Are Part-Time Workers Less Productive? Evidence from a Randomized Trial in Ethiopia

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Abstract

We study self-selection of workers into part-time jobs and its implications for productivity. In recruiting for data entry work in Ethiopia, we surveyed 20,595 households and randomly offered part-time or full-time job opportunities to 6,236 job-eligible women. We find that the part-time job attracts applicants with stronger preference to shorter working hours and lower job-specific skills. Also, they exhibit lower productivity during the training as measured by data entry speed. Demographics, socioeconomic status, and attitudes toward work do not explain the selection effects. (JEL J24, O15, M51)

Keywords: part-time, selection, productivity

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1 Introduction

A growing fraction of the workforce is employed under alternative (or nonstandard) work arrangements that permit work-hour flexibility (Abraham et al. 2018; Katz and Krueger 2019). In the United States, part-time work accounts for 27 percent and 14 percent of women's and men's employment, respectively (US Census Bureau 2018)[1]. In developing countries, part-time work arrangements are also common, comprising up to 60 percent of employment (IDB 2008). Despite this prevalence, most evidence thus far on the link between part-time employment and labor market outcomes has been limited to correlations (e.g., Hirsch 2005; Manning and Petrongolo 2008; Devicienti, Grinza, and Vannoni 2015). In particular, there is no experimental evidence on who select into part-time jobs and how this selection affects productivity of the workforce.

The selection effect of part-time work on labor productivity is theoretically ambiguous. On the one hand, part-time workers could be less productive, if workers who are more productive prefer full-time jobs (e.g., Mas and Pallaise 2017). On the other hand, preference to part-time jobs could be mainly driven by family situation such as child care responsibility, which is not necessarily related with productivity. Moreover, part-time works could be more productive if ability and preference to part-time are positively correlated: high ability workers value work-hour flexibility more than low ability workers.[2]

In this paper, we study the effects of part-time (versus full-time) work arrangements on worker selection and its impacts on productivity using a randomized experiment with potential applicants for actual data-entry jobs in Ethiopia. The data entry clerk position offered an attractive employment opportunity in our study areas with low employment rates in a formal sector. The experiment focused on

[1]About one-fifth of workers in OECD countries are employed part time, and the fraction has increased in the past decade (Garnero 2016).

[2]A causal effect mechanism for a positive association between part-time work and productivity is that part-time workers may suffer less of the stress and fatigue associated with working full time (e.g., Brewster, Hegewisch, and Mayne 1994). On the other hand, part-time workers may learn and increase productivity slowly because of shorter working hours.

women, who on average place more value on flexibility in work hours due to having greater family responsibilities (e.g., Goldin 2014; Wiswall and Zafar 2018). Thus, our experiment offers an ideal setting to examine the role of both socioeconomic characteristics (such as family structure and preferences for work and family) and ability to perform the job on selection into part-time versus full-time jobs with high economic stakes.

Our study is based on a large-scale search for job applicants in a data entry unit at Africa Future Foundation (AFF), a nongovernmental organization. Specifically, AFF advertised job vacancies to 6,236 women during a census of 20,595 households in its catchment areas, Holeta and Ejerie. 71 village groups in the catchment area were randomly assigned to either full- or part-time job treatment, and flyers describing the data entry jobs were distributed to women with a high school certificate. The full- and part-time jobs requires to work eight and four hours of data entry work per day, five days a week, respectively. Both jobs had identical task descriptions and per-hour wages.[3] Applicants first completed a baseline job survey and took aptitude tests measuring demographics, socioeconomic conditions, work preferences, and cognitive and physical abilities. They are then invited to train for three hours per day for three weeks. We measured workers' productivity during this training period using error-adjusted typing and data entry speed.

We obtain two main results. First, individuals who have lower ability to perform the data entry work and who place more value on work-hour flexibility are more likely to self-select into part-time relative to full-time work arrangements. We however do not find evidence that selection is explained by other observable characteristics including demographics and socioeconomic status as well as motivations regarding jobs. Second, applicants who were recruited through the part-time job announcement exhibit significantly lower productivity by 0.10 to 0.44 of a stan-

[3]Compensating differentials (e.g., Rosen 1986) suggest that to the extent time flexibility provided by part-time work is valuable to workers, the part-time job could offer lower wages conditional on productivity. In addition, if part-time jobs provide workers with diversification of their human capital across multiple jobs, equilibrium wages for part-time work could be lower. Thus, the difference in worker characteristics and productivity between part- and full-time workers in our setting is likely a lower bound, relative to a setting with a wage discount for part-time jobs.

dard deviation than those recruited through the full-time job announcement. This productivity gap exists from the first week of training, suggesting that (intrinsic) characteristics such as ability, rather than differential skill investments during training, drive the gap. Our results imply that more productive workers prefer to work full time.

This paper relates to three strands of the literature. The first strand examines how job attributes (e.g., compensation schemes, work arrangements) affect worker selection and productivity, with a focus on the role of financial (Lazear 2000; Shearer 2004; Dohmen and Falk 2011; Dal Bó, Finan, and Rossi 2013; Guiteras and Jack 2018) and nonfinancial incentives (Ashraf, Bandiera, and Lee 2016; Deserranno 2019; Kim, Kim, and Kim 2019). Our paper is the first to provide experimental estimates of the effects of part-time recruitment on worker selection and productivity.

The second strand examines the impacts of part-time job arrangements on worker and firm outcomes. Most previous research focuses on effects of part-time employment on wage, and finds a negative association between part-time employment and wages (e.g., Manning and Petrongolo 2008; Matteazzi, Pailhe, and Solaz 2014). Those focuses on productivity limited to show correlation, and present mixed results. For example, using Dutch data on the pharmacy sector, Kunn-Nelen, de Grip, and Fourage (2013) find that employing part-time workers could increase productivity by allowing firms to allocate their workforce more efficiently. In contrast, Specchia and Vandenbergh (2013) and Devicienti, Grinza, and Vannoni (2015) use observational data to find a negative relationship between the fraction of part-time employees and firm-level productivity. Yet, Ganero, Kampelmann, and Rycx (2014), using Belgian employer-employee matched data, find that women who work part time are as productive as those who work full time. To the best of our knowledge, we are the first to estimate the causal effect of part-time recruitment on labor productivity using worker-level productivity data and show that worker selection is a key mechanism underlying the effect.

Last, our paper is related to the literature on female labor markets, especially the gender pay gap (see, e.g., Goldin 2014; Goldin and Katz 2016; and Blau and Kahn 2017). Given that women are more likely to work part time than men, our finding that part-time arrangements attract less capable workers suggests that the gender wage gap is partly due to a productivity difference.

2 Study Setting and Design

2.1 Study setting

Ethiopia is one of the least developed countries in the world, with GDP per capita of US$707 in 2015 (World Bank 2017). Only 4 percent of women and 5 percent of men have completed secondary school or gone beyond secondary school, according to the 2016 Ethiopia Demographic and Health Survey (CSA and ICF 2016). The labor force participation rate for women, however, is relatively high: 87 percent of women aged 15 or above are employed, according to the World Bank.[4]

Firms in Ethiopia's manual data entry and management industry employ women for the most part. Our study is conducted in Holeta and Ejerie. Holeta is an urban town of approximately 28,000 people located about 31 miles west of the capital, Addis Ababa. Ejerie is a mostly rural district near Holeta with a population of approximately 59,000. The level of education is relatively high in these areas, with 60 percent and 38 percent of women holding high school diplomas in Holeta and Ejerie, respectively. The literacy rates are 70 percent in Holeta and 43 percent in Ejerie.

In the study areas, the data entry clerk is an attractive job for women because it is one of the few official sector jobs available and offers a competitive salary. The data entry process involves reading information from documents (in paper form) and entering it as a data field on a computer. The job requires basic computer skills, clerical ability to read a paper survey and input the information on a computer, fine motor skills to control hands and fingers, and perseverance to perform tedious work.

[4] http://datatopics.worldbank.org/gender/country/ethiopia, accessed on July 30, 2019.

Outside options for data entry clerks include household farming and other formal sector jobs. For instance, at the time of the baseline survey, 18.8 percent (65 of 345) of applicants were working for their family and 5.8 percent (20 of 345) were working for pay in formal sectors.

2.2 Experimental design

AFF established its data entry unit with plans to hire a maximum of 100 full-time equivalent (e.g., 70 full-time and 60 part-time) women from the catchment area. In May–June 2016, AFF conducted a census in Holeta and Ejerie, gathering information on 20,595 households. During the census, job flyers with a job description, working conditions, and expected salary and benefits were distributed to resident women with a high school diploma.

71 village groups—clusters of several villages— were randomly assigned into 35 part-time and 36 full-time groups, and distributed job flyers accordingly.[5] There are 234 villages in our sample. Panels A and B of Figure A1 show job flyers for the full- and part-time positions. To apply, applicants submitted a résumé and a copy of their high school graduation exam report at the NGO office located in the Holeta city center.

The full-time (part-time) job requires eight (four) hours of work per day with a monthly pay of 1,200 (600) Ethiopian birrs (approximately US$60 (US$30)). Both jobs require three weeks of training.[6] It is worth noting that there is no wage discount for the part-time job in our setting. Therefore, to the extent that higher salary attracts workers with higher productivity, the difference in productivity between

[5]The study design and the outcome variables considered in this study are pre-specified in the pre-analysis plan at the AEA RCT Registry. https://www.socialscienceregistry.org/trials/1829/history/12246 The original study design included 81 village groups. However, because of security concerns, 10 village groups in Ejerie were excluded from the study sample. The original design also included long-term employment and further randomization at the data entry unit. However, AFF was not able to keep the plan and had to evacuate from the study area because of political turmoil, during which more than 500 people are estimated to have been killed. See https://www.theguardian.com/world/2016/oct/02/ethiopia-many-dead-anti-government-protest-religious-festival.

[6]According to the authors' market survey in 2016, a typical data entry firm in Ethiopia paid the average worker 80 Ethiopian birrs (approximately US$4) per day as a baseline wage plus 2 Birr per additional accurate entry over 30 entries per day as an incentive.

part- and full-time workers in our setting should be a lower bound (relative to a setting with a wage discount).

An important advantage of our recruitment strategy is that through the census, we observe the population of potential job applicants in the catchment area. This contrasts with most existing studies in the literature, which only observe actual job applicants. Thus, our approach increases the external validity of our findings by allowing us to compare the characteristics of applicants with nonapplicants who meet the eligibility criteria in the population.

