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Explaining Worker Productivity: The Roles of Hidden Traits and Weather

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Abstract

Productivity variation both between and within firms can be substantially high. Understanding the extent of the variation and also the determinants associated with the variation can be important for promoting firm growth and enhance economic development in low and middle income countries. We carefully measure productivity for a set of workers who are involved in very similar tasks to produce homogeneous products. We find large variation in between worker productivity and also hourly wages. Formal education measured in terms of years of schooling has limited role in explaining the variation. However, factors such as cognitive traits and fine motor skills are strongly associated with productivity. We further tested the roles of weather in determining productivity and we find that lower temperature in winter season can lower productivity of the workers. Firm level investment addressing these factors can enhance firm productivity and contributes towards economic development and welfare of the workers.

Keywords: Labor Productivity, Cognitive Traits, Fine motor skills, Weather

JEL Classifications: J24, J31, J46

1 Introduction

The economics literature now recognizes wide productivity differential between sector, within sector between firms and within firms between production units and workers (Syverson 2011, Macchiavello, et al. 2015). Worker productivity is an important determinant of earnings and hence the factor contributing to productivity can determine earning distribution, skill formation and human capital accumulation over worker's life cycle (Becker 1994). The contribution of productivity to earning has both macro and micro implications in terms of roles of human capital formation in determining economic growth (Lucas 1988) and also captured in Mincer-type regression models, albeit in its typical reduced form and not without criticism (Heckman, Lochner and Todd 2003). Unobserved traits are often receive importance in the context of estimating skill earnings gradient and both hard and soft skills are considered important such estimation even though and perhaps more importantly many such traits remain unobserved specially to the econometricians (Heckman 2008).

In this study, we aim to carefully measure productivity and hourly wages of workers in a semi-formal manufacturing setting in Bangladesh. Using a Mincer-type regression model, we further estimate the returns to different factors such as schooling, experience as well as factors that are typically unobserved in such models. These include fluid intelligence and fine-motor skills of the workers. Fine motor skills can particularly be important determinants for our worker-tailors because of the characteristics of their tasks. Furthermore, lower temperature can also affect hand dexterity (Chen, Shih and Chi 2010). Hence, we further measure basic weather variables namely temperature and humidity to understand the roles of weather in determining worker productivity. This, we hope, will further contribute to the understanding of natural working conditions of workers and its role in determining productivity.

Bangladesh is a fast growing lower middle-income country. Ready-made garment (RMG) sector has contributed immensely to its economic growth and development and provides employment to over four million people of which 70 percent constitutes of women (Muhammad 2011). However, the labor market still comprises of a large informal sector (ADB/BBS 2012). While RMG sector is almost entirely export oriented, local informal and semi-formal manufacturers and traders often cater to the domestic demand. There is a growing effort to understand the productivity and management structure of the firms and the factories within the RMG and formal other industries but little focus is given on these informal manufacturing sectors (Macchiavello, et al. 2015). Our study aims to fill some of these gaps.

Here, we work with a large local not-for profit employer with different types of employment contracts. We work with a specific type of workers namely the tailors. We chose tailors because they have more stable employment relationships. Tailors also work more independently, unlike line operators in RMG sector in Bangladesh working primary collectively in lines. Hence, we can measure individual productivity. Moreover, all the tailors carry out very similar tasks, which involve sewing different pieces of fabrics to assemble dresses. This allows more appropriate comparisons across workers. We report the variation in individual productivity and estimate the contribution of different factors explaining the productivity workers.

2 Methods

2.1 Background

We partnered with a leading handicraft manufacturer in Bangladesh, which is vertically integrated with a prominent local brand. Both the supplier and the brand are not-for-profit social business aiming to create employment for women in the rural areas of Bangladesh. However, they also employ male workers in different roles. In this study, we work with the tailors employed through 13 different locations in different districts all over Bangladesh. We rely on production data and also human resource records to compile output or production at daily frequency and normalize to measure hourly efficiency and real wage. We measure daily productivity on multiple dates for the same workers allowing us to use fixed effect models to measure the impacts of weather related factors on worker productivity.

