclusions we draw.

[30]This assumption with respect to the wage measure is similar to that imposed by Attanasio et al. (2015b) in their extended measurement system. In addition we have 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.

[31]As we mentioned before we assume that learning parameters and the log of the wage are measured with no error. This implies that the corresponding factor loadings are set equal to one in $\Lambda$, and the corresponding standard deviations of the error in $\Sigma$ equal to zero.

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, $\mu_i$, and variance covariance matrix, $\Sigma^{i}$, and mixture weight, $\tau \in [0,1]$, for $i \in \{A, B\}$.[32] 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 $\varepsilon$ 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 each latent factor by matching the appropriate survey modules to each of the five dimensions of quality previously studied in the literature. Second, we use maximum likelihood to estimate an unconstrained mixture of normals for the distribution of measurements.[33] 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

[32] 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)).

[33] 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.

dataset from the joint distribution of the learning parameters (and log wage) 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

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 dynamic production 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 from the first step. That is, from the largest possible 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 variables (LHS). Finally, we estimate equations (3) for $\iota \in \{\alpha_i, \beta_i, \gamma_i, \delta_i\}$ using nonlinear least squares. We bootstrap the this third stage 100 times to construct the standard errors of the estimated coefficients.

## 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 $\alpha_i$, $\beta_i$, $\gamma_i$ and $\delta_i$ 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 dynamics change with increases in each of the dimensions of managerial quality (i.e., Tenure, Cognitive Skills, Autonomy, Personality, Control, Attention, and Relatability). 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 of the line (average skill grade, share of the highest skill, average gross salary, average age, share of females, share of workers speaking Kannada, 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: Learning (Experience in Days)

| | Log(Efficiency) (Actual Production/Target Production) | | |
|---|---|---|---|
| Log(Number of Days) | 0.152*** | 0.155*** | 0.157*** |
| | (0.0114) | (0.0110) | (0.0120) |
| Log(Total Days in Prior Production Runs) | 0.0642*** | 0.0678*** | 0.0701*** |
| | (0.0165) | (0.0164) | (0.0166) |
| Log(Prior Days) X Log(Days Since Prior Run) | -0.00909* | -0.00944* | -0.0105** |
| | (0.00492) | (0.00506) | (0.00509) |
| Observations | 36,938 | 36,938 | 36,938 |
| 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 ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$). Standard errors are clustered at the line level.

Table 3 shows that the estimated learning rate is between 0.152 and 0.157. This learning rate implies that productivity will increase on average 50% over roughly 25 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 0.07, 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 22 intervening days, 50% of the productive value of retained learning has depreciated.

These results are quite robust to alternate specifications and measures of productivity and experience. Note that the coefficients are very similar across the three specifications when we control for time fixed effects and days left of 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 the target quantity on the right-hand side. Table C1 shows nearly identical results to Table 3. Note that the coefficient for target quantity is close to 1, which suggests that there is no scale effects on the efficiency due to the complexity of different styles.

In Appendix D, we show the analogous to the results presented Table 3 measuring both current and prior experience by quantity produced in place of days. Table D1 shows a nearly identical pattern to Table 3. Learning rates are around 0.066, which implies that the average productivity will increase 50% after roughly 2000 units produced. Qualitatively, the results for the retained learning from previous runs and log days since last run are also very similar to Table 3. For the rest of the paper, we only present and discuss the results using log efficiency on the left hand side and days based measures of current and prior experience on the right hand side. We 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 and variable definitions are presented in the Appendix sections B through D

Next, we estimate model (1) with heterogeneous learning parameters using ordinary least squares line by line. 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.

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

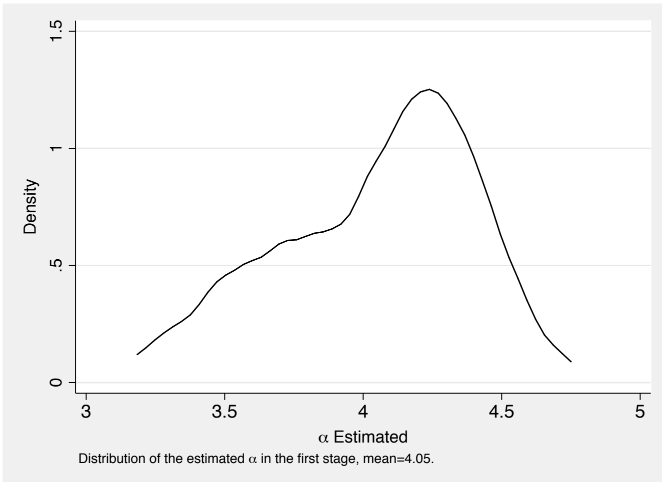
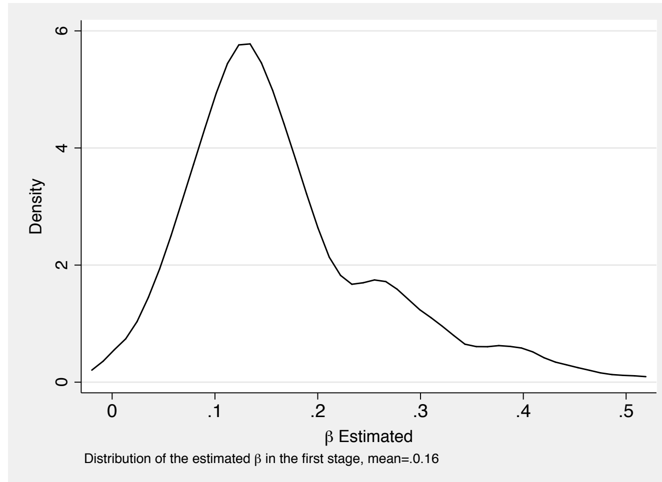



Figure 7B: Learning ($\hat{\beta}_i$)




Note: Figures 7A and 7B show the distribution of the estimates of the initial productivity (line fixed effects) and the rate of learning (individual slope) for the 96 lines, which is the largest connected set.

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

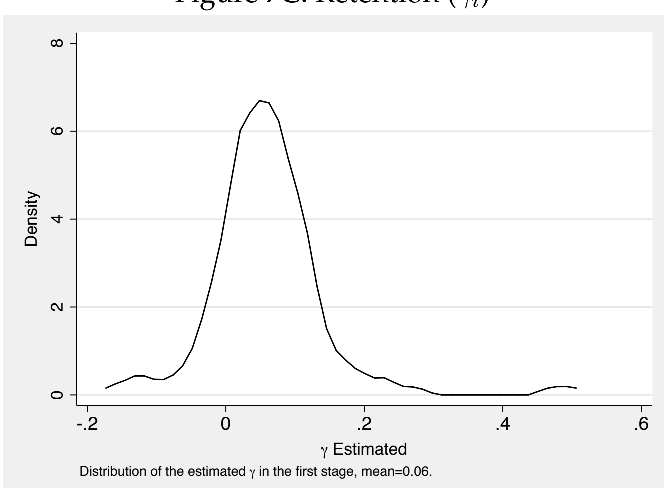
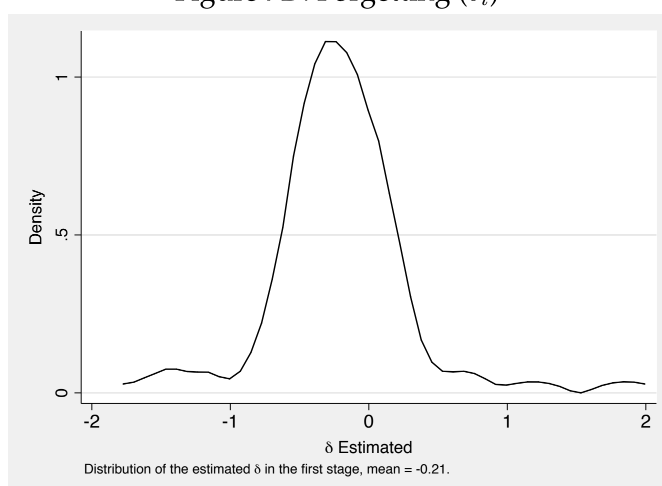



Figure 7D: Forgetting ($\hat{\delta}_i$)




Note: Figures 7C and 7D show the distribution of the estimates of the retention rate and forgetting rate for the 81 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 that we map using exploratory factor analysis the largest possible set of measures from the different modules of the survey into seven groups representing the following dimensions of managerial quality: Tenure, Cognitive

Skills, Autonomy, Personality, Control, Attention, and Relatability.[34]

Table 4: Loadings and Signal-to-Noise Ratios

| *Measures* | Tenure | Cognitive Skills | Autonomy | Personality | Control | Attention | Relatability | *Signal-to-noise Ratio* |
|---|---|---|---|---|---|---|---|---|
| | *Latent Factor* | | | | | | | |
| Total Years Working | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.8393 |
| Tenure in Garment Industry | 0.8344 | 0 | 0 | 0 | 0 | 0 | 0 | 0.6229 |
| Tenure as Supervisor | 0.497 | 0 | 0 | 0 | 0 | 0 | 0 | 0.33 |
| Tenure Supervising Current Line | 0.1499 | 0 | 0 | 0 | 0 | 0 | 0 | 0.027 |
| Digit Span Recall | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0.5343 |
| Arithmetic | 0 | 0.9082 | 0 | 0 | 0 | 0 | 0 | 0.4394 |
| Arithmetic Correct (%) | 0 | 0.3971 | 0 | 0 | 0 | 0 | 0 | 0.3445 |
| Initiating Structure | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0.7859 |
| Consideration | 0 | 0 | 0.7714 | 0 | 0 | 0 | 0 | 0.5733 |
| Autonomous Problem-Solving | 0 | 0 | -0.0391 | 0 | 0 | 0 | 0 | 0.0014 |
| Problem Identification | 0 | 0 | 0.6402 | 0 | 0 | 0 | 0 | 0.3558 |
| Conscientiousness | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.9146 |
| Perseverance | 0 | 0 | 0 | 0.9597 | 0 | 0 | 0 | 0.9308 |
| Self-Esteem | 0 | 0 | 0 | 0.618 | 0 | 0 | 0 | 0.4221 |
| Internal Locus of Control | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.7905 |
| Risk Aversion | 0 | 0 | 0 | 0 | 0.2909 | 0 | 0 | 0.0613 |
| Patience | 0 | 0 | 0 | 0 | -0.3133 | 0 | 0 | 0.0721 |
| Efforts to Meet Targets | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0.7026 |
| Monitoring Frequency | 0 | 0 | 0 | 0 | 0 | -0.4066 | 0 | 0.0809 |
| Active Personnel Management | 0 | 0 | 0 | 0 | 0 | 0.498 | 0 | 0.2223 |
| Communication | 0 | 0 | 0 | 0 | 0 | -0.7767 | 0 | 0.3902 |
| Demographic Similarity | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.9979 |
| Egalitarianism | 0 | 0 | 0 | 0 | 0 | 0 | 0.009 | 0.0003 |