As shown in Table 1, we identified 6,236 eligible women and provided flyers to them (or their family members) during the census. There were 3,171 eligible women in the part-time group villages and 3,065 in the full-time group villages. Among these eligible women, 230 (7.3 percent) in the part-time group villages and 226 (7.4 percent) in the full-time group villages submitted applications and supporting documents. Those who applied for the job (hereafter, job applicants) were asked to join a baseline job survey and aptitude tests at AFF's office in Holeta in December 2016. 162 (5.1 percent) and 171 (5.6 percent) job applicants in the part- and full-time village groups, respectively, completed the job survey and aptitude tests.

Although job aptitude tests already provide information on productivity of the applicants, everybody who completed the baseline job survey and aptitude tests (survey participants, hereafter), instead of top performers in the aptitude tests, were invited to three weeks of training, which entailed basic computer training, data entry practice, and daily tests. This is unique because it allows us to measure the impacts on productivity with different cutoffs used for the hiring decision.

To ensure that the participants could attend training independent of preferences for working hours, AFF offered the option to attend the training sessions either in the morning (9:00 a.m.–12:00 p.m.) or in the afternoon (2:00 p.m.–5:00 p.m.). Figure A2 shows details of the three-week-long training program. Among the survey participants, 62 (2.0 percent) in the part-time group and 61 (2.0 percent) in the full-time group participated in the training (trainees, hereafter). AFF invited the survey participants to training in five batches and each batch consists of 22 to 32 people. The administrative data collected during the training allowed us to measure the trainees' labor productivity.

Column 7 in Table 1 shows that the differences in the fractions of eligible women offered the part- and full-time job who move to the subsequent experimental stages are small and not statistically different. Therefore, any differences between the two groups of applicants in each stage are likely driven by compositional differences through self-selection.

3 Data

3.1 Data Sources

The primary data sources are the census data, baseline job survey, and administrative data collected during the job application and training. The census data cover approximately 87,000 individuals in 20,595 households in the study area and include demographic and socioeconomic variables such as age, marital status, education and employment, household assets, and family information about women's parents, spouse and children.

The baseline job survey collected comprehensive information for applicants such as (i) demographics and socioeconomic information, including educational background, employment history, household income, and assets; (ii) attitude and expectation toward work, including relative importance of the factors affecting job selection, intrinsic and extrinsic motivation, career expectations, accomplishment-seeking, status-seeking, and career concerns; and (iii) preference for working hours. The applicants also completed job aptitude tests that measure data entry ability (speed), computer literacy, clerical and computation abilities based on the O*NET, and manual dexterity ability in the Bruininks-Oseretsky Test of Motor Proficiency, 2nd edition (BOT$^{\text{TM}}$-2). Data Appendix B provides details of the specific survey modules and ability tests we employed.[7]

3.2 Sample Characteristics and Randomization Balance

In Table A2, we present descriptive statistics for a full sample of eligible women (Column 2), those in the part- and full- time groups (Columns 3 and 4), and the difference between two groups (Column 5). As shown in Panel A, the average age of job-eligible women is 26.5 years, about 73 percent of them belong to the Oromo ethnic group (the majority ethnicity in Ethiopia), and 57 percent speak the Oromo language. The fraction of eligible women who attained postsecondary education is 39 percent. Panels B and C present household- and community-level characteristics. Importantly, the table confirms that the randomization was successful: only 1 (fraction of working within household) out of 27 characteristics differs significantly at the 10 percent level (Column 6).

3.3 Outcome Variables

The prespecified primary outcomes for this study are error-adjusted typing and data entry speed during the training. Specifically, we first measure the number of total words correctly entered per minute (typing speed) using Mavis Beacon, a computer application designed to train typing, two times per training day.[8] Second, we measure the number of data fields correctly entered scaled by the time spent in data entry (data entry speed). For data entry, we gave the same set of census forms to all trainees on a given day and asked them to type in the information on the computer in 15 minutes per test.[9] To ensure accurate measurement of performance, two supervisors independently recorded each trainee's number of correct words or

[7]We do not find a systematic difference in demographic and socioeconomic characteristics between the job applicants who did and did not participate in the job survey (see Table A1).

[8]Each test lasted 7 to 15 minutes and asked the trainee to type in a series of words or sentences shown on the computer screen. See https://en.wikipedia.org/wiki/Mavis$_{B}eacon_{T}eaches_{T}yping$ for a description of the application.

[9]A "correctly entered field" is a nonmissing value in a census data field (e.g., a person's name) that is entered by the trainee without an error or a missing value that is not entered. All other entries are considered incorrect.

fields entered per minute for each test. For our empirical analysis, we standardize each of the two productivity measures by subtracting its mean and scaling by the standard deviation (see, e.g., Kling, Liebman, and Katz 2007).

4 Empirical Framework

4.1 Worker Selection

We first study the characteristics of applicants for the part-time and full-time jobs by estimating the following regression using a sample of 333 applicants who participated in the baseline job survey:

$$Char_{ij} = \alpha_0 + \alpha_1 Part_{ij} + \varepsilon_{ij} \tag{1}$$

where $Char_{ij}$ includes applicant characteristics measured in the baseline job survey; $Part_{ij}$ is an indicator equal to one if individual i in village group j was given a part-time job opportunity and applied for it, and zero if a full-time opportunity was given and applied for; and ε_{ij} is an error term clustered at the village group level.

In addition, we provide further evidence on worker selection by examining which characteristics of eligible women in the population affect their decision to apply for the part-time versus full-time job, conditional on receiving the job opportunities. We estimate the following regression using the sample of 6,236 eligible women identified through the census:

$$Applied_{ijk} = \beta_0 + \beta_1 Part_{ijk} + \beta_2 Char_{ijk} + \beta_3 Part_{ijk} \times Char_{ijk} + \mu_k + \varepsilon_{ijk} \tag{2}$$

where $Applied_{ijk}$ is an indicator equal to one if individual i in village group j and district k (i.e., Holeta or Ejerie) applied to a (full- or part-time) job, $Part_{ijk}$ is an indicator equal to one for individual i who resides in part-time village group, and zero in a full-time village group. $Char_{ijk}$ includes individual characteristics measured in the census, and $\mu_k$represents district fixed effects. ε_{ijk} is an error term clustered at the village group level. Our coefficient of interest is β_3, which captures a differential probability of job application for eligible women in the part-time relative to full-time villages based on individual characteristics. To the extent that different types of workers apply for part-time versus full-time jobs, β_3 would be significantly different from zero for some characteristics.

An important advantage of equation (1) compared to equation (2) is that we can test for a richer set of potential determinants of worker selection drawn from applicants' job surveys and tests. For example, the baseline job survey measures individual ability (e.g., data entry skill, clerical and computation ability, computer literacy, and manual dexterity), preferences for working hours, and attitudes and expectations toward work, which are potentially important determinants of job choices not measured in the census. In comparison, equation (2) allows us to compare the characteristics of applicants with nonapplicants satisfying the eligibility criteria in the population.

4.2 Labor Productivity

We measure the effects of part-time relative to full-time worker recruitments on labor productivity by comparing the performance of the two groups during the training. Specifically, we estimate the following regression using a sample consisting of worker-training day-trial observations:

$$Productivity_{iltsj} = \gamma_0 + \gamma_1 Part_{ij} + \upsilon_l + \lambda_t + \mu_s + \varepsilon_{iltsj} \tag{3}$$

where $Productivity_{iltsj}$ is either (i) typing speed (words per minute from Mavis Beacon) or (ii) data entry speed for individual i at trial l in day t in training batch s from village group j; υ_l, λ_t, and μ_s are trial, working day, and worker batch fixed effects, and $Part_{ij}$ is an indicator variable equal to one if worker i in village group j is recruited as part time, and zero otherwise. ε_{iltsj} is an error term clustered at the village group level.

We argue that γ_1, which captures a productivity difference between part- and full-time recruited trainees, is driven by selection in our setting. A key assumption is that there is a negligible incentive effect, in which those recruited through the part-time arrangement invest less in human capital (e.g., exert less effort) during the training because they face lower returns on the investment. We later test and discuss the plausibility of this assumption by examining training attendance as well as a trend in productivity difference between the part- and full-time groups in Section 5.3.

5 Results

5.1 Worker Selection

We begin our empirical analysis on the worker selection by examining the characteristics of women who applied for part-time versus full-time jobs. To investigate the selection of workers between part- and full-time jobs, we employ three samples of job applicants in this analysis: (i) all applicants; (ii) applicants who participated in job training (hereafter, trainees). We also show the characteristics of the trainees in the top and bottom 50 percent separately. The top 50 percent sample is the most relevant for a firm's hiring policy because it represents a subset of high-quality applicants that a data entry firm would hire in practice.[10] In Section 5.2, we examine the robustness of our results by varying the cutoff for hiring.

Table 2 presents the results of estimating equation (1), which compares the characteristics of applicants to part- and full-time jobs. Panel A shows that the part-time applicants have significantly lower ability test scores than their full-time counterparts. For example, the average part-time applicant in the full sample (columns 1–3) performs significantly worse in the data entry test by 0.24 standard deviations. We find a similar pattern in the standardized score combining the five ability tests:

[10] The median words per minute (WPM) for our training participants is 12. Indeed, AFF found applicants with average performance below the median largely unemployable. Karat et al. (1999) find that for a group of IBM employees who are experienced computer users and native speakers of English, the average typing speed is 33 WPM.

part-time applicants perform significantly worse by 0.13 standard deviations. Importantly, the difference in ability between part- and full-time groups is larger in magnitude when conditioning on top 50 percent training performance during training (columns 4–6); the absolute difference in standardized score combining the five ability tests increases to 0.46 standard deviations for trainees with top 50 percent performance. In contrast, trainees with performance in the bottom 50 percent show no significant difference in the ability measures between the part-time and full-time groups (columns 7–9).

In addition, as shown in Panel B, we find that the part-time applicants less likely to prefer work over family, and full-time work over part-time work. The difference is between the part- and full-time applicants is on average 0.14 standard deviations (columns 1–3). The difference among those in top 50 percent training performance is larger, although it is not statistically significant (columns 4-6).

However, as shown in Panels C and D, we find little evidence that demographic, socioeconomic variables, and attitude and expectations toward work drive selection between part- and full-time jobs. One exception is that full-time recruited women have a spouse who is more supportive of her work.