2.2 Measuring Productivity

As we have argued before, the tailors' tasks are fairly homogenous across workers and locations. A total piece of dress can be divided into finite number of simple tasks such as sewing the helms of different pieces of fabrics. The same tailor usually work on a complete set of dress, however, they also sometimes specialize in certain tasks temporarily. We also find instances where tailors work in line like production processes. But they are less common and even in this case payment information from HR data allows understanding which tasks or pieces they have worked on. The remuneration for a task varies depending on the time it takes to complete one. So, we can use the value of the remuneration of w_k for, say, task k as a weight to ascertain total amount of output for worker i on date t. Hence we can measure the efficiency value for a tailor on a particular date using the following expression,

$$Efficiency_{it} = \frac{Output\ Minutes_{it}}{Input\ Minutes_{it}} = \frac{\sum_k w_k v_{kit}}{T_{it}}$$

where, v_{kit} is the total number of tasks of type k carried out by worker-tailor i on date t and T_{it} is the total number of working hours of tailor i on date t. Hence, the ratio allows us measuring the real productivity of a particular worker on a given day.

We also measure hourly wage rates for the workers using detailed HR data. We have already mentioned the total number of working hours and the employer also keep track of daily payable to each worker because the workers are paid at piece rate. Hence, the real wage rate for a given month m for worker i is measured using the following formula

$$realwage_{im} = \frac{Payment_{im}}{T_{im}}$$

One should note that the salary data and the production data come from two different sources and piece-rate payment should suggest a perfect correlation between the real wage rates and daily productivity. There is high correlation between the two outcome variables, as we will show later. However, there are some discrepancies between the two measures. We use both as outcome variables and carry out analyses separately.

2.3 Cognitive Ability

Cognitive abilities can be multidimensional and in this study we focus on measuring the fluid intelligence using Matrix Reasoning Cognitive Test. The cognitive test is a common component of IQ test and measure the capacity to think logically and solve problems, independent of acquired knowledge. Accuracy of the response measured the cognitive control and the ability to guide a thought and action in accordance with the goal (Hossain and Uddin 2009).

2.4 Fine Motor Skills

We used Crawford Small Part Dexterity Test (CPSDT) to measure the workers' fine motor skill. The CSPDT test measure the speed in completing tasks using pins and screws and was highly reliable as it was in accordance to participants' daily task (Hossain and Roy 2014). The

work of our sample group demands high eye-hand coordination, accuracy and cognitive processing thus making it necessary we measure and test their ability.

2.5 Other factors

We further collected worker characteristics data sing structured survey as well as secondary data collected from institutions. The survey provided information on workers' socio-economic characteristics (household income and wealth), education level, age, self-reported tenure in years with the present employer and also as a sewing worker. We also use the administrative data to collect information on workers' daily work hours, output and wages.

2.6 Collection of Weather Variable

We installed hygrometers in the center of workplace to record the temperature and humidity for over three months. The recordings were maintained by assigned staff member on a daily basis. Temperatures were recorded in Degree Celsius (°C) and relative humidity was measured in percentage.

To increase the accuracy in measuring the effects of temperature and relative humidity on productivity, we further calculate heat index model (HI). This model is used to express the comfort or discomfort felt as a result of the combined effects temperature and humidity in the air (Adhvaryu and Nyshadham 2014). Introduced by Lans P. Rothfusz and described in a 1990 National Weather Service (NWS) Technical Attachment (SR 90-23), the regression equation is as follows (Rothfusz 1990)

$$\begin{aligned} HI_{lt} = -42.379 + 2.04901523T_{lt} + 10.14333127RH_{lt} - .22475541T\,RH_{lt} \\ - .00683783T_{lt}^2 - .05481717RH_{lt}^2 + .00122874\,T_{lt}^2RH_{lt} \\ + .00085282TRH_{lt}^2 - .00000199T_{lt}^2RH_{\mathrm{lt}}^2 \end{aligned}$$

where T_{lt} is temperature in degrees Fahrenheit and RH_{lt} is relative humidity in percentage. HI_{lt} is the heat index at location l on date t. The index also suggests two further adjustments:

- Adjustment 1: If relative humidity is less than 13 percent and the temperature reading is between 80 and 112 degree Fahrenheit, then the following adjustment need to be subtracted from HI_{lt}:

$$\frac{13 - RH_{lt}}{4}\sqrt{\frac{17 - |T_{lt} - 95|}{17}}$$

- Adjustment 2: If relative humidity is greater than 85 percent and temperature reading is between 80 and 87 degree Fahrenheit, the following adjustment needs to be added to HI:

$$\frac{RH - 85}{10} \frac{87 - T}{5}$$

The temperature and humidity was then standardized to enable further calculations. With the standardized temperature and relative humidity readings and the calculated heat index, we move on to exploring the effect of workers' productivity on these factors using the fixed effect model.

2.7 Econometric Analyses: Mincer Model

The Mincer model is one of the most commonly used empirical work where hourly earnings is explained by schooling years, labor-market experience and square of the experience (Andini 2010). We use the framework to estimate the partial contribution of different factors in determining productivity and individual wage rates.

$$lnY_i = \beta_0 + \beta_1 educ_i + \beta_2 exp_i + \beta_3 exp_i^2 + \varepsilon_i$$

where 'educ' is the years of education, 'exp' is the years of experience. β1, β2, β3 parameters are the returns to schooling and experience respectively (Pereira and Martins 2004).

The model was applied to quantify the association between productivity (efficiency and hourly wages) and different factors. The model focuses greatly on the concept of return to schooling and helps policy makers decide on future investment in education. There are number of challenges in estimating a Mincer equation. One issue is sorting or selection. For example, workers with different levels of education can sort into different types of occupations. However, occupation choice can be a result of self-selection and omitted variable can be a factor in this, which can correlate with education, resulting in obvious bias. However, we think such selection should be a lesser concern for use as we are looking into only one types of work within the same firm.

The simple structure of the Mincer Model allows flexibility of adding additional variables while at the same time defining the relationships between earnings, schooling and experience (Patrinos 2016). Beyond schooling and experience, cognitive and fine motor ability was included in the regression to test their contribution to overall productivity. We further included these factors in our previous model

$$lnY_i = \beta_0 + \beta_1 gend_i + \beta_2 age_i + \beta_3 educ_i + \beta_4 exp_i + \beta_5 exp_i^2 + \beta_6 cog_i + \beta_7 fine_i + \varepsilon_i$$

where 'gend' represents the gender of worker (a dummy variable), 'age' is the age of workers (measured in years), 'cog' correspond to the cognitive test scores and 'fine' signify outcome of the fine motor skills assessments using CSPDT (both standardized). We focused on cognitive and

fine motor ability because workers primarily performed sewing tasks on different pieces of clothes and assemble them into a final product. Research on cognitive abilities has been an interest in economics for long to observe if unobserved abilities effects both education and worker's productivity.

2.8 Fixed Effect Model to Understand the Effects of Weather

To measure the impact of weather factors on worker productivity, we use worker fixed effect models to control the worker level unobserved heterogeneity in the most flexible manners and minimum assumption on the underlying data generating process. Fixed effect models allow arbitrary correlation between unobserved heterogeneity, which are constant over time and observed explanatory variables (Wooldridge 2002). The term 'fixed' evolved as the unobserved variants are time-invariant thus fixed and the model allows to soaks up all these variants when evaluating the relationship between dependent and independent variable that vary over time (Gardiner, Luo and Roman 2009). Removal of time-invariant characteristics allowed us to assess the net effect between workers' productivity and weather factors. We use within tailor variation in the fixed effect model to understand the impact of temperature on productivity using the following model:

$$\ln y_{it} = \delta weather_{it} + \eta_i + \varepsilon_{it}$$

where, $\ln y_{it}$ is the log productivity in daily frequency for a worker. We use three different weather variables (temperature, humidity and heat index, see above) and δ is the coefficient on the daily weather variable. We control the workers specific unobserved abilities using fixed effect η_i. Hence, this model captures the variation in productivity from a mostly exogenous variation in daily weather for the same worker.