Note: The first loading of each factor is normalized to 1. Signal to noise ratio 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 ($\alpha$, $\beta$,$\gamma$, and $\delta$) and the mean of log wage (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 describes 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-to-noise ratio (the variance of the contribution to the latent factor over the residual variance of the measure). Table 4 shows that the measures we use for Tenure are highly informative. Particularly, the first three measures, total years working, years in the garment industry, and years as supervisor present signal to noise ratio above 83%,

[34]The details of the variable construction are presented in Appendix **??**. Note that the restrictions of the measurement system include: 1) the number of observations in the second stage (131 managers across 79 lines) when estimating a complete system for all the learning parameters (including retention and forgetting) and the log wage; 2) the discreteness of the variables (i.e., we assumed that measures follow a mixture of normals so discrete variables of course violate this assumption); and 3) any extreme redundancy or noise across measures (i.e., some measures within a module show high correlation (above 90-95%) such that only one of these measures should be included in the system and others appeared uncorrelated with all other measures and productivity.

62%, and 33%, with loadings on the Tenure latent factor of 1, .83, and 0.5, respectively.

For Cognitive Skills, Table 4 shows that digit span recall, arithmetic (number correct) and arithmetic correct (%) are highly informative, although the signal is higher for the first measure, 53%, than for the other two measures, 43% and 34%, respectively. Note that the sign of the three loadings are positive as would be expected. For Autonomy, the two leadership behavior measures, initiating structure and consideration, are highly informative (signals of 79% and 57%, respectively), Problem Identification is also informative (35%), whereas Autonomous Problem-Solving provides minimal informative content (only 3.9% signal) above these other 3 measures.

Regarding Personality, conscientiousness and perseverance are highly informative. The two measures present signal to noise ratio above 91% and 93%, with loadings on the Personality latent factor of 1 and 0.95, respectively. Self-Esteem is less informative than the other two, but also contributes with a loading of 0.62 and a signal to noise ratio above 42%. With respect to Control, internal locus of control has the highest loading and a signal of 79% justifying our naming this factor after this measure. Risk aversion contributes also with a loading of .29 but contains much more noise (signal of 6.1%). While less appetite for risk and stronger feelings of control increase the personality factor, the patience measure has a negative loading. That is, any positive contributions we see of Personality to productivity will indicate value returns to more internal locus of control and risk aversion, but less patience. Note however, that the patience measure is noisy with a signal of 7.2%.

For Attention, efforts to meet target is the strongest contributor and a highly informative (signal of 70%). Communication and active personnel management also contribute but are less precise measures (signals of 39% and 22%, respectively). Monitoring frequency exhibits a very low signal of only 8%. Finally, for Relatability, the loading is largest for demographic similarity with signal of 99%; while both the contribution and signal of egalitarianism are negligible (0.009 and 0.3%).

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, however, 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: learning contributions of managerial quality

Table 5 reports the estimates of the CES functions for the initial level of productivity, the rate of learning, retained learning, and rate of forgetting. We see in column 1 that the initial level of productivity is most strongly impacted by Tenure and Control, followed by Cognitive Skills, Autonomy, and Attention. The estimated coefficients for Personality and Relatability are not significantly different from zero.

Table 5: Contributions of Managerial Quality to Productivity Dynamics

| | Initial Productivity ($\alpha$) | Rate of learning ($\beta$) | Retention ($\gamma$) | Forgetting ($\delta$) |
|---|---|---|---|---|
| Tenure | 0.258*** | 0.279*** | 0.286*** | 0.348*** |
| | (0.016) | (0.014) | (0.016) | (0.020) |
| Cognitive Skills | 0.236*** | 0.204*** | 0.255*** | 0.098*** |
| | (0.029) | (0.025) | (0.027) | (0.036) |
| Autonomy | 0.125*** | 0.195*** | 0.161*** | 0.141*** |
| | (0.019) | (0.016) | (0.019) | (0.027) |
| Personality | 0.000 | 0.000 | 0.001 | 0.001 |
| | (0.000) | (0.000) | (0.003) | (0.004) |
| Control | 0.269*** | 0.131*** | 0.064*** | 0.213*** |
| | (0.025) | (0.020) | (0.023) | (0.030) |
| Attention | 0.113*** | 0.191*** | 0.234*** | 0.199*** |
| | (0.020) | (0.018) | (0.021) | (0.027) |
| Relatability | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Productivity Parameter | 1.028*** | 1.041*** | 1.039*** | 1.038*** |
| | (0.028) | (0.025) | (0.028) | (0.031) |
| Complementarity Parameter | 0.003 | -0.017 | -0.012 | -0.009 |
| | (0.084) | (0.076) | (0.088) | (0.089) |
| Elasticity of Substitution | 1.348 | 1.387 | 1.401 | 1.533 |
| Std. Dev. of Dep. Variable | 0.2982 | 0.1055 | 0.8461 | 0.1623 |
| First Stage | $log$(Eff) | $log$(Eff) | $log$(Eff) | $log$(Eff) |

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

For the rate of learning, we find that Tenure and Cognitive Skills still contribute strongly, but Autonomy and Attention contribute just as strongly to the rate of learning as does the Cognitive Skills factor. That is, Autonomy and Attention both contribute more strongly to the rate of learning than to initial levels of productivity. Control, on the other hand, contributes only half as strongly to the rate of learning as to initial productivity. Once again, Personality and Relatability exhibit no discernible contribution.

Table 5 shows that, as expected, the pattern of contributions to retention are qualitatively similar to those for learning. That is, Tenure and Cognitive Skills contribute strongly; Autonomy and Attention contribute more strongly than they do to initial productivity; and Control contributes much less to retention than to initial productivity. Personality and Relatability continue to be insignificant. Tenure once again contributes most strongly to forgetting, but Cognitive Skills contribute less strongly to forgetting than to the other learning parameters. Autonomy and Attention contributions resemble the learning and retention results, while Control contributes nearly as strongly to forgetting as it does to initial productivity. For all the CES functions across the learning parameters, we find that the complementarity parameter is not statistically significant different from zero which indicates that the different dimensions of managerial quality are independent in their contributions to each dimension of the learning curve.

#### 6.3.1 Simulated Learning Curves with Higher Quality Managers

Given the complex and non-linear 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. In this section, we simulate the contribution of a one standard deviation (SD) increase in each of the seven factors to productivity at all points along the learning curve. 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 efficiency for each value of days producing in the current run.

We first evaluate the curve with each factor in each learning parameter fixed to its mean (baseline), and then increase sequentially each factor by one standard deviation. Figures 9A through 9F show the contribution to the learning curve for Tenure, Cognition, Autonomy, Personality, Control, and Attention, respectively. We compute the results for both first runs (i.e., with days of experience from prior runs set to 0) and subsequent runs (i.e., with days of experience from prior runs and intervening days both set to their mean observed when a style has been produced before).

From figures 9A-9F we observe that Tenure has the largest impact on efficiency. In particular note that the initial productivity and the rate of learning increase substantially when we simulate an increase of Tenure, compared to the simulated increases of the other factors. Moreover, when we incorporate retained learning from previous runs, the gains on efficiency are even larger for Tenure as compared to other factors. For example, if we compare efficiency on day 15 (the median of days producing on current run) of the order, an increase of one SD of Tenure increases efficiency from roughly .5 to more than 1.8 on the first run and even higher on subsequent runs.

A one SD increase in Control has the second largest impact on efficiency. Comparing efficiency on day 15 for the Control simulations reveals an increase from .5 at baseline to nearly 1.4. The same comparison for Cognitive Skills yields an increase from .5 at baseline to roughly 1.1.; while the comparisons for Autonomy and Attention yield increases from .5 to above .9 for both factors. As expected, for Personality and Relatability, the comparisons yield negligible differences.