In addition, Table A3 presents the results of estimating equation (2) by employing demographic and socioeconomic characteristics collected from the census. Column 1 shows that the average job application rate is statistically not different between women who are offered part-time and full-time job opportunities. We find that most of the coefficients on $Part \times Char$ are insignificant at the 5 percent level across demographic and socioeconomic characteristics, confirming the Table 2 findings. The only exception is that women with a spouse who strongly supports her working tend to apply more to full-time jobs (column 12), which is significant at the 5 percent level. This result is consistent with a similar finding in Table 2, Panel C. Overall, both in Tables 2 and A3, we do not find evidence that socio-demographic characteristics are limited to explain the worker selection.

5.2 Effects on Productivity

The finding that part-time job applicants have lower ability than full-time job applicants suggests that they may also exhibit lower productivity at work. As explained in Section 2.2, all job applicants were invited to three hours per day of training for three weeks (i.e., 15 days). Figure 1 presents trends in standardized labor productivity during the training period.[11] Panel A shows that productivity increases over time both for the part-time (solid line) and full-time (dashed line) trainees in the top 50% performer sample. As expected from the selection result in Section 5.1, we find that trainees recruited through the part-time arrangement perform worse than those recruited through the full-time arrangement from the beginning of the training. Panel B shows that the difference is statistically significant at the 5% level during the training. In contrast, Panels C and D show that, for the bottom 50% performers, the difference between the part- and full-time groups is insignificant.

Now we turn to Table 3, which presents corresponding results from the regression in equation (3) for the top 50 percent performers (columns 1–4) and the bottom 50 percent performers (columns 5–8). Panels A–C show results for overall standardized productivity, typing speed, and data entry speed. In columns 3 and 4 and columns 7 and 8, we further include the variable *Day* and its interaction term with a part-time indicator. This specification allows us to estimate differential time trends in productivity between trainees recruited through part- and full-time job opportunities. In particular, the specification in columns 4 and 8 is our preferred one, given that it controls for training day-trial and batch fixed effects and estimates the dynamics of productivity difference between the part- and full-time recruited trainees.

Column 4 shows patterns among the top 50 percent performers. The initial productivity difference is 0.43 standard deviations ($= -0.436 + 0.005 \times 1$ day), which is larger than the initial difference for the full sample (0.28 standard deviations).

[11] Specifically, the figure presents coefficient estimates from a variant of equation (3), which controls for various fixed effects and replaces the Part indicator with the indicators for part-time and full-time workers, interacted with indicators for training days (from 1 through 15).

Further, the part- and full-time groups do not converge on productivity over time. Panels B and C show that results for each productivity measure (typing and data entry speed) exhibit similar patterns, although some coefficients are estimated less precisely in part because of a smaller sample size.[12] Column 8 shows different patterns of the bottom 50 percent performers, and we do not find evidence between the part- and full-time groups.

To further examine the sources of the difference in the effect of part-time recruiting on productivity across the top and bottom performer samples, we estimate quantile regressions of standardized productivity. Table A4 shows that the productivity difference is insignificant below the third quartile, and becomes statistically and economically significant above the top decile. Figure A4 also shows the first-order stochastic dominance of CDF of full-time trainees over part-time trainees among the top 50 percent performers. These findings suggest that the lower productivity of the part-time recruited trainees is largely driven by those in the very top portion of the distribution, who are more employable applicants.

5.3 Further Results

Employment cutoffs Given the larger productivity difference between part- and full-time recruited trainees among the top 50 percent sample relative to the bottom 50 percent sample, a natural question is how the difference would vary as we change the cutoff to define a top-performers. This question has important implications for practice because firms could decide to hire different fractions of job applicants depending on their labor demand, for example. By observing labor productivity across all training participants, we can estimate the effect of part-time recruiting on employee productivity by varying the performance cutoff to hire employees. We apply cutoffs ranging from no restriction (i.e., 100 percent) to top 45 percent in 5 percent increments.[13]

[12]Figure A3 plots productivity changes over time for the part-time and full-time groups by task.

[13]We stop at the top 45 percent, given that the fraction of part-time recruited trainees in the sample changes considerably past the threshold.

Figure 2 shows the results. The x-axis presents the percentile that defines a study sample, and the y-axis presents the productivity difference between part- and full-time recruited workers. We find that the productivity gap between the two groups is generally larger among subsamples with higher performance cutoffs. The productivity difference is statistically significant for most subsamples from top 75 percent to 45 percent performers. This finding suggests that when a firm hires top performers among applicants (which would naturally occur), the productivity gap between the part- and full-time recruited employees would be more pronounced.

Incentive effects One might argue that the productivity difference during the training is driven by incentive effects, in addition to our proposed selection effects. For example, trainees who expect to work full time could have a stronger incentive to make an effort because their future return on the human capital investment would be higher once they are employed. However, this incentive effect is unlikely to explain the observed productivity difference, for a couple of reasons. First, productivity of part-time recruits increases faster than or at least on par with productivity of full-time recruits (Table 3). Second, the incentive effect cannot explain the significant difference in productivity that exists at the beginning of training. Third, we do not find evidence on difference in training participation between the part- and full-time recruits, which would be an important investment for their human capital (Table A5).

What explains the productivity difference? Next, we examine the extent to which measurable ability, preferences for work hour flexibility, and attitudes and expectation toward work can explain the effect of part-time recruitments on productivity. To this end, we reestimate equation (3) by including controls for: (i) ability; (ii) preferences and attitudes for work and family; and (iii) both, which are examined in Table 2.

Table A6 presents the estimation results. Columns 1–4 and 5–8 show estimates for the full and top 50 percent trainee samples, respectively. Columns 1 and 5 show the baseline estimates excluding the controls for subsamples of workers with the control variables. In columns 2 and 6, we find that including the ability proxies measured in the job aptitude tests considerably reduces the productivity difference. For example, the ability proxies can explain 78.0 percent (= $[0.419 - 0.092]/0.419$) of the productivity difference, whereas work and family preferences can explain only 13.4 percent (= $[0.419 - 0.363]/0.419$) for the top 50 percent trainee sample (Panel A, columns 5–8).[14] These findings are consistent with the result in Table 2 that the part- and full-time applicants are significantly different in observable job-specific ability, whereas they are similar in variables capturing family and work preferences. Panel B includes these controls and their interaction terms with the variable *Day* and shows that individual characteristics do not explain the differential trends in productivity.

6 Conclusion

Understanding how a part-time work arrangement affects employee selection and productivity is an important issue, given its increasing prevalence across both developing and developed economies. We explore this issue by implementing a randomized field experiment that provides part- and full-time data entry job opportunities to women. We find that applicants with lower job-specific ability and with preference to shorter working hour are more likely to select into part-time relative to full-time arrangements, and they exhibit lower productivity at work. Other observable characteristics capturing demographics, socioeconomic status, and attitudes and expectation toward work barely explain the selection effect on productivity.

Our findings imply that the wage penalty associated with part-time employment found in previous research (e.g., Hirsch 2005; Manning and Petrongolo 2008) could be explained, at least in part, by lower ability and productivity of part-time employees. In addition, our finding that high ability workers prefer full-time jobs suggests

[14]Following Gelbach (2016), we decompose the effect of part-time recruitment that is explained by covariates capturing (i) ability and (ii) preferences for work and family in column 5 of Panel A (-0.419). We find that the portion explained by the former is -0.340 (significant at the 1% level), whereas that by the latter is insignificant at 0.033.

that measured individual abilities and working hours are complementary.

A limitation of the study is that we measure productivity only during job training. Because real-life employment goes beyond training and lasts much longer, future work could build on our framework by examining whether the demonstrated effect holds over a longer employment horizon. Relatedly, the current experimental design does not allow us to examine how part-time arrangements affect worker retention, another important aspect of productivity.

Last, our paper offers implications for women's labor market issues, the gender pay gap in particular (see, e.g., Goldin 2014; Goldin and Katz 2016; and Blau and Kahn 2017). Given the greater concentration of women in part-time jobs, our finding that part-time arrangements attract low-ability workers suggests the gender wage gap is partly due to a productivity difference. Thus, future research that investigates the role of workplace flexibility–such as the part-time option we examine–for mitigating the pay gap should take into account a negative selection effect on workers' ability.

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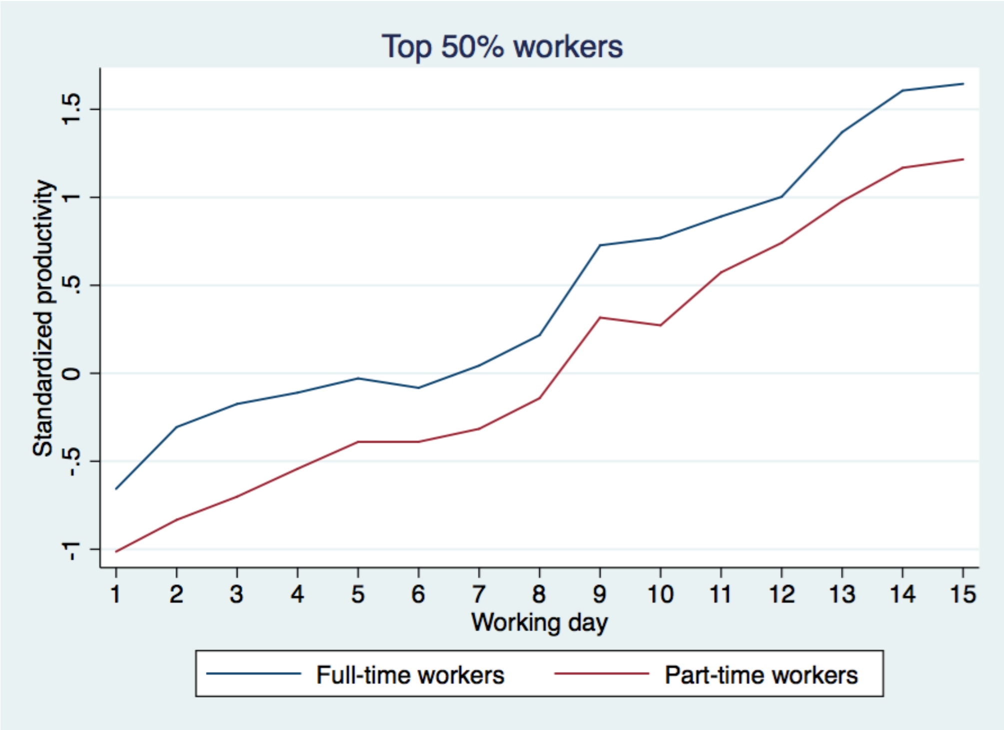
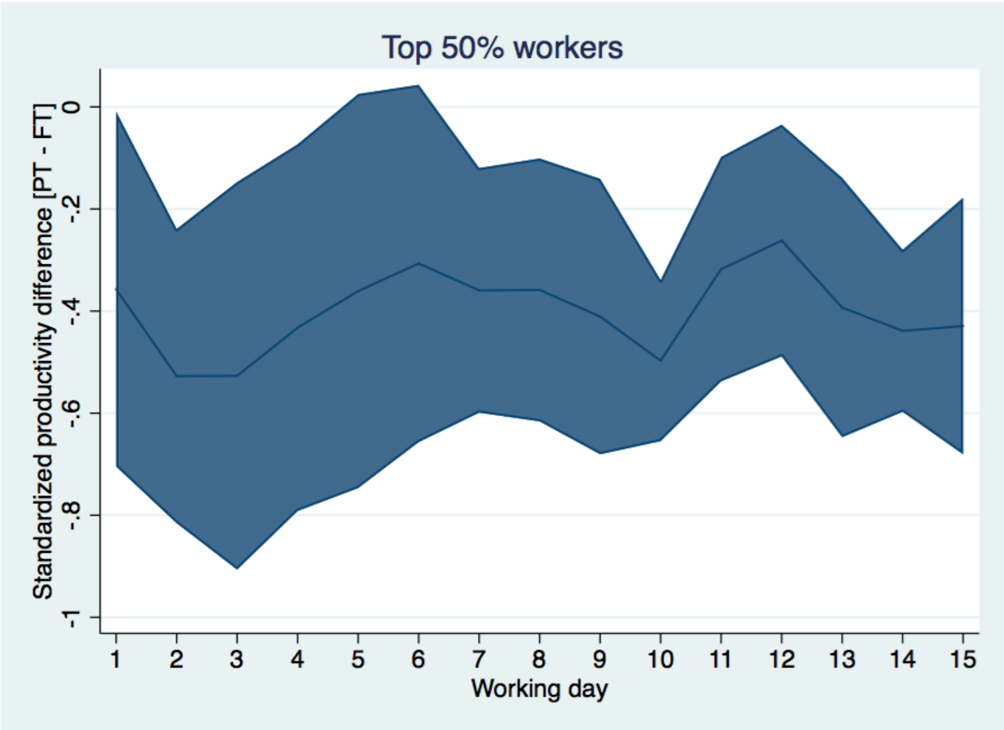
Figure 1: Productivity of part-time and full-time workers over time