3 Results

3.1 Summary Statistics

Among the workers participating in the study, 16.5 percent were male with an average age of 25 years. As seen in Table 1, the mean education level is 8.3 years of schooling. This finding suggests participant workers have higher education level than national average. Workers also have a relatively high experience level. Older workers are seen to be more productive with 1.7

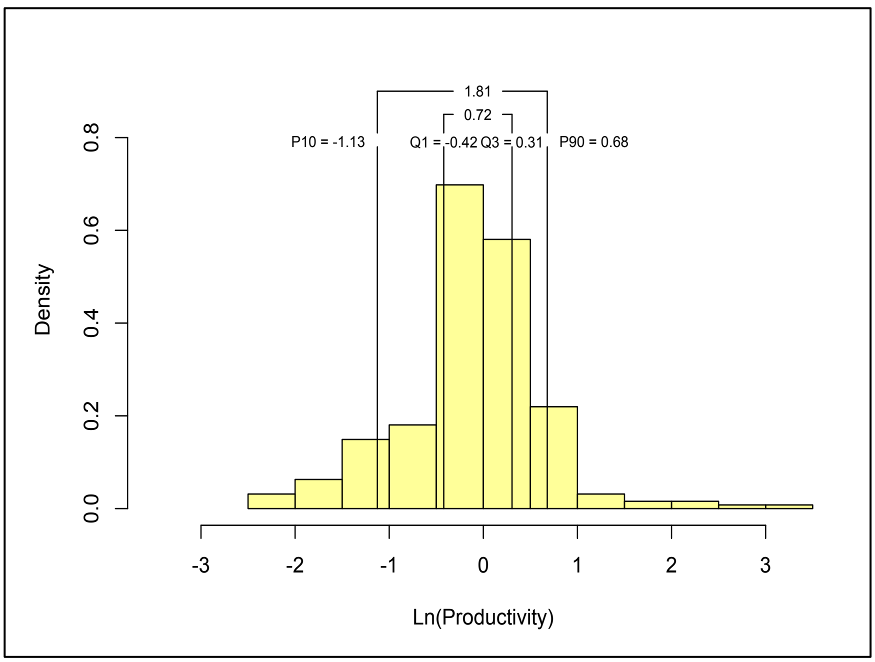
percent increase with each year of age. Cognitive tests had a scoring out of 20 with a pass mark of 12. Results suggest workers perform poorly and only 23 percent passed the test. Fine motor ability on the other hand shows promising results.

Table 1: Descriptive statistics of workers (N = 253)

	Mean	SD
Female, percent	16.5	
Age, years	25	??
Schooling, years	8.3	2.8
Work Experience, years	5.0	5.0
Cognitive Test Score, out of 20	7.4	4.2
Fine Motor Skill Test Score, minutes	14.7	6.2

Note: Based on household surveys.