Figure 9A: Tenure Simulation

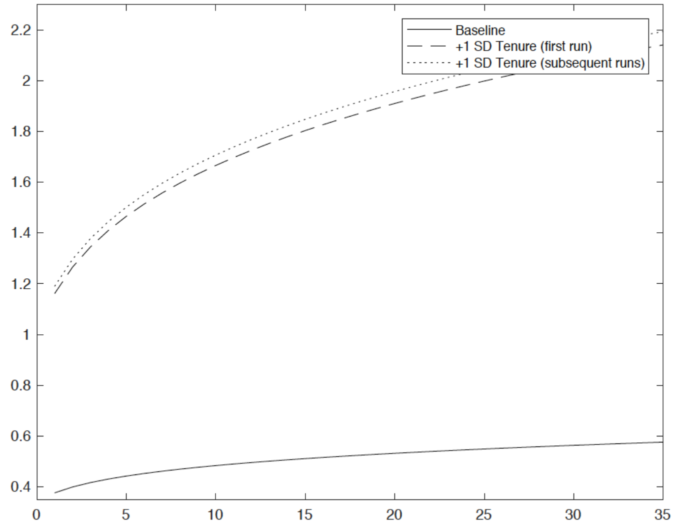
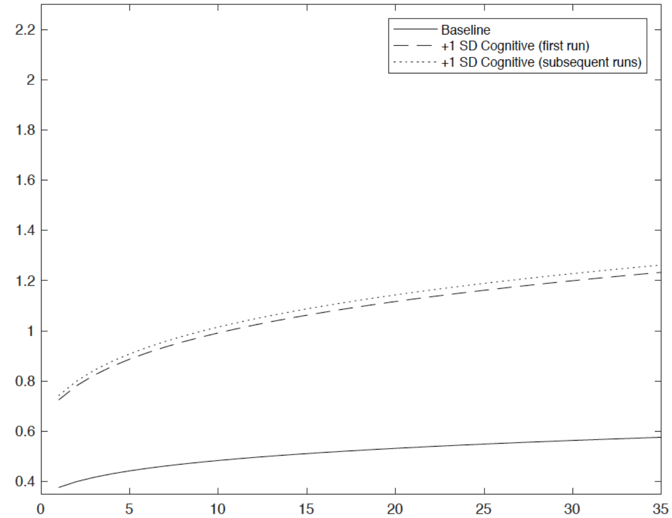



Figure 9B: Cognitive Simulation




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

Figure 9C: Autonomy Simulation

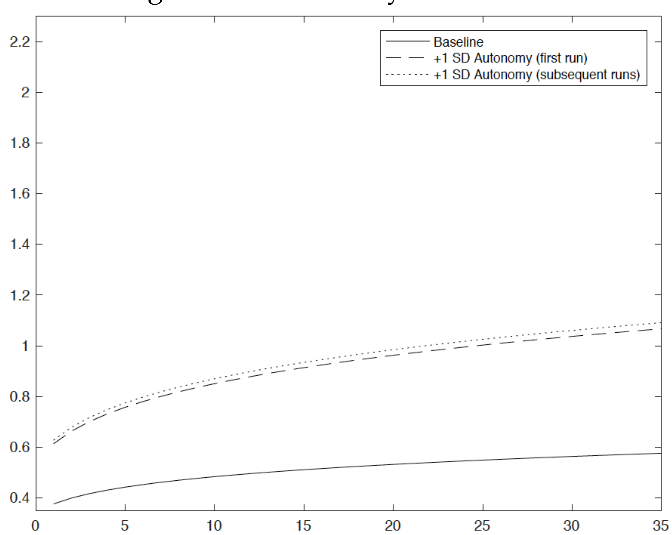
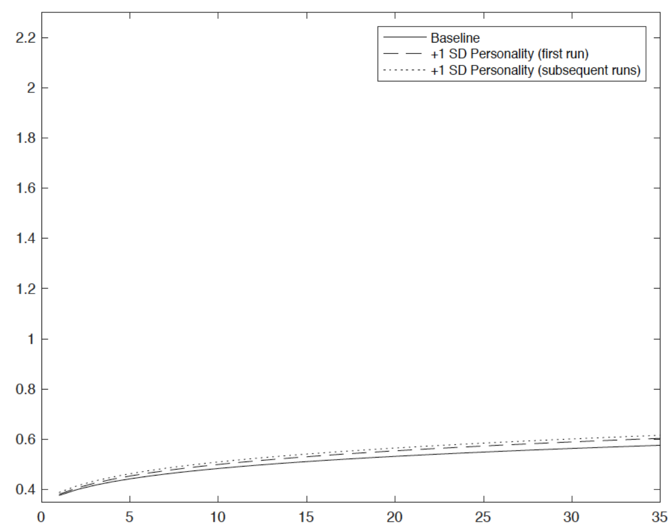



Figure 9D: Personality Simulation




Note: Figures 9C and 9D show the contribution of Autonomy 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.

Figure 9E: Control Simulation

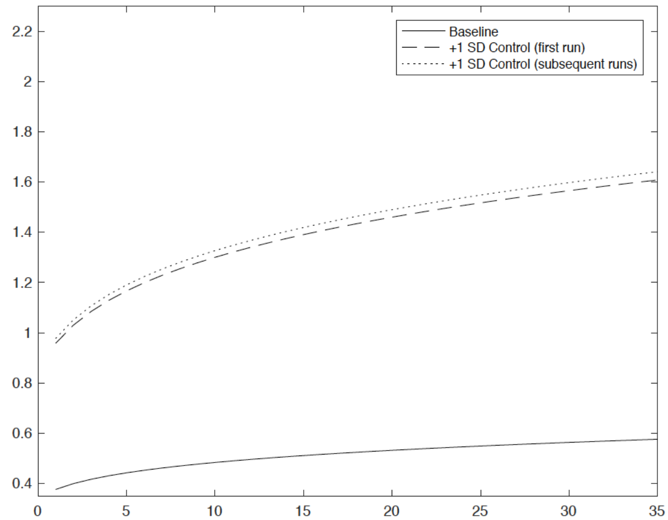
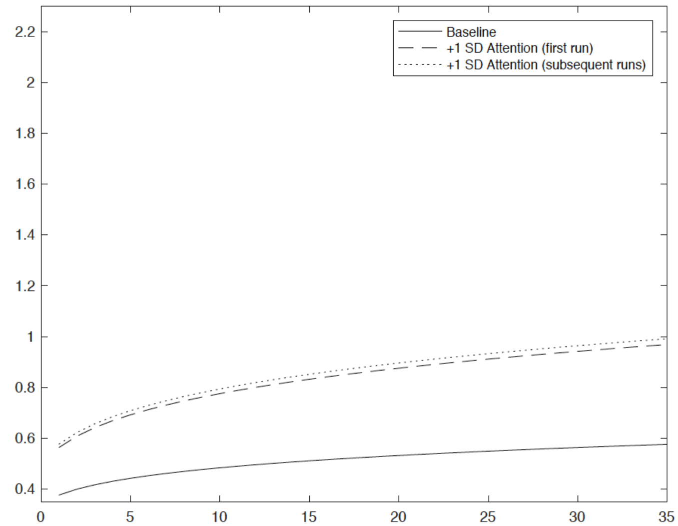



Figure 9F: Attention Simulation




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

## 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 firm 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 and maybe Cognitive Skills to determine the offered wage. Furthermore, if the firm's market power approaches a monopsony, the firm may not have incentives to adjust the wages fully in response to productivity.

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

Table 6 presents the results of this analysis of supervisor pay. As expected, Tenure has the strongest contribution to supervisor pay. Autonomy is the second most important factor, with Cognitive Skills a close third. Control and Attention are reflected in pay, though less strongly than the other factors. Perhaps unsurprisingly Personality and Relatability are not reflected in pay, consistent with the lack of contributions to productivity. Note, however, that overall this pattern is not entirely consistent with the rank of factors' contributions to productivity. For example, Control showed one of the largest impacts on productivity in the simulations but is the least 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 those in from figures 9A-9F in which we increase each dimension of quality by one SD in turn and note impacts on pay. We can then compare these simulated impacts on pay to the simulated impacts on efficiency presented in Figures 9A-9F.

Table 6: Contributions of Managerial Quality to Pay

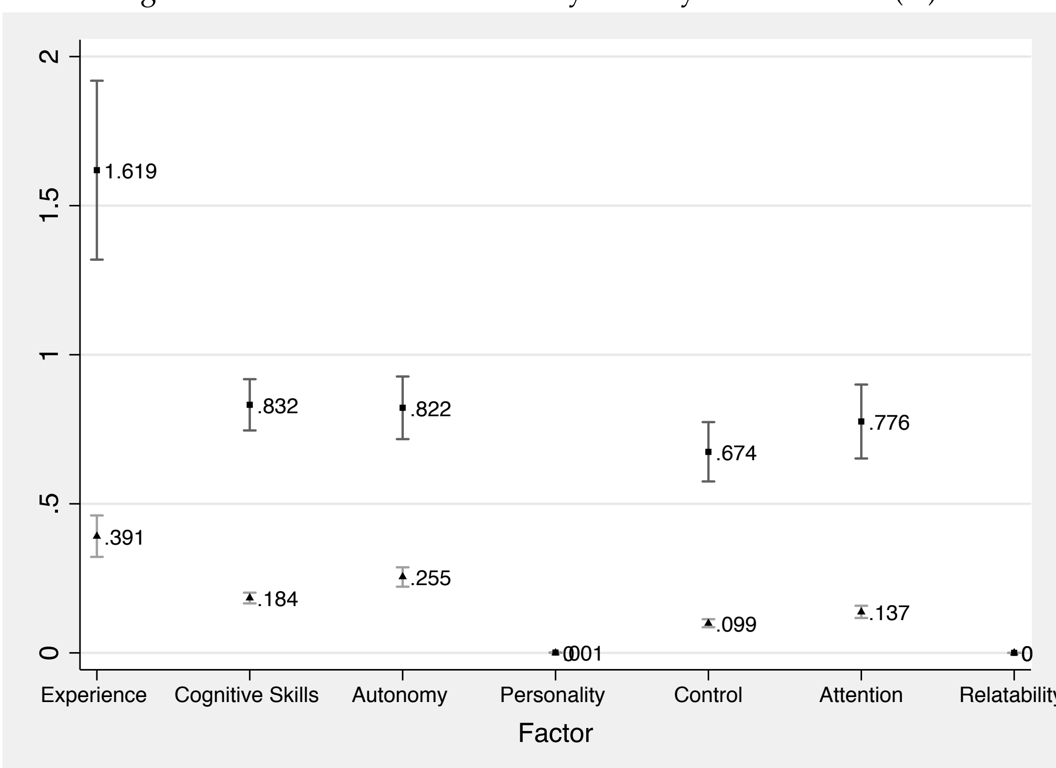
| | Pay |
|---|---|
| Tenure | 0.309*** |
| | (0.013) |
| Cognitive Skills | 0.209*** |
| | (0.021) |
| Autonomy | 0.229*** |
| | (0.015) |
| Personality | 0.000 |
| | (0.000) |
| Control | 0.107*** |
| | (0.017) |
| Attention | 0.147*** |
| | (0.016) |
| Relatability | 0.000 |
| | (0.000) |
| Productivity Parameter | 1.022*** |
| | (0.021) |
| Elasticity of substitution | 1.447 |
| Std. Dev. of Dep. Variable | 0.1011 |
| First Stage | *log* (Eff) |

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

### 6.4.1 Simulation: Pass-through of Productivity Contributions of Managerial Quality to Pay

In this section we compare the contribution of a simulated 1 SD increase in each of the 7 factors to efficiency vs. supervisor pay. For efficiency, we simply evaluate the mean across the simulated curves in Figures 9A through 9F, weighting first and subsequent runs according to their observed frequency in the data. For pay simulations, we substitute the estimated coefficients of factors presented in Table 6 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. Finally, we compute the pass-through of productivity to pay by dividing the simulated change in pay by the simulated change in efficiency for the one SD increase in each factor. [35]

Figure 10: Contribution to Efficiency and Pay of Each Factor (%)




Note: the *squares* are the contribution (percentage change) of an increase of one standard deviation of each factor to the efficiency and the *triangles* to the wages. The vertical lines are the 95% confidence intervals for each mean.