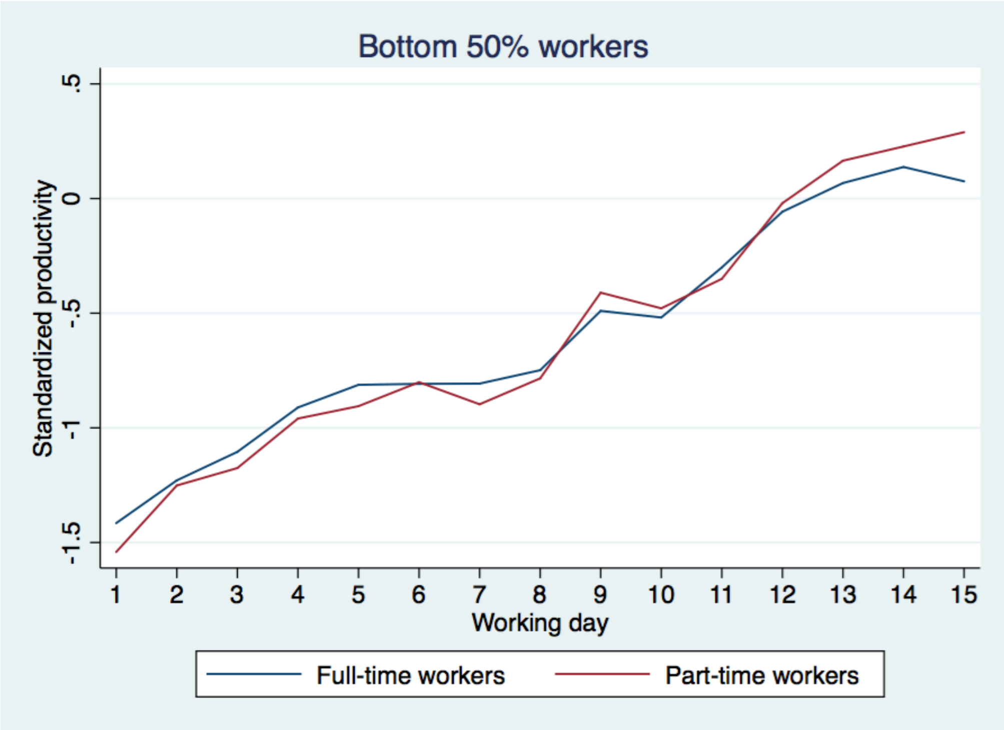
Panel A. Top 50 percent performers



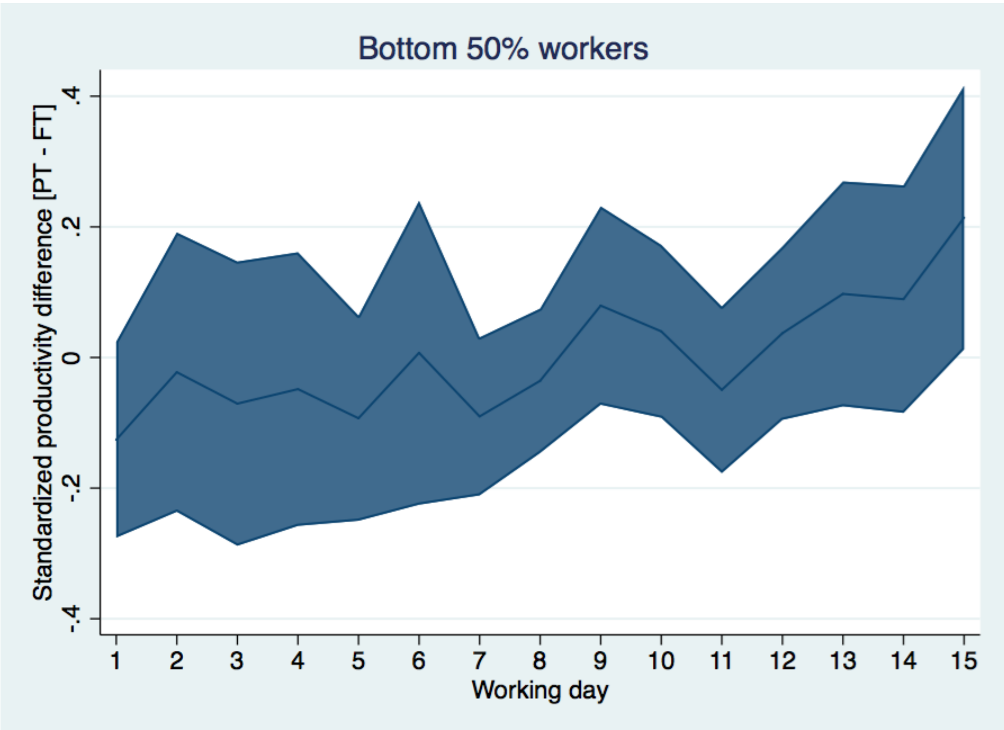
Panel B. Top 50 percent performers – difference



Panel C. Bottom 50 percent performers



Panel D. Bottom 50 percent performers – difference



Note: The figure presents coefficient estimates and standard errors (clustered at the village group level) from a variant of equation (3) which replaces the *Part* indicator with the indicators for part-time and full-time workers, interacted with indicators for training days (from 1 through 15).

Figure 2: Average productivity difference between part-time and full-time workers conditional on hypothetical hiring cutoffs

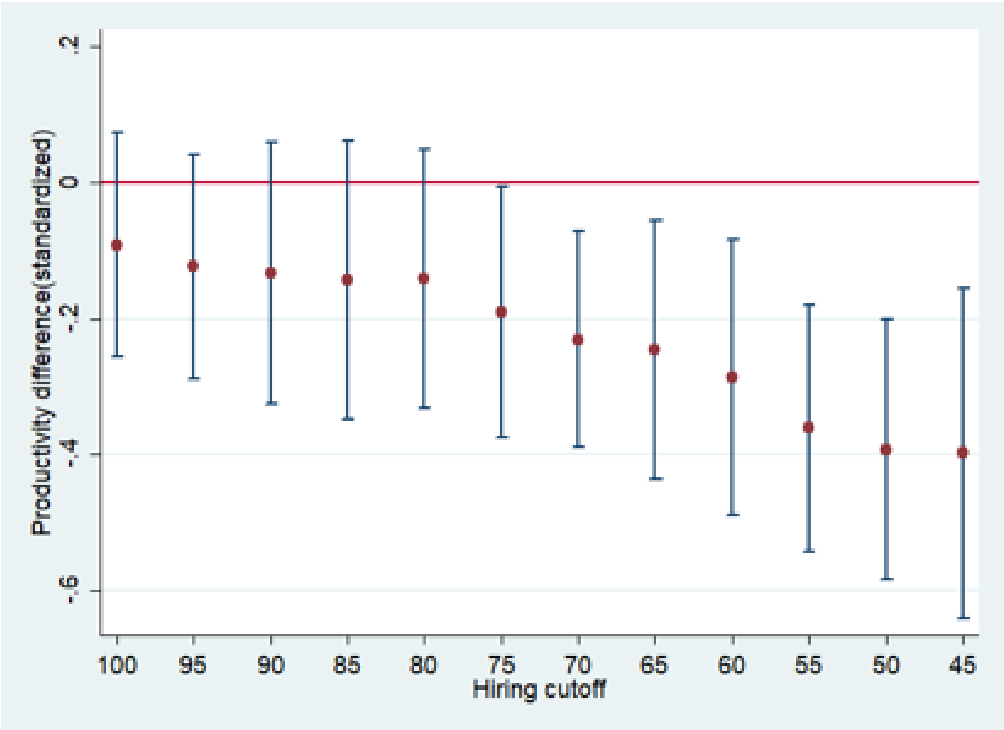


Table 1: Experiment stages

		Number and percentage of individuals					(3) - (5)
Approximate time	Experimental stage	Part-time		Full-time		Total	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
May to July 2016	Census (job flyers distributed)	3,171	100.0%	3,065	100.0%	6,236	-
July to August 2016	Submitted job application	230	7.3%	226	7.4%	456	0.87
December 2016	Participated in job survey and aptitude tests	162	5.1%	171	5.6%	333	0.77
August to December 2017	Participated in job training (more than a week)	62	2.0%	61	2.0%	123	0.72

Note: The proportion of individuals remaining over experiment stages is in parentheses. For example, the number of participants in stage B is divided by the number of participants in initial stage A.