Figure 1: Distribution of Log Productivity



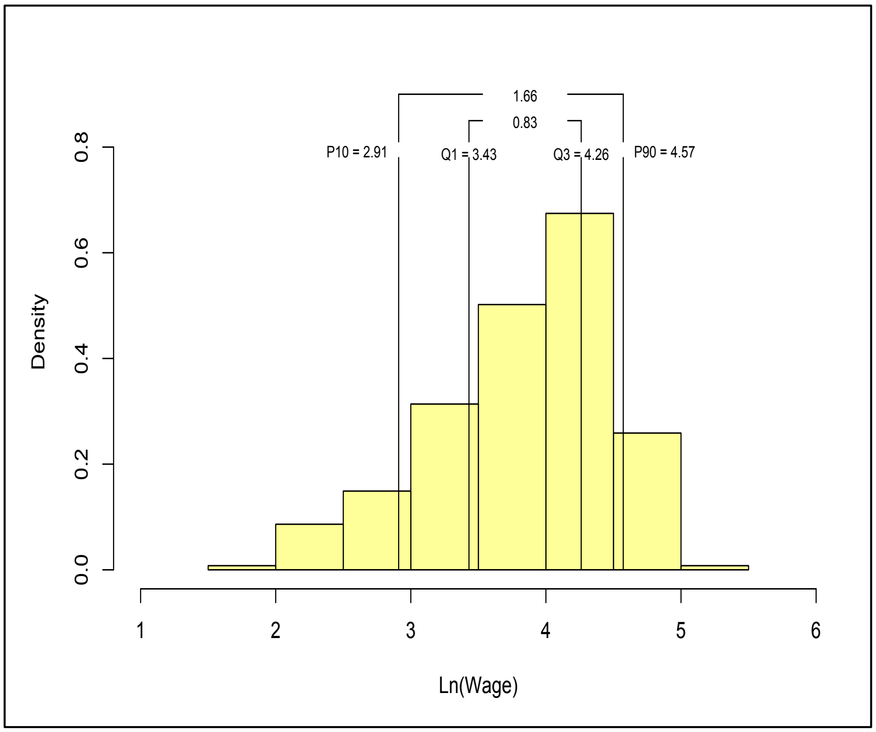
Notes: The daily productivity is measured dividing daily outputs by total hours worked on a certain date. Here we show the average daily productivity for each of the 253 workers.

3.2 Distribution in Productivity and Wage Rates

We show the distribution in log productivity in Figure 1. As we have discussed before, the productivity is a quantity index measure for relative worker efficiency and it is more meaningful to focus on the relative dispersion between workers. We find there is a wide variation in relative productivity within workers. The interquartile difference in log productivity is about 0.72

suggesting the worker at the third quartile in terms of productivity is 72 percent more productive compared to a first quartile one. The difference between 90th percentile worker and the 10th percentile worker suggests the 90th percentile worker is 181 percent or almost three times more productive that a 10th percentile worker.

Figure 2: Distribution of Log Wage



Notes: The hourly wage is measured dividing monthly salaries divided by total hours worked in a certain month. Here we show the average hourly wages for each of the 253 workers.

We also see a similar variation in real wage rates as well. The average wage is about 45 taka per hour. The third quartile worker earns about 83 percent more than a first quartile worker. Similarly, the 90th percentile worker earns about 166 percent more than a 10th percentile worker. So we indeed find a large variation in both productivity and hourly earnings. We also find that there is a strong correlation between wage rates and productivity (see Appendix Figure 1), suggesting understanding the determinants of productivity may have important implications earnings and worker welfare.

3.3 Multivariate Association

We present the multivariate associations between productivity and add different covariates in Table 2. Male tailors in our sample are on average 11.8 percent less productive compared to

the female counterparts (see Column [1], Table 1), however, these differences are not statistically significant. The productivity of the tailors increases with age on average, each successive year of age is associated with about 2.1 percent higher productivity. Interestingly, we find a very weak association between education (measured in terms of year(s) of schooling) and productivity. While there is a 2.1 percent higher return on schooling in terms of productivity, the coefficient is not statistically significant. As customary, we include a quadratic term for experience and we find both the linear and the quadratic terms statistically significant. A simple plotting suggests productivity is the highest with about 15 years of experience (see Appendix Figure 2).