Figure 10 compares the mean simulated efficiency gains to the simulated pay increases. The *squares* in Figure 10 are the mean of the percentage increase in efficiency across days of an order and first and

[35]To compute the standard errors of the percentage increase we follow a similar procedure as in the previous section. From stage 2, we draw a synthetic dataset for the learning parameters, factors and log of pay that allow us to estimate a CES function for each learning parameter and log pay. We compute the impact (difference) on the log efficiency and log pay due to an increase of 1 standard deviation of each factor. Finally, we replicate this procedure 100 times, and compute the standard deviation of the percentage increase of efficiency and pay and the ratio of the two, each divided by the square root of $N$.

subsequent runs and the *triangles* are the percentage increases in pay, both due to an increase of one standard deviation of each factor. The vertical lines are the 95% confidence intervals. Figure 10 shows that the increase in efficiency from an increase of one standard deviation in Tenure is 162%, Cognitive Skills 83%, Autonomy 82%, Attention 78%,Control 67%, and Personality and Relatability both 0%. Note that the contributions of each factor to pay are substantially lower; the impact of Tenure is 39%, Cognitive Skills 18%, Autonomy 26%, Attention 14%, and Personality and Relatability 0%.

Table 7: Pass-through of Productivity to Pay

| | |
|---|---|
| Tenure | 24.17% |
| Cognitive Skills | 22.10% |
| Autonomy | 30.99% |
| Control | 14.73% |
| Attention | 17.68% |

Note: we compute the pass-through of productivity to the wages, dividing the contribution to efficiency by the contribution to the wages, of an increase of one standard deviation of each factor, i.e., the coefficients in Figure 10

Table 7 summarizes the pass-through of impacts on productivity to pay as the ratio of the percent change in pay to the percent change in productivity as a result of a one SD increase in each factor. We see that the pass-through is in general quite low with a maximum of 31%. This is consistent with the firm paying almost entirely fixed salaries with limited role for performance-contingent bonuses and with anecdotal evidence of labor market frictions like imperfect competition and wage rigidity. This is also consistent with the executives of each factory being unable to effectively measure dimensions of managerial quality and evaluate which dimensions to reward.

Additionally, we see that some factors produce larger pass-through (e.g., Cognitive Skills, Autonomy, and Tenure) than do others (e.g., Control and Attention). We interpret these results as consistent with differences in the observability of these skills on the part of the firm and awareness of their importance for productivity. Tenure and Cognitive Skills are traditional dimensions of ability that are often reflected in applications and interviews. Autonomy though likely less immediately observable in the hiring process reflects a style of leadership perhaps more obviously productive in this high pressure manufacturing environment. On the other hand, whether a manager will take control of the production environment and avoid unnecessary risks or how much attention and effort the manager will put forth in daily personnel and production activities are likely difficult to assess in the hiring process. The limited impact on pay of these productive but hard to measure dimensions of quality are consistent with information frictions in the hiring and wage-setting process.

# 7 Checks and Robustness

## 7.1 Monte Carlo Experiment

We present the result of the Monte Carlo experiment for the initial productivity, $\alpha_i$, the rate of learning, $\beta_i$, retention, $\gamma_i$ and rate of forgetting, $\delta_i$. We compute the percentage mean bias for the estimated coefficients for the 96 lines for $\alpha_i$ and $\beta_i$ and 81 lines for $\gamma_i$ and $\delta_i$, and then we compute the average of the absolute value of the mean bias for each line. The results of this experiment suggest that the bias is small (less than 0.5%) for almost all of the estimated coefficients for the initial productivity and the learning rate. For the retention rate and the forgetting rate, there are 3 lines that have a large bias on the estimated coefficients. If we exclude these 3 lines,[36] the average of the absolute value of the mean bias for each line is 12,76% and 10,39%, for the retention and the forgetting rate, respectively, when we perform 1,000 replications. Note that these averages decrease to 6.43% and 5.93% when we increase the number of replications to 10,000.

## 7.2 Days Left

We repeat our previous procedure controlling by days left to the end of each order in the first stage (equation 1), to control for any reference point effect (e.g., productivity increase close to the end of the order). Table B1 reports the estimated measurement system, Table B2 reports the estimates of the CES productions function for the learning parameters, e.g., initial level of productivity the rate of learning, previous experience (retention) and forgetting rate (analogous to Table 5), Table B3 presents the results of the CES function using the wages as the outcome variable instead, and Figure B1 presents the contribution (percentage change) of an increase of each factor by one standard deviation, for the average number of days of an order. Note that the loadings and the signal-to-noise ratio of each measure are very to our previous results, in Table 4. Similarly, the coefficients of the CES function for the learning parameters and the wage are almost identical to the previous results, e.g., Table 5 and 6. Finally, note that the contribution of each factor to the efficiency and wages are nearly identical e.g., compare Figure B1 and 10.

[36]We also drop these 3 lines to estimate the second and third stage described in Section 5.2 and 5.3

### 7.3 Log Quantity

Similarly, we repeat our three-steps procedure using log quantities produced in the first stage, controlling for log of target quantity, instead of log efficiency. Table C2 reports the results of the estimated measurement system, Table C3 the estimates of the CES production function for the learning parameters, and Table C4 for the wages. Finally, Figure C1 shows the contribution (percentage change) of an increase of each factor by one standard deviation, for the average number of days of an order. Again, the results for these three tables and the figure are very similar to the results in Tables 4, 5 and 6, and Figure 10.

### 7.4 Cumulative Quantity Produced

In Appendix B we used cumulative quantity produced as a measure of accrued experience of the current run, in the first stage, instead of days runnings. We first confirm in Table D1 that the results of the production function with homogeneous learning parameters show a nearly identical pattern to Table 3. Learning rates are around 0.066, which implies that the average productivity will increase 50% roughly after 465 units produced. Next, we repeat our three-steps procedure.

Table D2 reports the results of the estimates of the measurement system. Here we find small differences with respect our previous results. Particularly, the loadings for patience and locus of control have oposite sign, although its signal-to-noise ratio are small (less than 5.2%). Table D3 reports the estimates of the CES productions function for the learning parameters. In general, we observed similar patterns to Table 5, although we find a larger coefficient for Cognitive Skills for the initial productivity, the rate of learning, and the retention rate. We find that besides Experience and Cognitive Skills the third most important factor for the initial productivity is Personality and for the rate of Learning is Autonomy. For the retention rate Cognitive Skills is the second most important factor. These are similar patterns to the ones observed in Table 3.

Finally, Figure D1 presents the contribution (percentage change) of one standard deviation of each factor to the efficiency and the wages for the average number of units produced of an order. Figure D1 shows that an increase of one standard deviation of Experience increase efficiency by 71%, Autonomy 16.4%, Personality 7.1%, Cognitive Skills, 22.18 %, and Relatability 4.9%. Note that the contribution to the wages are substantially lower; for Experience is 17%, Autonomy 3.5%, Personality 0.475% and Cognitive Skills, 6.24%.

## 8 Conclusion

We match granular production data from several garment factories in India to rich data from a management survey conducted on all line supervisors to answer the following research questions: Do production teams supervised by better managers start at higher productivity levels? Do they learn faster? What managerial characteristics matter most?

Estimating a non-linear latent factor model in 3 stages, we identify 5 distinct dimensions of managerial quality: vocation-specific experience, managerial autonomy, cognitive skills, personality (e.g., risk and time preferences and psychometrics), and demographic relatability to workers. We find that some dimensions of quality (e.g., cognitive skills and personality) of the supervisor contribute to initial productivity of the line, but do not significantly impact the rate of learning. On the other hand, production lines with supervisors exercising greater managerial autonomy learn at significantly faster rates, but do not start product runs at higher initial productivity levels. Vocation-specific experience of the supervisor impacts both initial productivity and the rate of learning of the line. Additional results indicate that these dimensions of quality are imperfectly substitutable in the production function and generally undervalued in existing wage contracts. More easily observed dimensions of quality like experience and cognitive skills, though still undervalued, contribute to wages in closer proportions to their impacts on productivity; while less easily measured or less obviously productive dimensions such as managerial autonomy and demographic relatability are negatively rewarded. Firms could employ more productive line supervisors and more quickly and consistently achieve peak production by better measuring and rewarding dimensions of managerial quality beyond traditional measures like experience.