Table 2: Selection by part-time recruitment

Sample	All applicants			Top 50%			Bottom 50%		
Variable	Observation	PT applicants	Mean diff. (PT-FT)	Observation	PT applicants	Mean diff. (PT-FT)	Observation	PT applicants	Mean diff. (PT-FT)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Ability Test Scores (Standardized)									
Data entry test	330	-0.141	-0.242**	63	0.134	-0.652	60	-0.044	-0.08
Clerical ability	330	-0.032	-0.053	63	0.067	-0.464	60	-0.309	-0.119
Computation ability	328	-0.011	0.01	62	0.140	-0.129	60	-0.027	0.146
Computer literacy	326	-0.046	-0.105	63	-0.090	-0.627	59	-0.080	0.097
Manual dexterity ability	329	-0.108	-0.232**	63	0.053	-0.429	59	0.047	0.093
Standardized Score	1643	-0.065	-0.126*	314	-0.196	-0.456***	298	0.013	0.024
Panel B. Preferences for Work Hours and Family (Standardized)									
Preference for family to work	328	0.071	0.105	63	-0.146	0.163	58	0.217	0.05
Preference for non-work, working part- to full-time	267	0.104	0.185	52	-0.076	0.065	50	0.204	0.163
Preference for part-time to full-time work	323	0.076	0.147	62	0.086	0.361	59	0.023	0.062
Standardized Score	918	0.082	0.143**	177	-0.044	0.2	167	0.143	0.086
Panel C. Individual Characteristics									
Age	284	22.525	-0.061	56	22.438	1.396	50	22.783	0.783
Married	322	0.288	-0.073	60	0.371	0.091*	60	0.185	-0.239
Number of household members	313	4.000	0.288	58	4.394	0.314	56	3.400	0.142
Subjective health status [1-5]	327	4.475	0.002	63	4.500	0.204	60	4.333	-0.334
Have a child(ren)?	330	0.237	-0.028	63	0.306	0.084	60	0.222	-0.051
Number of Children	330	0.313	-0.028	63	0.333	0	60	0.259	-0.014
Currently in school	322	0.195	-0.069	61	0.306	-0.174	60	0.259	0.138
Working status	287	0.299	-0.028	55	0.241	-0.028	54	0.320	-0.094
Family business	286	0.234	0.019	55	0.172	-0.02	54	0.200	-0.076
Official Sector	285	0.059	-0.022	55	0.069	0.031	54	0.120	-0.018
Asset score [1-10]	280	5.124	-0.114	55	5.581	0.081	46	5.000	0.826
Supportive spouse for job [1-5]	267	4.103	-0.338**	48	3.870	-0.701	48	4.023	-0.477
Panel D. Motivations Regarding Jobs									
Motivation for choosing a job [1-20]:									
a. Good future career	326	4.875	0.369	62	4.444	-0.287	60	4.519	-0.087
b. Earns respect and high status	308	3.758	-0.173	54	3.531	0.076	59	4.000	-0.091
c. Pays well	310	3.416	-0.491	58	3.286	-0.757	59	3.346	-0.593
d. Interesting job	320	4.146	0.171	60	3.917	-0.625	60	4.259	0.532
e. Acquire useful skills	320	5.013	0.13	63	5.333	0.333	56	4.640	-0.102
Importance in choosing a job [1-4]:									
Intrinsic motivation	309	3.420	0.019	35	3.490	0.182	57	3.418	-0.019
Extrinsic motivation	309	0.228	0.001	35	0.233	0.012	57	0.228	-0.001
Career expectation	315	3.260	-0.014	36	3.347	-0.031	58	3.295	0.014
Accomplishment	318	3.535	-0.012	35	3.574	-0.008	58	3.497	-0.066
Status	314	3.317	-0.009	35	3.312	-0.069	57	3.416	0.008
Career progress	329	2.785	-0.089	36	2.778	-0.271	60	2.938	0.09
Compensation and benefits	325	3.225	0.027	35	3.120	-0.154	60	3.281	0.117

Note: See Data Appendix for detailed definitions of each variable. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively, based on robust standard errors clustered at the village group level. Asset score is the number of items owned by a household among the following: electricity, a watch/clock, a television, a mobile phone, a landline phone, a refrigerator, a bed with a mattress, an electric *mitad* (grill), and a kerosene lamp.

Table 3: Impact of part-time recruitment on labor productivity

	Top 50% trainees				Bottom 50% trainees			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Standardized productivity								
Part	-0.354***	-0.392***	-0.436**	-0.431**	0.109*	0.020	-0.023	-0.133
	(0.109)	(0.098)	(0.193)	(0.192)	(0.062)	(0.050)	(0.091)	(0.100)
Day	-	-	0.170***	0.166***	-	-	0.111***	0.110***
	-	-	(0.009)	(0.009)	-	-	(0.006)	(0.006)
Part × Day	-	-	0.005	0.005	-	-	0.016	0.016*
	-	-	(0.013)	(0.013)	-	-	(0.010)	(0.009)
Constant	0.634***	0.656***	-1.475***	-0.885***	-0.493***	-0.458***	-0.916***	-1.532***
	(0.097)	(0.095)	(0.037)	(0.163)	(0.046)	(0.028)	(0.161)	(0.030)
Task type fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.033	0.526	0.481	0.511	0.007	0.531	0.451	0.513
N	2638	2638	2638	2638	2428	2428	2428	2428
Panel B: Typing speed (Standardized)								
Part	-0.466***	-0.443***	-0.414**	-0.357**	0.115	-0.011	-0.036	-0.181
	(0.136)	(0.124)	(0.183)	(0.173)	(0.068)	(0.053)	(0.106)	(0.122)
Day	-	-	0.160***	0.159***	-	-	0.098***	0.099***
	-	-	(0.007)	(0.007)	-	-	(0.007)	(0.007)
Part × Day	-	-	-0.011	-0.010	-	-	0.021	0.021
	-	-	(0.010)	(0.010)	-	-	(0.013)	(0.013)
Constant	0.710***	0.696***	-1.263***	-0.610***	-0.500***	-0.450***	-0.582***	-1.314***
	(0.126)	(0.119)	(0.048)	(0.158)	(0.053)	(0.029)	(0.161)	(0.034)
R^2	0.063	0.587	0.549	0.584	0.008	0.605	0.492	0.597
N	1739	1739	1739	1739	1609	1609	1609	1609
Panel C: Data entry speed (Standardized)								
Part	-0.136	-0.286***	-0.037	-0.139	0.098	0.079	-0.084	-0.125
	(0.092)	(0.078)	(0.264)	(0.291)	(0.062)	(0.057)	(0.158)	(0.157)
Day	-	-	0.264***	0.257***	-	-	0.164***	0.153***
	-	-	(0.017)	(0.017)	-	-	(0.008)	(0.008)
Part × Day	-	-	-0.013	-0.013	-	-	0.017	0.017
	-	-	(0.024)	(0.024)	-	-	(0.015)	(0.015)
Constant	0.485***	0.574***	-2.206***	-2.325***	-0.479***	-0.472***	-2.465***	-2.347***
	(0.054)	(0.062)	(0.093)	(0.220)	(0.035)	(0.034)	(0.206)	(0.096)
Day fixed effects		Y				Y		
Batch fixed effects		Y		Y		Y		Y
Trial fixed effects		Y		Y		Y		Y
R^2	0.004	0.573	0.458	0.531	0.005	0.520	0.437	0.453
N	899	899	899	899	819	819	819	819

Note: Robust standard errors clustered at the village group level are reported in parentheses. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Appendix Figures and Tables

Figure A1. Job flyers

Panel A. Full-time job flyer

Panel B. Part-time job flyer

Figure A2. Training schedule

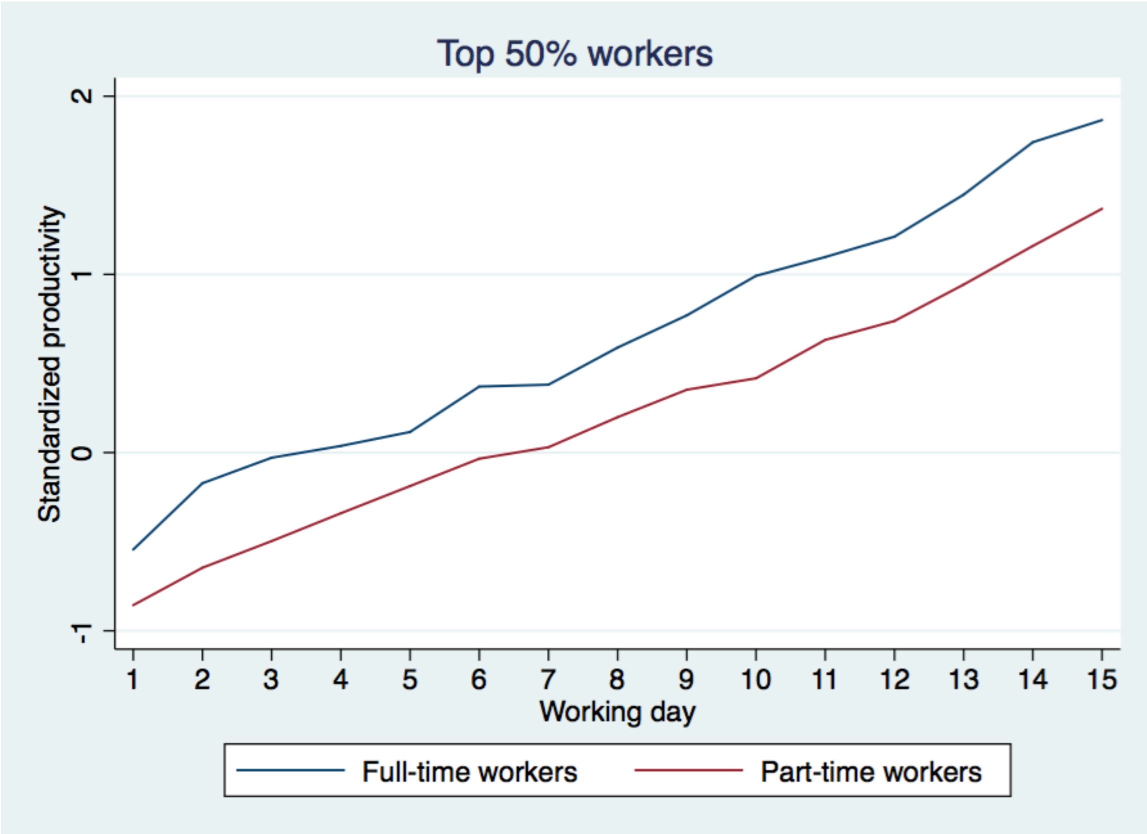
1st Week	1st	2nd	3rd	4th	5th
9:00-9:30	Introduction	Lecture 2: Microsoft Word - Saving + Opening + Editing + Typing + Copy & Paste	Lecture 3: Microsoft Word - Tables(Create + edit) + Inserting Pictures	Lecture 4: Microsoft Word - Spell Check + Printing and if time allows to create a	Final Quiz
9:30-10:00	Pre Assesment Test (Via Google Form)				
10:00-10:30	Lecture 1: Basic Computer Skills + Operating a Computer(Typing + Using a Mouse + Turning on a computer + Navigating applications)	Typing(Speed Test at the beginning for 7 minutes and at the end for 7 minutes) + Lessons Only			Typing (Mavis Beacon) Speed Test (7 minutes Each) + Lessons Only
10:30-11:00					
11:00-11:30	Typing (Speed Test at the beginning for 7 mintues and at the end for 7 minutes) + Lessons Only				Introduction to Epidata
11:30-12:00					
12:00 - 12:30	Self Practice (At will)				