In Column (2), Table 1, we report the estimated coefficients from the same model, but now we include both the measures of cognitive ability and fine motor skills. First, we notice that all the coefficients decreased in absolute value suggesting some of the effects are partially controlled by the unobserved traits such as cognitive ability and fine motor skills of the workers. For cognitive ability, we find that one standard deviation for the higher reasoning scores is associated with 8.6 percent higher productivity. As for fine motor skills, one SD higher time to finish the CPSDT tasks is associated with 9.4 percent lower productivity.

Table 2: Regression Results of Productivity and Hourly wages

	(1)	(2)	(3)	(4)
VARIABLES	**Ln Productivity**		**Ln Wages per Hour**	
Gender (male)	-0.118	-0.098	-0.095	-0.068
	(0.127)	(0.127)	(0.083)	(0.080)
Age	0.021**	0.019*	-0.002	-0.005
	(0.008)	(0.008)	(0.005)	(0.005)
Education	0.021	0.008	0.016	0.001
	(0.018)	(0.019)	(0.014)	(0.014)
Experience	0.094***	0.089***	0.166***	0.159***
	(0.020)	(0.02)	(0.015)	(0.015)
Experience (square)	-0.003***	-0.003***	-0.005***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Cognitive Scores (standardized scores)		0.086*		0.108***
		(0.045)		(0.032)
Fine Motor Skills (standardized minutes)		-0.094**		-0.129***
		(0.049)		(0.027)
Observations	253	253	253	253
R-squared	0.156	0.187	0.367	0.441

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

The results are similar for hourly wage rates. We focus on the full model when we control for the cognitive ability and fine motor skills (see Column [4] in Table 2). Men earn about 6.8 percent lower than the women workers. However, the difference is not statistically significant. We also find the hourly wages going down with age. Again, the differences are not statistically significant either. We again find the non-linear hump shape relationship between wages and experience (see Appendix Figure 2). As before, one SD higher cognitive reasoning score is associated with 10.8 percent higher wages. As for fine motor skills, we find that one SD higher time finish the test is associated with 12.9 percent lower wages.

3.4 Findings for Weather Variation

A relatively wide range of indoor air temperature was observed and the result shows that the daily indoor average temperature was 25.5°C (also see Appendix Figure 3). There has been small change in temperature within the day. The maximum observed temperature was 30°C and minimum 20.6°C. The relative humidity mean was 58.74% with a minimum recorded as 30% and the maximum was 84%. And the Heat Index mean was 79.5°C with a maximum of 98.8°C and minimum 71.4°C.

Table 3: Results from the Fixed Effect Models

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
VARIABLES		**Ln Productivity**			**Ln Wages per Hour**	
Temperature (standardized)	0.104***			-0.000		
	(0.000)			(0.992)		
Humidity (percent, standardized)		-0.071***			-0.043	
		(0.006)			(0.107)	
Heat Index (standardized)			0.109*			-0.081
			(0.051)			(0.158)
Observations	2,938	2,938	2,938	2,938	2,938	2,938
R-squared	0.430	0.428	0.427	0.245	0.245	0.245

Notes: pval in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.5 Results from Fixed Effect Models

We use a series of fixed effect models to understand the impact of winter temperature and humidity on worker productivity. We find that one SD higher indoor temperature in the factory setting is associated with 10.4 percent higher productivity for the same worker (since we have worker fixed effects in our model). Our study spans one winter season in Bangladesh and the

factories are mostly in rural settings. The tailors are more exposed to weather variation in general.

We further look at humidity and we find that one SD higher humidity is associated with 7.1 percent lower productivity. As for the composite heat index based on daily temperature and humidity, we find higher index in our sample for the winter season for our study is associated with 10.9 percent higher productivity. We estimate the same models for wages and interestingly we do not find any significant association between wage rates and weather variables.

4 Discussion

A slow productivity growth is believed to have contributed to slow recovery from the recent global recession. Thus a better understanding on factors that contribute to individual productivity is essential. This will be particularly important in low and middle income countries where welfare growth of the workers may very well depend on productivity enhancement through skill formation and human capital investment. The roles of business training have shown limited success (McKenzie and Woodruff 2008). Training and overall investment will certainly depend on addressing the factors that are associated with productivity and we identify some of those factors here.