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# APPENDIX

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

Table A1: Sorting of Workers' and Managers Characteristics

| *Supervisor Characteristics* | *Efficiency** | | | | *Grade workers* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Full Sample* | *High* | *Low* | *Difference* | *Full Sample* | *High* | *Low* | *Difference* |
| Tenure Supervising Current Line / Tenure in Garment Industry | -0.002 | -0.006 | 0.001 | -0.007 | 5.970 | 5.965 | 5.974 | -0.009 |
| | (0.003) | (0.003) | (0.005) | (0.006) | (0.079) | (0.118) | (0.106) | (0.159) |
| Tenure as Supervisor / Tenure in Garment Industry | -0.002 | -0.006 | 0.001 | -0.008 | 5.970 | 5.975 | 5.965 | 0.009 |
| | (0.003) | (0.003) | (0.004) | (0.006) | (0.079) | (0.120) | (0.104) | (0.159) |
| Autonomous Problem-Solving | -0.002 | 0.000 | -0.005 | 0.005 | 5.970 | 6.114 | 5.840 | 0.274 |
| | (0.003) | (0.004) | (0.004) | (0.006) | (0.079) | (0.108) | (0.113) | (0.157) |
| Production Monitoring Frequency | -0.002 | -0.003 | -0.002 | 0.000 | 5.970 | 5.887 | 5.990 | -0.103 |
| | (0.003) | (0.007) | (0.003) | (0.007) | (0.079) | (0.193) | (0.087) | (0.199) |
| Risk Aversion | -0.002 | -0.003 | -0.002 | 0.000 | 5.970 | 5.834 | 6.045 | -0.211 |
| | (0.003) | (0.005) | (0.003) | (0.006) | (0.079) | (0.148) | (0.091) | (0.164) |
| Locus of Control | -0.002 | -0.001 | -0.004 | 0.003 | 5.970 | 5.949 | 5.989 | -0.041 |
| | (0.003) | (0.003) | (0.004) | (0.006) | (0.079) | (0.124) | (0.101) | (0.159) |
| Digit Span Recall | -0.002 | -0.008 | 0.000 | -0.008 | 5.970 | 5.982 | 5.963 | 0.019 |
| | (0.003) | (0.005) | (0.004) | (0.006) | (0.079) | (0.149) | (0.093) | (0.167) |
| Demographic Similarity | -0.002 | -0.002 | -0.002 | 0.000 | 5.970 | 5.904 | 6.020 | -0.116 |
| | (0.003) | (0.005) | (0.003) | (0.006) | (0.079) | (0.123) | (0.103) | (0.160) |

Table A2: Sorting of Workers' and Managers Characteristics

| *Supervisor Characteristics* | *Highest-Skill workers* | | | | *Pay* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Full Sample* | *High* | *Low* | *Difference* | *Full Sample* | *High* | *Low* | *Difference* |
| Tenure Supervising Current Line / Tenure in Garment Industry | 0.171 | 0.161 | 0.182 | -0.021 | 6,715.26 | 6,676.27 | 6,754.25 | -77.98 |
| | (0.009) | (0.011) | (0.014) | (0.017) | (30.95) | (41.18) | (45.96) | (61.71) |
| Tenure as Supervisor / Tenure in Garment Industry | 0.171 | 0.161 | 0.182 | -0.021 | 6,715.26 | 6,667.17 | 6,761.38 | -94.21 |
| | (0.009) | (0.012) | (0.012) | (0.017) | (30.95) | (37.18) | (48.51) | (61.48) |
| Autonomous Problem-Solving | 0.171 | 0.179 | 0.165 | 0.014 | 6,715.26 | 6,674.23 | 6,753.01 | -78.78 |
| | (0.009) | (0.012) | (0.012) | (0.018) | (30.95) | (47.65) | (39.83) | (61.75) |
| Production Monitoring Frequency | 0.171 | 0.164 | 0.173 | -0.009 | 6,715.26 | 6,758.58 | 6,704.57 | 54.02 |
| | (0.009) | (0.019) | (0.010) | (0.022) | (30.95) | (35.25) | (37.58) | (77.89) |
| Risk Aversion | 0.171 | 0.152 | 0.182 | -0.030 | 6,715.26 | 6,711.91 | 6,717.10 | -5.19 |
| | (0.009) | (0.015) | (0.011) | (0.018) | (30.95) | (46.37) | (40.89) | (65.06) |
| Locus of Control | 0.171 | 0.162 | 0.180 | -0.018 | 6,715.26 | 6,685.87 | 6,742.30 | -56.43 |
| | (0.009) | (0.013) | (0.012) | (0.018) | (30.95) | (43.18) | (44.26) | (62.01) |
| Digit Span Recall | 0.171 | 0.171 | 0.172 | -0.001 | 6,715.26 | 6,737.56 | 6,703.03 | 34.53 |
| | (0.009) | (0.013) | (0.012) | (0.018) | (30.95) | (41.41) | (42.36) | (64.96) |
| Demographic Similarity | 0.171 | 0.165 | 0.176 | -0.011 | 6,715.26 | 6,695.81 | 6,729.76 | -33.96 |
| | (0.009) | (0.013) | (0.012) | (0.018) | (30.95) | (43.40) | (43.50) | (62.80) |

## Table A3: Sorting of Workers' and Managers Characteristics

| *Supervisor Characteristics* | *Gender ( 1[Female] )* | | | | *Tenure* | | | |
|---|---|---|---|---|---|---|---|---|
| | *Full Sample* | *High* | *Low* | *Difference* | *Full Sample* | *High* | *Low* | *Difference* |
| Tenure Supervising Current Line / Tenure in Garment Industry | 0.877 | 0.899 | 0.856 | 0.043** | 1.854 | 1.854 | 1.854 | 0.000 |
| | (0.011) | (0.008) | (0.020) | (0.021) | (0.047) | (0.067) | (0.067) | (0.094) |
| Tenure as Supervisor / Tenure in Garment Industry | 0.877 | 0.889 | 0.866 | 0.023 | 1.854 | 1.809 | 1.898 | -0.089 |
| | (0.011) | (0.008) | (0.020) | (0.022) | (0.047) | (0.072) | (0.060) | (0.094) |
| Autonomous Problem-Solving | 0.877 | 0.885 | 0.870 | 0.015 | 1.854 | 1.913 | 1.800 | 0.113 |
| | (0.011) | (0.022) | (0.006) | (0.022) | (0.047) | (0.068) | (0.064) | (0.093) |
| Production Monitoring Frequency | 0.877 | 0.890 | 0.874 | 0.015 | 1.854 | 2.000 | 1.818 | 0.182* |
| | (0.011) | (0.013) | (0.013) | (0.027) | (0.047) | (0.108) | (0.051) | (0.117) |
| Risk Aversion | 0.877 | 0.892 | 0.870 | 0.022 | 1.854 | 1.765 | 1.903 | -0.139 |
| | (0.011) | (0.010) | (0.016) | (0.023) | (0.047) | (0.095) | (0.050) | (0.097) |
| Locus of Control | 0.877 | 0.896 | 0.860 | 0.036* | 1.854 | 1.848 | 1.860 | -0.012 |
| | (0.011) | (0.008) | (0.019) | (0.021) | (0.047) | (0.076) | (0.057) | (0.094) |
| Digit Span Recall | 0.877 | 0.849 | 0.893 | -0.044 | 1.854 | 1.765 | 1.903 | -0.139 |
| | (0.011) | (0.027) | (0.007) | (0.022) | (0.047) | (0.085) | (0.055) | (0.097) |
| Demographic Similarity | 0.877 | 0.893 | 0.866 | 0.028 | 1.854 | 1.780 | 1.909 | -0.129 |
| | (0.011) | (0.009) | (0.017) | (0.022) | (0.047) | (0.074) | (0.060) | (0.094) |

## Table A4: Sorting of Workers' and Managers Characteristics

| *Supervisor Characteristics* | *Non-migrant ( 1[Bengalore] )* | | | |
|---|---|---|---|---|
| | *Full Sample* | *High* | *Low* | *Difference* |
| Tenure Supervising Current Line / Tenure in Garment Industry | 0.809 | 0.819 | 0.798 | 0.021 |
| | (0.008) | (0.012) | (0.012) | (0.017) |
| Tenure as Supervisor / Tenure in Garment Industry | 0.809 | 0.808 | 0.809 | -0.001 |
| | (0.008) | (0.013) | (0.010) | (0.017) |
| Autonomous Problem-Solving | 0.809 | 0.822 | 0.797 | 0.024* |
| | (0.008) | (0.010) | (0.013) | (0.017) |
| Production Monitoring Frequency | 0.809 | 0.830 | 0.804 | 0.027 |
| | (0.008) | (0.013) | (0.010) | (0.021) |
| Risk Aversion | 0.809 | 0.812 | 0.807 | 0.004 |
| | (0.008) | (0.015) | (0.010) | (0.017) |
| Locus of Control | 0.809 | 0.815 | 0.803 | 0.012 |
| | (0.008) | (0.012) | (0.011) | (0.017) |
| Digit Span Recall | 0.809 | 0.830 | 0.797 | 0.033 |
| | (0.008) | (0.015) | (0.010) | (0.017) |
| Demographic Similarity | 0.809 | 0.810 | 0.808 | 0.001 |
| | (0.008) | (0.013) | (0.011) | (0.017) |

Table A5: Bias Learning Parameters

| Parameter | Bias (%) | Bias (%) |
|---|---|---|
| Initial Productivity ($\alpha$) | 0.12% | 0.16% |
| Rate of learning ($\beta$) | 0.32% | 0.67% |
| Previous Experience ($\gamma$) | 5.93% | 7.58% |
| Forgetting ($\delta$) | 6.43% | 8.21% |
| Simulated Error | White Noise | AR(1) |

Table A6: Correlation of the factors

| *Factor* | Tenure | Cognitive Skills | Autonomy | Personality | Control | Attention | Relatability |
|---|---|---|---|---|---|---|---|
| Tenure | 1 | | | | | | |
| Cognitive Skills | -0.080 | 1 | | | | | |
| Autonomy | -0.107 | 0.309 | 1 | | | | |
| Personality | -0.113 | 0.317 | 0.794 | 1 | | | |
| Control | -0.014 | 0.459 | 0.294 | 0.250 | 1 | | |
| Attention | 0.007 | 0.312 | 0.347 | 0.254 | 0.341 | 1 | |
| Relatability | 0.049 | 0.105 | 0.131 | 0.061 | 0.434 | 0.142 | 1 |