2nd Week	1st	2nd	3rd	4th	5th
9:00-9:30	Pre Assessment Test (Via Google Form	Excel: Basic Making Lists	Excel: Sums + Average + Calculations	Final Assessment Test(Via showing the assistants)	Test (14minutes) + Bubble Pop (15 Minutes) + Lesson (Rest of Time)
9:30-10:00	Excel: Lecture 1				
10:00-10:30		Test (14minutes) + Gumball Gambit(15 Minutes) + Lesson (Rest of Time)	Test (14minutes) + Shark Attack (15 Minutes) + Lesson (Rest of Time)	Test (14minutes) + Road Trip (15 Minutes) + Lesson (Rest of Time)	
10:30-11:00	Test (14minutes) + Road Race Game (15 Minutes) + Lesson (Rest of Time)				Data Entering (Average 15 minutes) 5th
11:00-11:30					
11:30-12:00	Data Entering (Average 15 minutes) 1st	Data Entering (Average 15 minutes) 2nd	Data Entering (Average 15 minutes) 3rd	Data Entering (Average 15 minutes) 4th	
12:00 - 12:30	Self Practice (At will)				

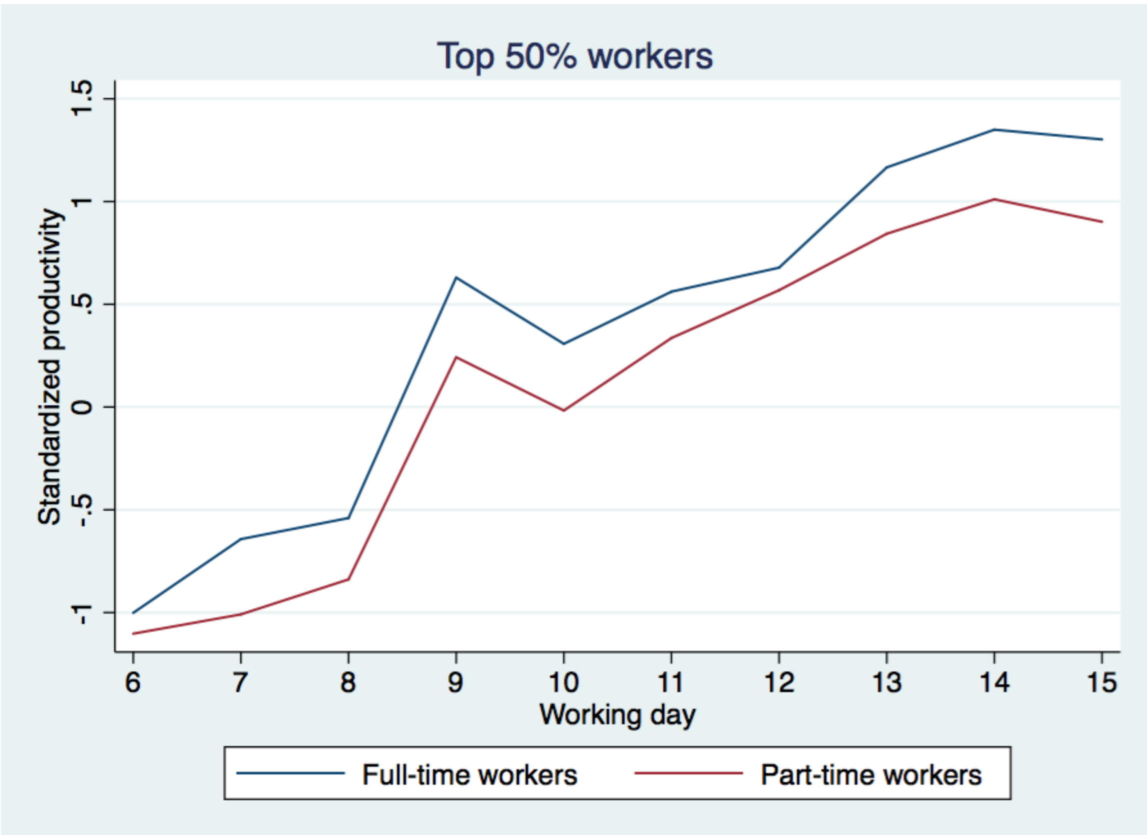
3rd Week	1st	2nd	3rd	4th	5th
9:00-9:30	Test (14minutes) + Road Race Game (15 Minutes) + Lesson (Rest of Time)	Test (14minutes) + Gumball Gambit (15 Minutes) + Lesson (Rest of Time)	Test (14minutes) + Shark Attack (15 Minutes) + Lesson (Rest of Time)	Test (14minutes) + Road Trip (15 Minutes) + Lesson (Rest of Time)	Test (14minutes) + Bubble Pop (15 Minutes) + Lesson (Rest of Time)
9:30-10:00					
10:00-10:30	Inform the students of their speed and errors				
10:30-11:00	Data Entering (Average 15 minutes) 3 Per Day				
11:00-11:30					
11:30-12:00					
12:00 - 12:30	Self Practice (At will)				

Figure A3. Productivity of part-time and full-time workers over time by task

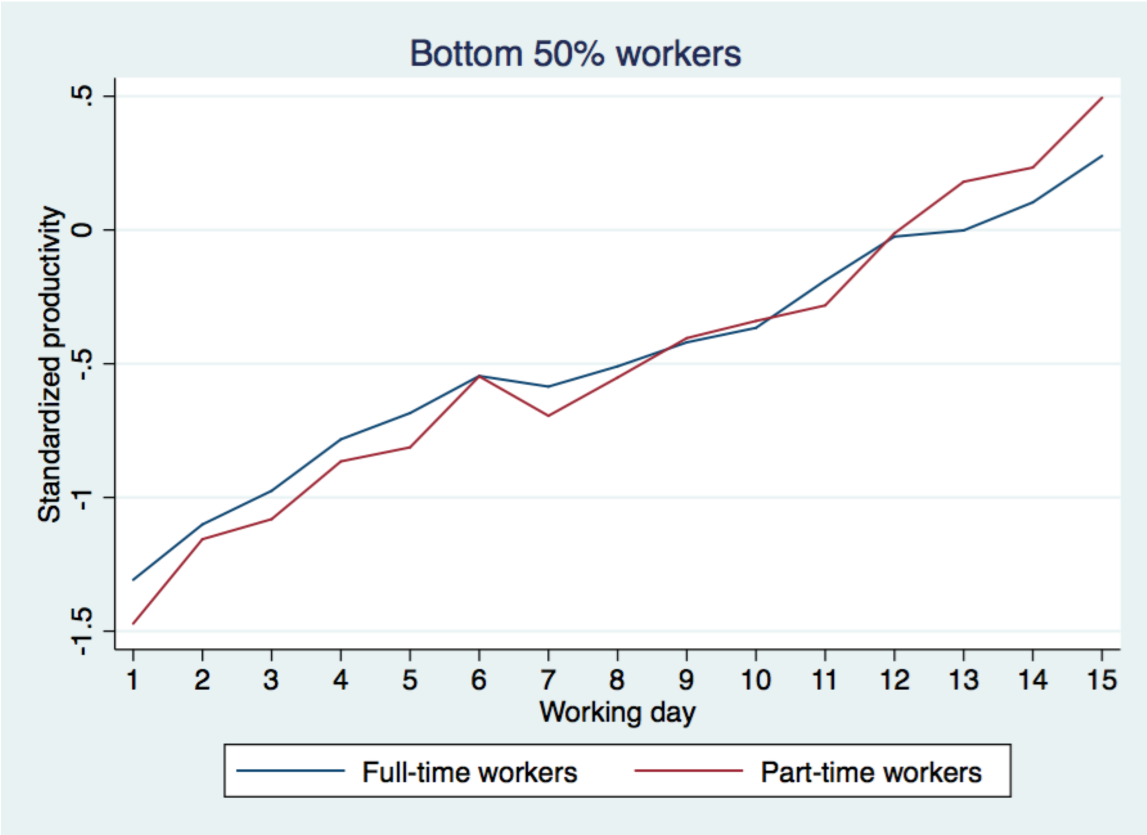
Panel A. Top 50 percent performers – typing speed