Our results show that formal education scarcely contributes towards productivity for the tailors we have studied here. Typically formal education does not include the types of skills required to become a tailor. Bangladesh, like many other developing countries, relies heavily on the informal and semi-formal sectors where the majority of the workers are employed. Working experience of a tailor matters for productivity and also for real wages. However, the most importantly, the cognitive traits are strong determinants for productivity and wages, suggesting typically unobserved traits play important roles in determining productivity even for tasks of the tailors which are otherwise more menial and do not require very high level of skills.

Not surprisingly, the fine motor skills or finger nimbleness are important determinants in this context. However, fine motor skills are affected by environment especially low temperature. We collected data in a winter specially covering the month with typically the lowest temperatures. Lower temperature and heat indices are associated with lower temperature. Our empirical analyses involve using a fixed effect model using both spatial and temporal variation in weather variables. The exogenous variation in the in-door weather factors can affect productivity in meaningful way.

Different training programs have been typically used to enhance productivity of workers in developing country contexts. However, the roles of cognitive traits of the workers and also the fine motor skills suggest training can have limitations for workers work low-skilled tasks. This also suggests the importance of moving to more skilled tasks and move up the value chain in the manufacturing sector in general where formal skill formation can be more effective. Moreover, simple investments such as weather proofing the factory setting can also enhance productivity. It is important to explore how much factories know about the productivity variation and how much the management can follow up those. However, simple steps such as environmental control can help firms become more productive and understanding the barriers inhibiting the adoption of the productivity enhancing technology. Future studies should contribute more towards understanding such constraints.

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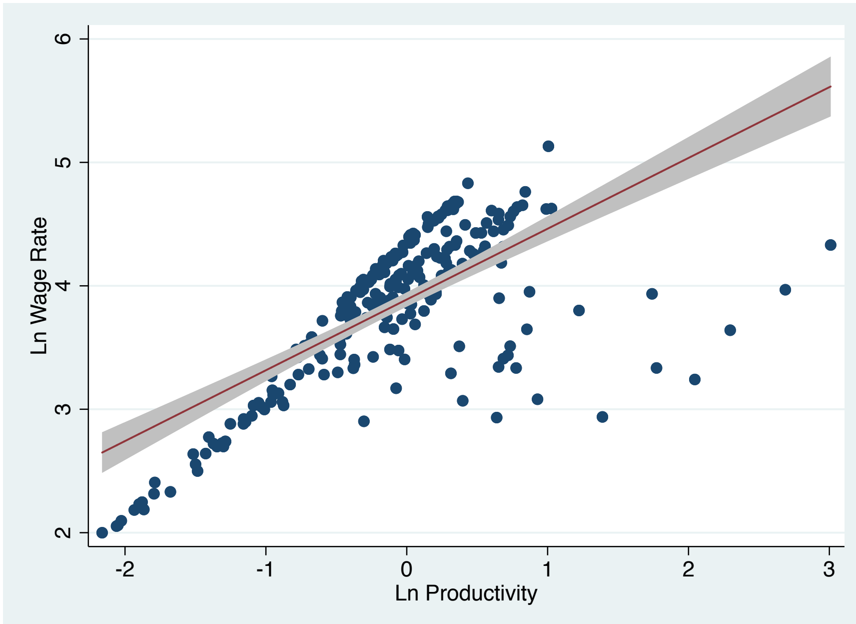
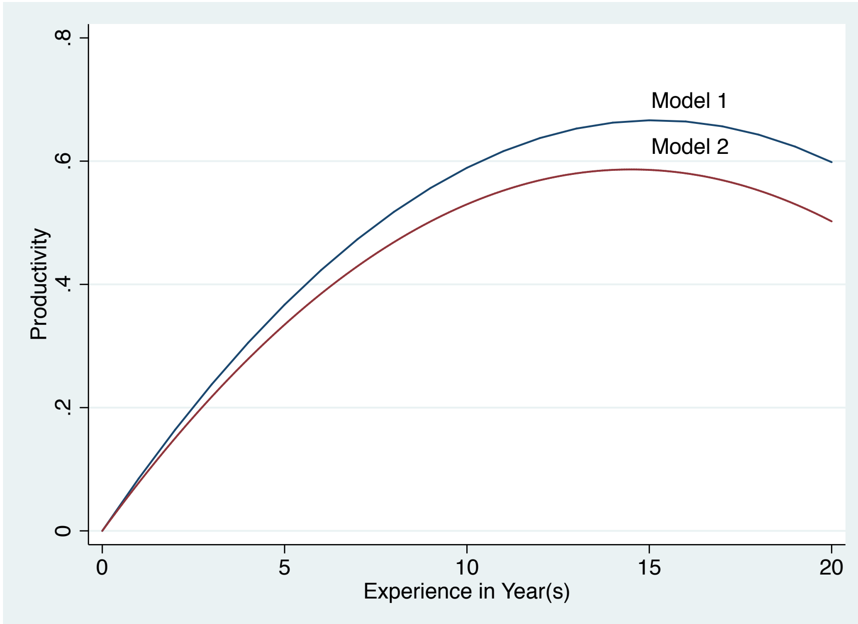
Appendix Figure 1: Scatterplot between Productivity and Wage Rates