# B Reference Points: Robustness to Controlling for Days Left

Table B1: Loadings and Signal-to-Noise Ratios

| *Measures* | Tenure | Cognitive Skills | Autonomy | Personality | Control | Attention | Relatability | *Signal-to-noise Ratio* |
|---|---|---|---|---|---|---|---|---|
| | *Latent Factor* | | | | | | | |
| Total Years Working | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.908 |
| Tenure in Garment Industry | 0.9033 | 0 | 0 | 0 | 0 | 0 | 0 | 0.743 |
| Tenure as Supervisor | 0.304 | 0 | 0 | 0 | 0 | 0 | 0 | 0.127 |
| Tenure Supervising Current Line | 0.0358 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 |
| Digit Span Recall | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0.502 |
| Arithmetic | 0 | 0.9837 | 0 | 0 | 0 | 0 | 0 | 0.466 |
| Arithmetic Correct (%) | 0 | 0.4073 | 0 | 0 | 0 | 0 | 0 | 0.344 |
| Initiation | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0.777 |
| Consideration | 0 | 0 | 0.7644 | 0 | 0 | 0 | 0 | 0.568 |
| Autonomous Problem-Solving | 0 | 0 | -0.0479 | 0 | 0 | 0 | 0 | 0.002 |
| Problem | 0 | 0 | 0.6491 | 0 | 0 | 0 | 0 | 0.362 |
| Conscientiousness | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.946 |
| Perseverance | 0 | 0 | 0 | 0.9224 | 0 | 0 | 0 | 0.889 |
| Self-Esteem | 0 | 0 | 0 | 0.6201 | 0 | 0 | 0 | 0.447 |
| Locus of Control | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.824 |
| Risk Aversion | 0 | 0 | 0 | 0 | 0.2502 | 0 | 0 | 0.045 |
| Patience | 0 | 0 | 0 | 0 | -0.3251 | 0 | 0 | 0.078 |
| Target Practice Index | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0.841 |
| Monitor Index | 0 | 0 | 0 | 0 | 0 | -0.3258 | 0 | 0.058 |
| Active Management | 0 | 0 | 0 | 0 | 0 | 0.488 | 0 | 0.261 |
| Talk Index | 0 | 0 | 0 | 0 | 0 | -0.6681 | 0 | 0.365 |
| Demographic Similarity | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.571 |
| Egalitarianism | 0 | 0 | 0 | 0 | 0 | 0 | 0.0696 | 0.011 |

Note: The first loading of each factor is normalized to 1. Signal to noise ratio 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 ($\alpha$, $\beta$,$\gamma$, and $\delta$) and the mean of log wage (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: CES Production of the Learning Parameters

| | Initial Productivity ($\alpha$) | Rate of learning ($\beta$) | Retention ($\gamma$) | Forgetting ($\delta$) |
|---|---|---|---|---|
| Tenure | 0.256*** | 0.277*** | 0.288*** | 0.280*** |
| | (0.014) | (0.013) | (0.015) | (0.026) |
| Cognitive Skills | 0.290*** | 0.261*** | 0.306*** | 0.000 |
| | (0.027) | (0.026) | (0.027) | (0.000) |
| Autonomy | 0.104*** | 0.180*** | 0.147*** | 0.181*** |
| | (0.020) | (0.018) | (0.019) | (0.035) |
| Personality | 0.000 | 0.000 | 0.000 | 0.003 |
| | (0.000) | (0.000) | (0.000) | (0.009) |
| Control | 0.271*** | 0.143*** | 0.083*** | 0.361*** |
| | (0.025) | (0.021) | (0.023) | (0.037) |
| Attention | 0.078*** | 0.139*** | 0.176*** | 0.168*** |
| | (0.022) | (0.020) | (0.021) | (0.034) |
| Relatability | 0.000 | 0.000 | 0.000 | 0.007 |
| | (0.000) | (0.000) | (0.000) | (0.011) |
| Productivity Parameter | 1.015*** | 1.028*** | 1.027*** | 1.032*** |
| | (0.027) | (0.023) | (0.026) | (0.047) |
| Complementarity Parameter | 0.026 | 0.002 | 0.006 | -0.025 |
| | (0.091) | (0.075) | (0.081) | (0.137) |
| Elasticity of substitution | 1.344 | 1.384 | 1.404 | 1.389 |
| Std. Dev. of Dep. Variable | 0.2982 | 0.1055 | 0.8461 | 0.1623 |
| First Stage | $log$(Eff) | $log$(Eff) | $log$(Eff) | $log$(Eff) |

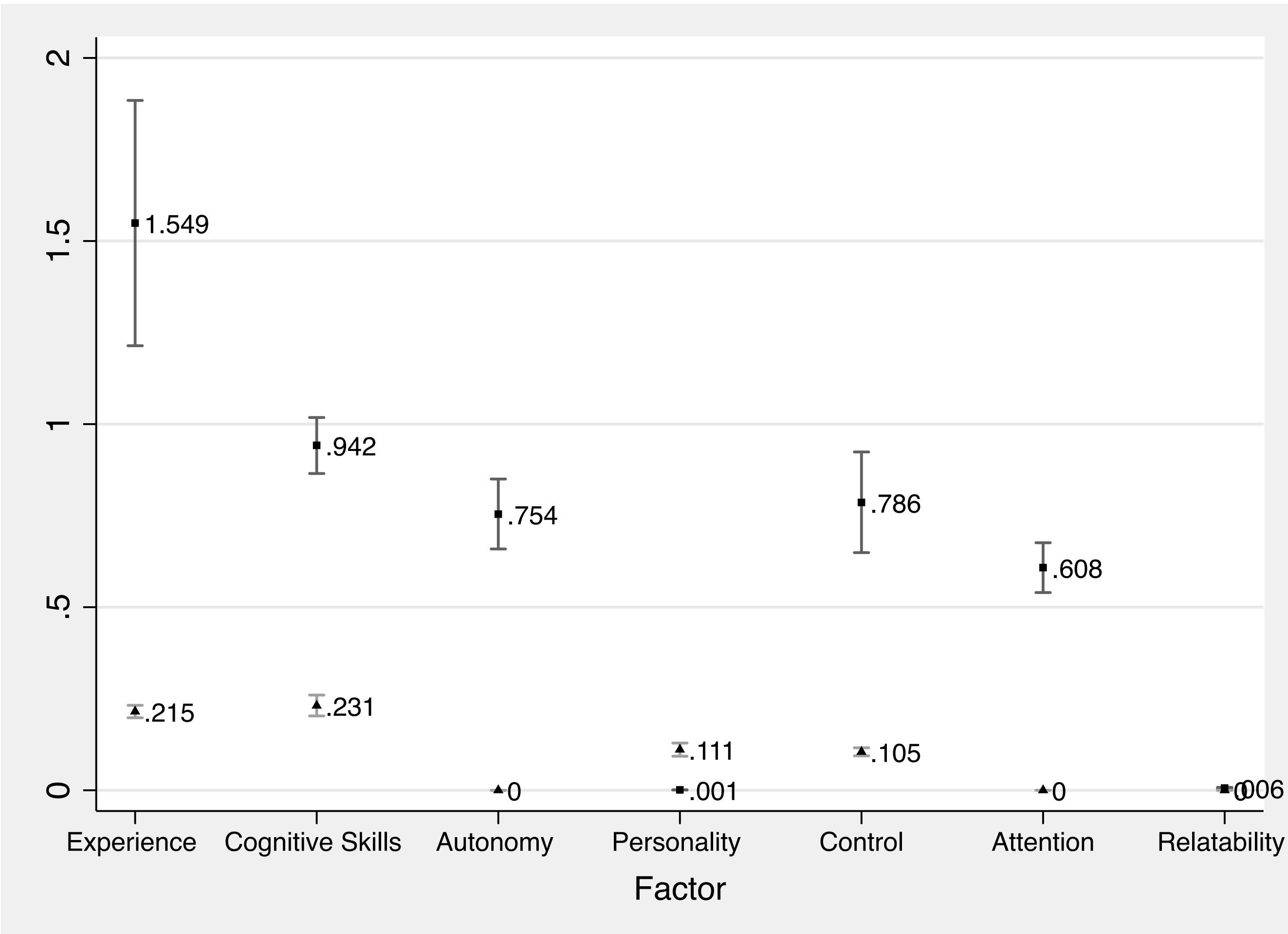
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

Table B3: CES Function *Wages*

| | Pay |
|---|---|
| Tenure | 0.304*** |
| | (0.013) |
| Cognitive Skills | 0.257*** |
| | (0.021) |
| Autonomy | 0.214*** |
| | (0.017) |
| Personality | 0.000 |
| | (0.000) |
| Control | 0.119*** |
| | (0.019) |
| Attention | 0.107*** |
| | (0.018) |
| Relatability | 0.000 |
| | (0.000) |
| Productivity Parameter | 1.014*** |
| | (0.020) |
| Complementarity Parameter | -0.014 |
| | (0.064) |
| Elasticity of substitution | |
| | 1.436 |
| Std. Dev. of Dep. Variable | 0.1011 |
| First Stage | *log*(Eff) |

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

Figure B1: Contribution to Efficiency and Pay of Each Factor (%)




Note: the *squares* are the contribution (percentage change) of an increase of one standard deviation of each factor to the efficiency and the *triangles* to the wages. The vertical lines are the 95% confidence intervals for each mean.