Panel B. Top 50 percent performers – data-entry speed



Panel C. Bottom 50 percent performers – typing speed



Panel D. Bottom 50 percent performers – data-entry speed

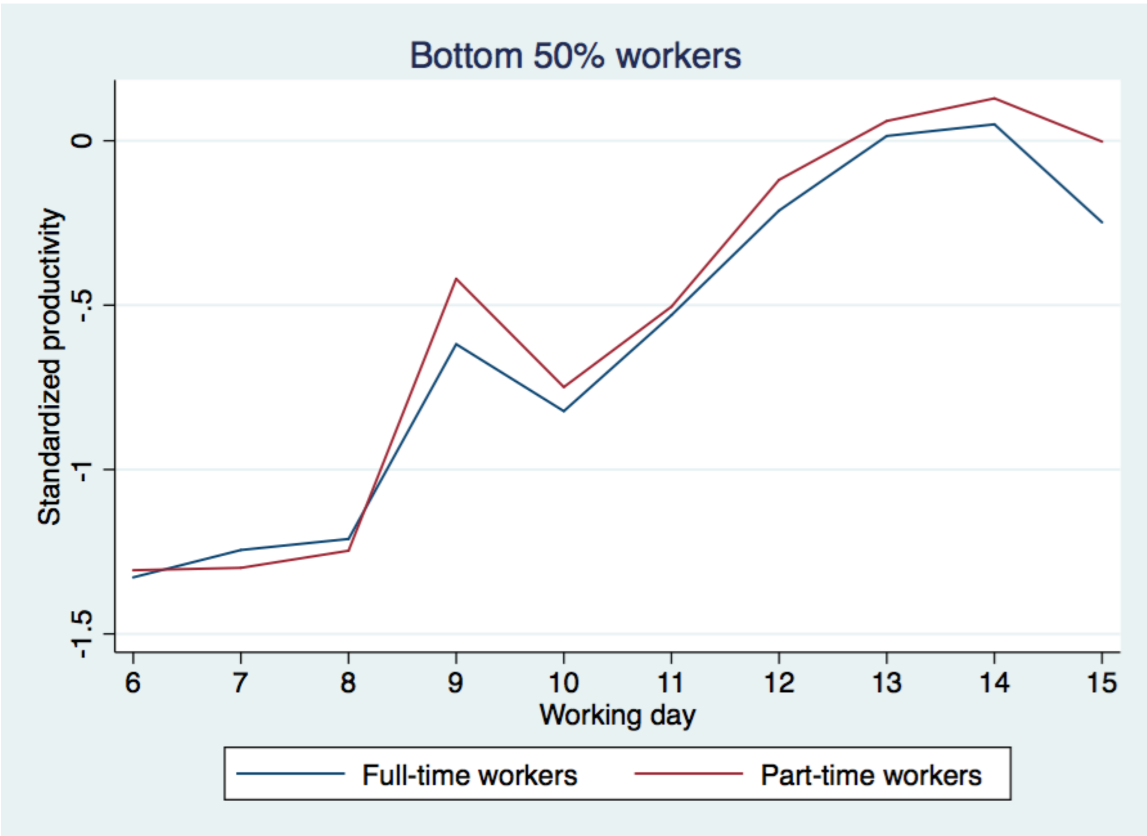
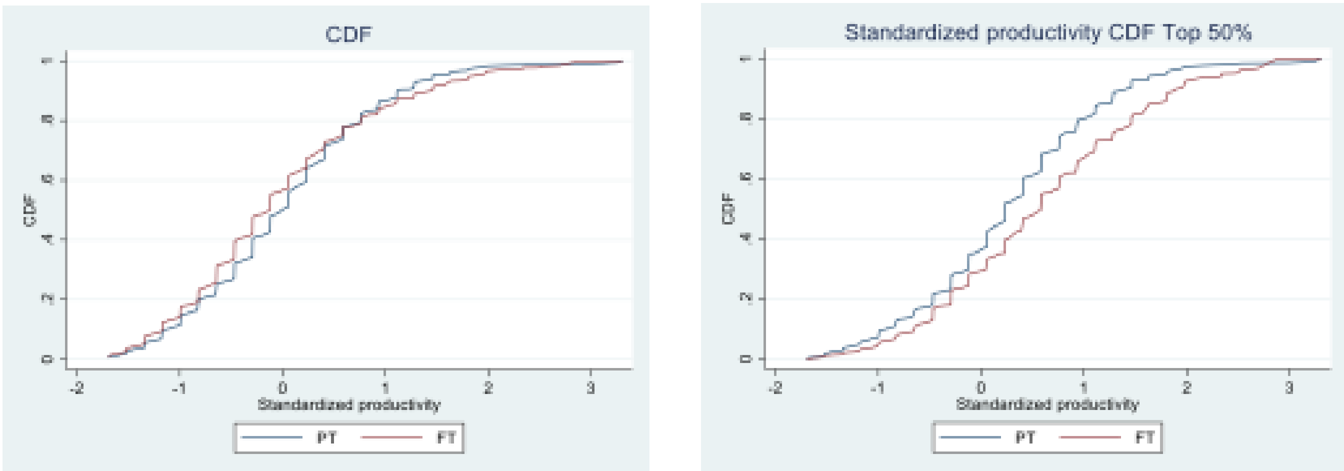
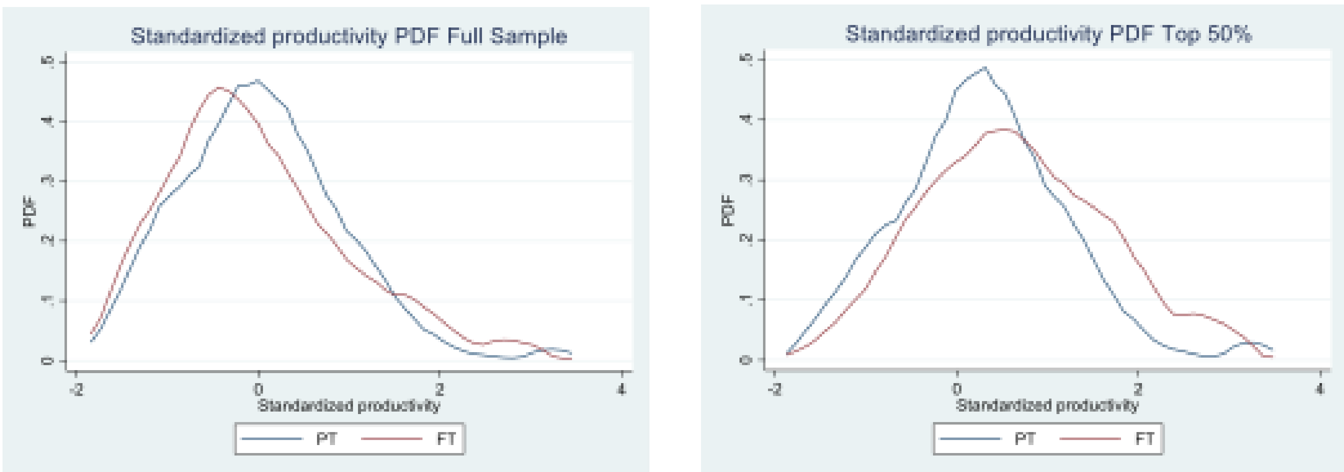


Figure A4. CDF and PDF of standardized productivity for part-time and full-time workers

Panel A. CDFs



Panel B. PDFs



Note: Panels A and B present the cumulative distribution function (CDF) and probability distribution function (PDF) of standardized productivity during the training for the full sample (left) and top 50% performers (right).

Table A1. Comparison of job survey participants vs. nonparticipants

Variable / Sample	(1) Job survey nonparticipants (Obs.)	(2) Job survey nonparticipants (Mean)	(3) Job survey participants (Obs.)	(4) Job survey participants (Mean)	(5) Difference (2)-(4)
Age (/100)	101	0.225	306	0.232	-0.007
Married	99	0.273	313	0.294	-0.021
Ever birth	75	0.307	270	0.337	-0.030
Working	100	0.250	316	0.184	0.066
Official sector work	100	0.150	314	0.121	0.029
Post-Secondary+	101	0.475	323	0.474	0.001
Asset score	98	7.031	314	6.927	0.104
N. of household members	100	4.450	317	3.855	0.595
N. of children	75	0.360	270	0.511	-0.151
Supportive spouse for PT job	86	4.116	270	4.278	-0.162
Supportive spouse for FT job	86	4.163	271	4.255	-0.092

Note: * denotes the significance level at 10%.

Table A2. Baseline characteristics and balance of randomization

Variable	(1) N	(2) All	(3) Part-time	(4) Full-time	(5) Difference	(6) p-value
Panel A. Individual Characteristics						
Age	6,098	26.512	26.187	26.841	-0.654	0.346
Married	6,123	0.418	0.440	0.396	0.044	0.165
Ethnicity						
Amhara	6,177	0.203	0.178	0.228	-0.05	0.198
Oromo	6,177	0.734	0.753	0.714	0.039	0.425
Language						
Amharic	6,236	0.413	0.370	0.458	-0.088	0.228
Oromigna	6,236	0.574	0.614	0.533	0.081	0.271
Religion						
Orthodox	6,179	0.693	0.658	0.729	-0.071	0.188
Protestant	6,179	0.250	0.275	0.224	0.051	0.299
Muslim	6,179	0.022	0.026	0.016	0.01	0.177
Post-secondary education	6,236	0.391	0.378	0.404	-0.026	0.516
Working						
Within household	6,101	0.131	0.089	0.174	-0.085*	0.073
Official Sector	6,076	0.194	0.193	0.196	-0.003	0.950
Panel B. Household Characteristics						
Number of household members	20,255	4.216	4.166	4.267	-0.101	0.499
Asset score	20,164	4.719	4.621	4.821	-0.2	0.701
Having saving account	20,382	0.278	0.266	0.292	-0.026	0.695
Receiving government subsidy	20,371	0.016	0.018	0.013	0.005	0.307
Panel C. Village Characteristics						
Ijere (=0) vs. Holeta (=1)	234	0.644	0.601	0.688	-0.087	0.5
Mortality rate (per 1,000)	234	10.036	6.256	13.947	-7.691	0.202
Migration rate (per 1,000)	234	8.616	10.832	6.324	4.508	0.334
Marriage rate (per 1,000)	234	2.588	3.797	1.338	2.459	0.28
Number of population	234	371.427	356.235	387.148	-30.913	0.458
Gender ratio (F/M)	234	0.51	0.505	0.516	-0.011	0.571
Number of household members	234	4.394	4.417	4.37	0.047	0.814

Note: * denotes the significance level at 10%.