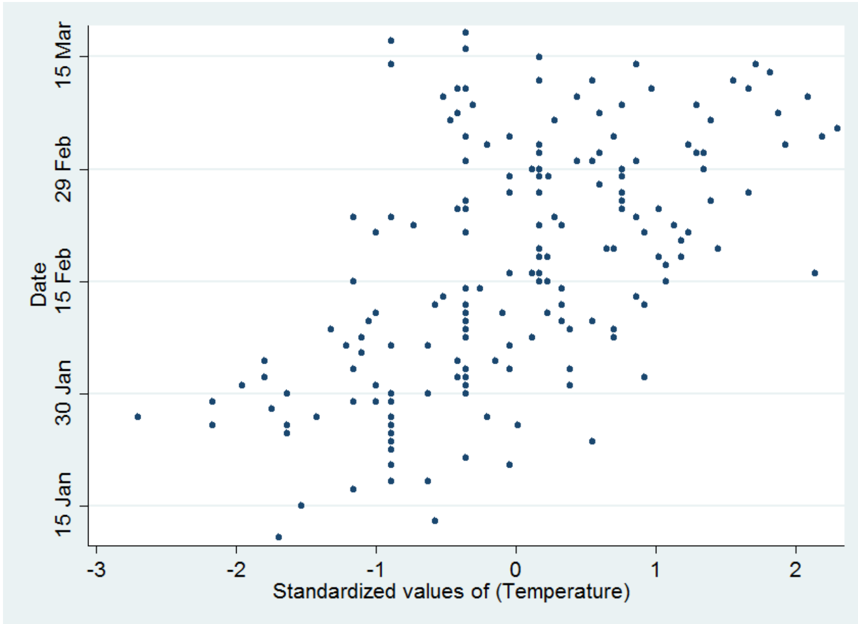
Notes: The red line shows a linear fit between average daily productivity and hourly wage rate, both taken in logs. The shaded region depicts the 95% confidence interval for the fitted line.

Appendix Figure 2: Plot of Fitted Productivity against Year(s) of Experience



Notes: Productivity (measured in logs) are simulated using the coefficients for experience and squared experience from Table 2, Columns (1) [Model 1 in the figure] and (2) [Model 2 in the figure].

Appendix Figure 3: Temperature variation over time



Notes: The temperatures are measured at daily frequencies against different worker locations. The values are standardized for the entire sample.