# 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) | 0.153*** | 0.155*** | 0.158*** |
| | (0.0115) | (0.0111) | (0.0121) |
| Log(Total Days in Prior Production Runs) | 0.0639*** | 0.0675*** | 0.0698*** |
| | (0.0169) | (0.0168) | (0.0171) |
| Log(Prior Days) X Log(Days Since Prior Run) | -0.00899* | -0.00936* | -0.0104** |
| | (0.00496) | (0.00512) | (0.00517) |
| Log(Target Quantity) | 1.033*** | 1.041*** | 1.039*** |
| | (0.0158) | (0.0152) | (0.0150) |
| Observations | 36,938 | 36,938 | 36,938 |
| 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 |

Table C2: Loadings and Signal-to-Noise Ratios

| *Measures* | Tenure | Cognitive Skills | Autonomy | Personality | Control | Attention | Relatability | *Signal-to-noise Ratio* |
|---|---|---|---|---|---|---|---|---|
| | *Latent Factor* | | | | | | | |
| Total Years Working | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0.908 |
| Tenure in Garment Industry | 0.8235 | 0 | 0 | 0 | 0 | 0 | 0 | 0.743 |
| Tenure as Supervisor | 0.4148 | 0 | 0 | 0 | 0 | 0 | 0 | 0.127 |
| Tenure Supervising Current Line | 0.0954 | 0 | 0 | 0 | 0 | 0 | 0 | 0.002 |
| Digit Span Recall | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0.502 |
| Arithmetic Correct (%) | 0 | 0.3787 | 0 | 0 | 0 | 0 | 0 | 0.344 |
| Initiation | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0.777 |
| Consideration | 0 | 0 | 0.7724 | 0 | 0 | 0 | 0 | 0.568 |
| Autonomous Problem-Solving | 0 | 0 | -0.0502 | 0 | 0 | 0 | 0 | 0.002 |
| Problem | 0 | 0 | 0.6258 | 0 | 0 | 0 | 0 | 0.362 |
| Conscientiousness | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0.946 |
| Perseverance | 0 | 0 | 0 | 0.9656 | 0 | 0 | 0 | 0.889 |
| Self-Esteem | 0 | 0 | 0 | 0.6265 | 0 | 0 | 0 | 0.447 |
| Internal Locus of Control | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0.824 |
| Risk Aversion | 0 | 0 | 0 | 0 | 0.281 | 0 | 0 | 0.045 |
| Patience | 0 | 0 | 0 | 0 | -0.301 | 0 | 0 | 0.078 |
| Target Practice Index | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0.841 |
| Monitor Index | 0 | 0 | 0 | 0 | 0 | -0.4061 | 0 | 0.058 |
| Active Management | 0 | 0 | 0 | 0 | 0 | 0.494 | 0 | 0.261 |
| Talk Index | 0 | 0 | 0 | 0 | 0 | -0.7703 | 0 | 0.365 |
| Demographic Similarity | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0.571 |
| Egalitarianism | 0 | 0 | 0 | 0 | 0 | 0 | 0.0126 | 0.011 |

Table C3: CES Production of the Learning Parameters

| | Initial Productivity ($\alpha$) | Rate of learning ($\beta$) | Retention ($\gamma$) | Forgetting ($\delta$) |
|---|---|---|---|---|
| Tenure | 0.244*** | 0.264*** | 0.274*** | 0.298*** |
| | (0.017) | (0.014) | (0.017) | (0.021) |
| Cognitive Skills | 0.247*** | 0.208*** | 0.258*** | 0.027 |
| | (0.026) | (0.023) | (0.024) | (0.024) |
| Autonomy | 0.096*** | 0.168*** | 0.137*** | 0.208*** |
| | (0.019) | (0.017) | (0.021) | (0.029) |
| Personality | 0.000 | 0.000 | 0.001 | 0.009 |
| | (0.000) | (0.000) | (0.005) | (0.017) |
| Control | 0.285*** | 0.152*** | 0.082*** | 0.253*** |
| | (0.027) | (0.023) | (0.024) | (0.031) |
| Attention | 0.128*** | 0.208*** | 0.248*** | 0.206*** |
| | (0.024) | (0.021) | (0.024) | (0.031) |
| Relatability | 0.000 | 0.000 | 0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| Productivity Parameter | 1.018*** | 1.033*** | 1.029*** | 1.036*** |
| | (0.027) | (0.023) | (0.026) | (0.034) |
| Complementarity Parameter | 0.020 | -0.015 | -0.003 | -0.022 |
| | (0.089) | (0.076) | (0.085) | (0.104) |
| Elasticity of substitution | 1.322 | 1.359 | 1.378 | 1.425 |
| Std. Dev. of Dep. Variable | 0.2982 | 0.1055 | 0.8461 | 0.1623 |
| First Stage | $log$(Eff) | $log$(Eff) | $log$(Eff) | $log$(Eff) |

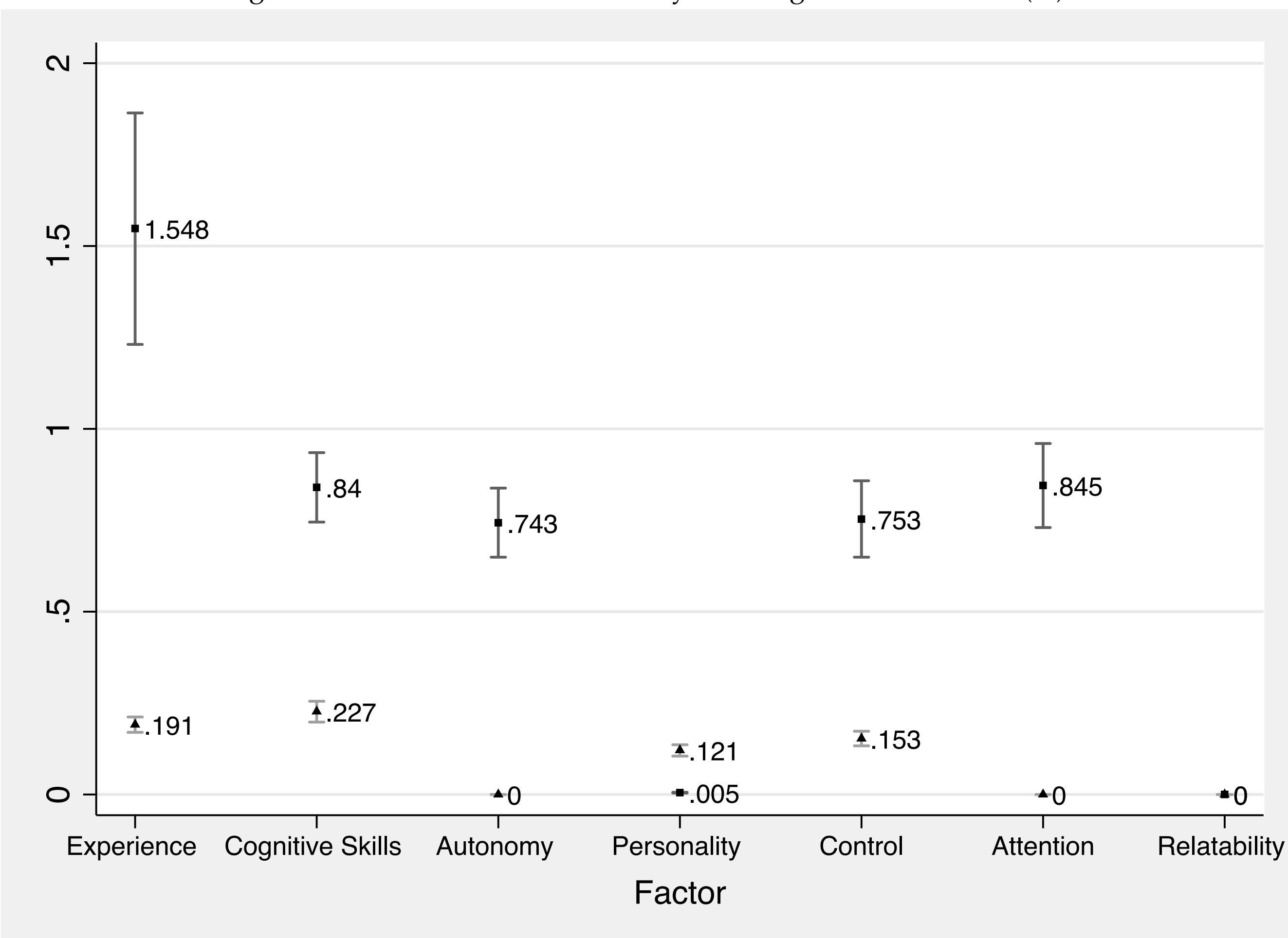
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

Table C4: CES Function *Wages*

| | Pay |
|---|---|
| Tenure | 0.292*** |
| | (0.013) |
| Cognitive Skills | 0.212*** |
| | (0.020) |
| Autonomy | 0.202*** |
| | (0.015) |
| Personality | 0.000 |
| | (0.001) |
| | (0.021) |
| Attention | 0.163*** |
| | (0.019) |
| Relatability | 0.000 |
| | (0.000) |
| Productivity Parameter | 1.014*** |
| | (0.020) |
| Complementarity Parameter | -0.009 |
| | (0.063) |
| Elasticity of substitution | |
| | 1.412 |
| Std. Dev. of Dep. Variable | 0.1011 |
| First Stage | *log* (Eff) |

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

Figure C1: Contribution to Efficiency and Wages of Each Factor (%)




Note: the *squares* are the contribution (percentage change) of an increase of one standard deviation of each factor to the efficiency and the *triangles* to the wages. The vertical lines are the 95% confidence intervals for each mean.

# D Alternative Learning Measure: Robustness to Measuring Experience in Cumulative Quantity Produced

In this section, we test for the patterns depicted in Section 3 using cumulative quantity as a measure of experience of current run, in the first stage, instead of days running of the order. We use log efficiency in the left hand side. We first report and discuss the results assuming homogeneous learning parameters across the lines, and then move on to present the results of the regression analysis of the production function with heterogeneous learning parameters.

Table D1 presents the results of the production function with homogeneous learning parameters. As before, 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 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 D1 shows a nearly identical pattern to Table 3; learning rates are around 0.066, which implies that the average productivity will increase 50% roughly after 465 units produced.

Table D2 describes the set of measures used to proxy each *latent* factor and the respectively estimated loading, which are exactly the same measures used before. We also compute the signal to noise ratio (ratio of the variance of the latent factor to the variance of each measurement) for each measurement. Table D2 presents the results.

Table D3 reports the estimates of the CES productions function for the initial level of productivity the rate of learning, previous experience (retention) and forgetting rate, for the model with cumulative units produced as a measure of experience of current run.

Figure D1 presents the contribution (percentage change) of one standard deviation of each factor to the efficiency and the wages for the average number of units produced of an order. The *squares* in Figure D1 are the mean of the percentage increase on the efficiency and the *triangles* on the wages. Figure D1 shows that an increase of one standard deviation of Experience increase efficiency by 71%, Autonomy 16.4%, Personality 7.1%, Cognitive Skills, 22.18 %, and Relatability 4.9%. Note that the contribution to the wages are lower, i.e., for Experience is 17%, Autonomy 3.5%, Personality 0.475% and Cognitive Skills, 6.24%.

Table D1: Learning (Experience in Cumulative Quantity Produced)

| | Log(Efficiency) (Actual Production/Target Production) | | |
|---|---|---|---|
| Log(Cumulative Quantity Produced) | 0.0670*** | 0.0673*** | 0.0705*** |
| | (0.00534) | (0.00530) | (0.00628) |
| Log(Total Units in Prior Production Runs) | 0.0197*** | 0.0204*** | 0.0280*** |
| | (0.00569) | (0.00560) | (0.00731) |
| Log(Prior Units) X Log(Days Since Prior Run) | -0.00444** | -0.00441** | -0.00696*** |
| | (0.00172) | (0.00173) | (0.00209) |
| Observations | 36,938 | 36,938 | 36,938 |
| 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 Units left |

Table D2: Loadings and Signal-to-Noise Ratios

| *Measures* | *Latent Factor* | | | | | *Signal-to-noise Ratio* |
|---|---|---|---|---|---|---|
| | Experience | Cognitive Skills | Autonomy | Personality | Relatability | |
| Tenure Supervising Current Line / Tenure in Garment Industry | 1 | 0 | 0 | 0 | 0 | 79.5% |
| Tenure as Supervisor / Tenure in Garment Industry | 0.674 | 0 | 0 | 0 | 0 | 49.9% |
| Tenure as Supervisor / Total Years Working | 0.596 | 0 | 0 | 0 | 0 | 41.0% |
| Digit Span Recall | 0 | 1 | 0 | 0 | 0 | 64.7% |
| Arithmetic | 0 | 0.808 | 0 | 0 | 0 | 40.8% |
| Autonomous Problem-Solving | 0 | 0 | 1 | 0 | 0 | 98.4% |
| Autonomous Style | 0 | 0 | 0.448 | 0 | 0 | 15.4% |
| Risk Aversion | 0 | 0 | 0 | 1 | 0 | 52.0% |
| Patience | 0 | 0 | 0 | -0.336 | 0 | 5.21% |
| Locus of Control | 0 | 0 | 0 | -0.066 | 0 | 0.2% |
| Demographic Similarity | 0 | 0 | 0 | 0 | 1 | 99.8% |
| Egalitarianism | 0 | 0 | 0 | 0 | -0.002 | 0.0% |

Table D3: CES Production Function

| | Initial Productivity ($\alpha$) | Rate of learning ($\beta$) | Previous Experience ($\gamma$) | Forgetting ($\delta$) |
|---|---|---|---|---|
| Tenure | 0.739*** | 0.811*** | 0.825*** | 0.992*** |
| | (0.030) | (0.014) | (0.013) | (0.016) |
| Cognitive Skills | 0.131*** | 0.095*** | 0.100*** | 0.000 |
| | (0.024) | (0.010) | (0.009) | (0.000) |
| Autonomy | 0.011 | 0.076*** | 0.071*** | 0.000 |
| | (0.013) | (0.009) | (0.009) | (0.000) |
| Personality | 0.095*** | 0.018 | 0.004 | 0.008 |
| | (0.032) | (0.013) | (0.007) | (0.016) |
| Relatability | 0.024*** | 0.000 | 0.000 | 0.000 |
| | (0.008) | (0.000) | (0.000) | (0.000) |
| Productivity Parameter | 0.965*** | 1.010*** | 1.007*** | 0.995*** |
| | (0.020) | (0.010) | (0.009) | (0.020) |
| Complementarity Parameter | 0.028 | -0.046 | -0.105 | 0.196 |
| | (0.282) | (0.177) | (0.197) | (0.523) |
| Elasticity of substitution | 1.029 | 0.956 | 0.905 | 1.244 |
| Std. Dev. of Dep. Variable | 0.3865 | 0.1019 | 0.6657 | 0.1013 |
| First Stage | *log* (Eff) | *log* (Eff) | *log* (Eff) | *log* (Eff) |

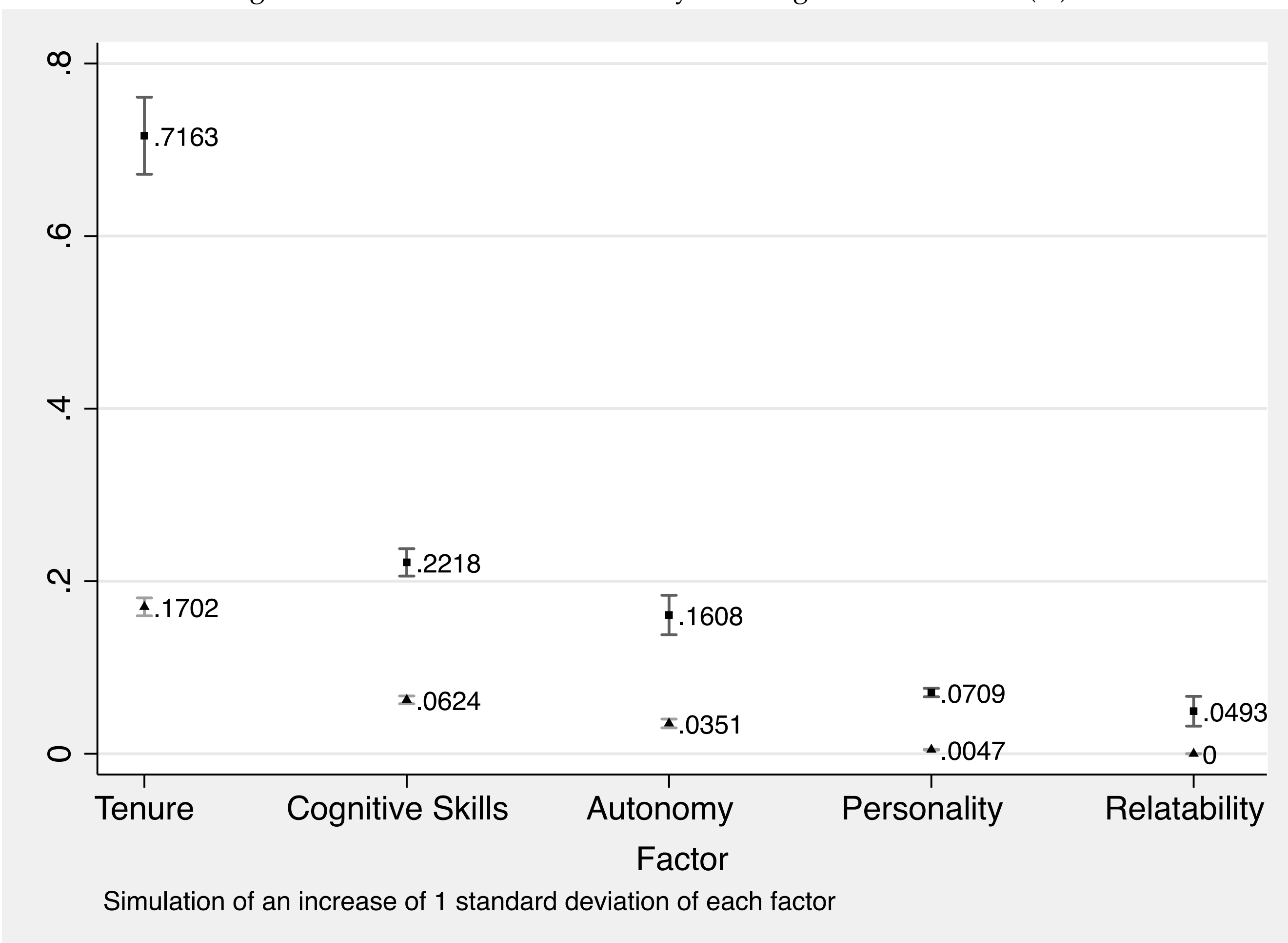
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

Table D4: CES function Wages

| | Wages |
|---|---|
| Tenure | 0.824*** |
| | (0.015) |
| Cognitive Skills | 0.116*** |
| | (0.011) |
| Autonomy | 0.050*** |
| | (0.010) |
| Personality | 0.010 |
| | (0.010) |
| Relatability | 0.000 |
| | (0.000) |
| Productivity Parameter | 1.008*** |
| | (0.012) |
| Complementarity Parameter | -0.039 |
| | (0.271) |
| Elasticity of substitution | 0.962 |
| Std. Dev. of Dep. Variable | 0.1127 |
| First Stage | *log* (Eff) |

Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses based on 100 bootstrap replications.

Figure D1: Contribution to Efficiency and Wages of Each Factor (%)




Note: the *squares* are the contribution (percentage change) of an increase of one standard deviation of each factor to the efficiency and the *triangles* to the wages. The vertical lines are the 95% confidence intervals for each mean.