Table A3. Job application by part-time offer and individual characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	1 (Apply to job)					
Characteristic:		Age (/100)	Married	Ever birth	Working	Working in official sector
Characteristic	-	-0.230***	-0.030***	-0.043***	-0.028*	-0.024**
	-	(0.032)	(0.010)	(0.008)	(0.014)	(0.010)
Part	-0.003	-0.006	0.005	0.001	-0.002	-0.000
	(0.011)	(0.019)	(0.013)	(0.015)	(0.014)	(0.014)
Part × Characteristic	-	0.009	-0.010	-0.005	-0.007	-0.008
	-	(0.045)	(0.014)	(0.013)	(0.019)	(0.018)
Constant	0.065***	0.125***	0.075***	0.089***	0.074***	0.070***
	(0.009)	(0.015)	(0.010)	(0.011)	(0.010)	(0.010)
R^2	0.000	0.008	0.005	0.008	0.004	0.002
N	6236	6082	6123	4839	6136	6076
Control group mean	-	0.26	0.40	0.48	0.32	0.20

	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable:	1 (Apply to job)					
Characteristic:	Post-Secondary+	Asset score	N. of HH members	Grandparents & children	N. of children	Supportive spouse for job
Characteristic	0.035***	-0.003	-0.011***	0.032**	-0.021***	0.025***
	(0.010)	(0.002)	(0.003)	(0.013)	(0.005)	(0.005)
Part	-0.008	-0.034	-0.030	0.012	-0.024	0.061***
	(0.010)	(0.027)	(0.023)	(0.009)	(0.022)	(0.021)
Part × Characteristic	0.016	0.004	0.006*	-0.023	0.010	-0.016**
	(0.017)	(0.003)	(0.004)	(0.017)	(0.006)	(0.007)
Constant	0.051***	0.086***	0.115***	0.022***	0.086***	-0.054***
	(0.008)	(0.022)	(0.021)	(0.005)	(0.018)	(0.012)
R^2	0.008	0.001	0.006	0.003	0.013	0.010
N	6236	6140	6173	2731	2325	2381
Control group mean	0.40	7.32	4.62	0.37	0.99	3.97

Note: Robust standard errors clustered at the village group level are reported in parentheses. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively. Column (11) uses a subsample of women who have at least two children, and columns (11) and (12) use a subsample of married women.

Table A4. Quantile regression of standardized productivity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Var.:	Standardized productivity							
Estimates:	OLS	Quantile regression						
		0.05	0.1	0.25	0.5	0.75	0.9	0.95
Part	-0.092	-0.015	-0.012	-0.012	-0.015	-0.014	-0.269	-0.438***
	(0.084)	(0.058)	(0.061)	(0.058)	(0.058)	(0.122)	(0.213)	(0.137)
Task type fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Day fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Batch fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Trial fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.505	0.499	0.484	0.487	0.499	0.499	0.469	0.406
N	5066	5066	5066	5066	5066	5066	5066	5066

Note: Robust standard errors clustered at the village group level are reported in parentheses. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively. Column 1 presents reproduces the OLS estimates in column 2 of Table 3, Panel A. Columns 2 through 8 presents quantile regression estimates with varying quantiles from 0.05 to 0.95 of the standardized productivity distribution.

Table A5. Training participation

	All trainees		Top 50% trainees	
	(1)	(2)	(3)	(4)
Dep. Var.:		Attend		
Part	-0.023	-0.032	0.013	-0.001
	(0.023)	(0.024)	(0.030)	(0.035)
Constant	0.914***	0.919***	0.916***	0.924***
	(0.012)	(0.013)	(0.022)	(0.023)
Batch fixed effects	Y	Y	Y	Y
Trial fixed effects	Y	Y	Y	Y
R^2	0.002	0.042	0.001	0.038
N	3712	3712	1885	1885

Note: Robust standard errors clustered at the village group level are reported in parentheses. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively.

Table A6. Standardized productivity with controls included

	All trainees				Top 50% trainees			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Standardized productivity							
Panel A: Without time trend								
Part	-0.112	0.050	-0.083	0.050	-0.419***	-0.092	-0.363***	-0.114
	(0.095)	(0.056)	(0.091)	(0.046)	(0.103)	(0.095)	(0.112)	(0.094)
Constant	0.093	-2.907***	-1.034***	-2.919***	0.680***	-2.991***	0.022	-2.992***
	(0.069)	(0.652)	(0.219)	(0.676)	(0.099)	(0.713)	(0.339)	(0.736)
R^2	0.498	0.622	0.526	0.629	0.526	0.641	0.546	0.649
N	4639	4639	4639	4639	2512	2512	2512	2512
Panel B: With time trend								
Part	-0.308***	-0.161*	-0.288**	-0.165**	-0.431**	-0.187	-0.372*	-0.204
	(0.108)	(0.080)	(0.109)	(0.076)	(0.197)	(0.175)	(0.204)	(0.175)
Day	0.135***	0.131***	0.134***	0.131***	0.169***	0.159***	0.169***	0.160***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.010)	(0.008)	(0.010)	(0.009)
Part × Day	0.021***	0.023***	0.022***	0.023***	0.002	0.011	0.002	0.011
	(0.007)	(0.007)	(0.007)	(0.007)	(0.013)	(0.012)	(0.013)	(0.012)
Constant	-1.154***	-4.134***	-2.283***	-4.148***	-0.887***	-4.465***	-1.555***	-4.478***
	(0.073)	(0.637)	(0.211)	(0.661)	(0.172)	(0.701)	(0.356)	(0.717)
Ability controls		Y		Y		Y		Y
Work preference controls			Y	Y			Y	Y
Task type fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Batch fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Trial fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.488	0.617	0.522	0.631	0.510	0.638	0.556	0.656
N	4639	4639	4639	4639	2512	2512	2512	2512

Note: Robust standard errors clustered at the village group level are reported in parentheses. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively. Columns 2 and 6 include ability variables shown in Panel A of Table 2, including data entry test score, clerical ability, computation ability, computer literacy, and manual dexterity ability. Columns 3 and 7 include work preference variables shown in Panel B of Table 2, including family orientation and work preference over life. Columns 4 and 8 include both the ability and work preference variables.

Data Appendix

B.1 Ability tests

O*NET Ability Profiler (O*NET score): clerical and computation ability tests

The O*NET Ability Profiler was originally developed by the US Department of Labor as "a career exploration tool to help understand job seekers on their work skills" (O*NET Resource Center 2010, 1). We use the clerical and computation ability tests of the Ability Profiler because these skills are most relevant for the data entry clerk.

(A) The **clerical perception test** measures an individual's ability to see details in written materials quickly and correctly. It involves noticing if there are mistakes in the text and numbers, or if there are careless errors in working math problems (O*NET Resource Center 2010, 2). The following is an example of the test questionnaire

Practice Questions

		Answer	
3.	Brimms Co. — Brimms Company	1 = Same	2 = Different
4.	Wesson & Wyle — Wesson & Wyle	1 = Same	2 = Different
5.	Remington, D. E. — Remington, D. F.	1 = Same	2 = Different
6.	Linda Small — Lynda Small	1 = Same	2 = Different
7.	Strong Ltd. — Strong Inc.	1 = Same	2 = Different
8.	James Reagon — James Reagon	1 = Same	2 = Different

(B) The **computation test** measures an individual's ability to apply arithmetic operations to calculate solutions to mathematical problems. It consists of 20 questions. The following is an example of the test questionnaire:

15. Multiply

$$\begin{array}{r} 8{,}733 \\ \times \quad 4 \\ \hline \end{array}$$

A. 32,822
B. 32,932
C. 34,932
D. 35,932
E. none of these

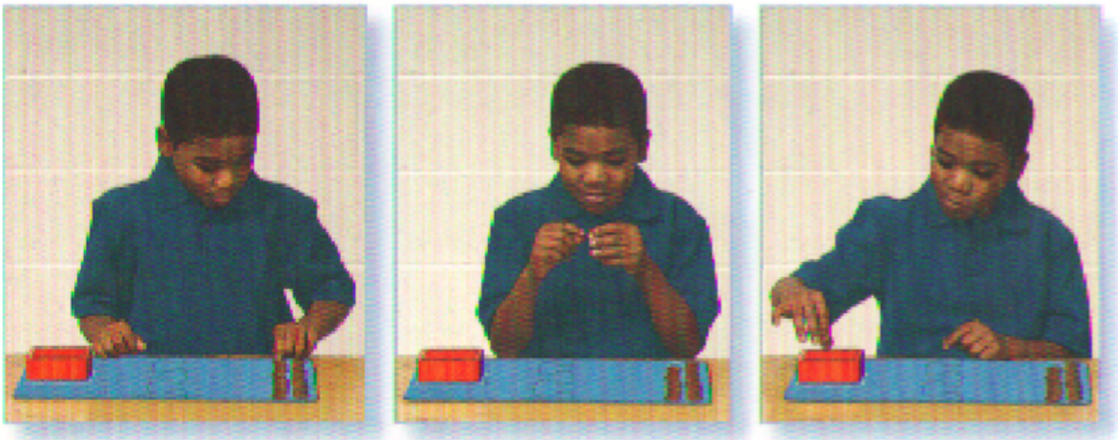
16. Divide

$$14 \overline{\smash{)}29{,}554}$$

A. 2,116
B. 2,121
C. 2,131
D. 2,146
E. none of these

Bruininks-Oseretsky Test of Motor Proficiency, 2nd edition (BOT$^{\text{TM}}$-2)

The BOT$^{\text{TM}}$-2 was developed to measure various types of motor skills. It consists of eight tasks: fine motor precision, fine motor integration, manual dexterity, bilateral coordination, balance, running speed and agility, upper limb coordination, and strength. We used the manual dexterity test, which is most relevant to the data entry clerk. We asked survey participants to transfer 20 small coins from the table to the small box in 15 seconds. Study participants could try twice, and the larger number is the final score.



B.2 Measures for preferences to working hours

We measure the applicants' preferences for (more) work using three set of measures. First measure compares work over family using 10 survey questions regarding the importance of work and family. We calculate a composite score of preference for working (over family) by subtracting the average score for family (Q401–Q405) from that for work (Q406–Q410). Score could range 5 to 50, and higher score implies stronger preference for working.

Section IV. Preference for Work

At this time, we would like to ask how you think about women's work? Circle one that applies.

		1= strongly agree	2= agree	3= neither agree nor disagree	4= disagree	5= strongly disagree	99= don't know
401	A working mother can establish just as warm and secure a relationship with her children as a mother who does not work.						
402	A pre-school child is likely to suffer if his or her mother works						
403	All in all, family life suffers when the woman has a full-time job.						
404	A woman and her family will all be happier if she goes out to work.						
405	A job is allright, but what most women really want is a home and children.						
406	Being a housewife is just as fulfilling as working for pay.						
407	Having a job is the best way for a woman to be an independent person.						

Second, we measure preference for work arrangements among full-time work, part-time work, and do not work in each stage of life.In order to calculate a composite score, we assign 3, 2, 1 for full-time, work part-time work, and no work, respectively, and add each score of Q411 to Q415. As a result, higher score implies stronger preference for working.

Please answer the following question: Do you think that women should work outside the home full-time, part-time or not at all under these circumstances? Circle one that apply.

		1= work full-time	2= work part-time	3= stay home	99= don't know
411	Before marriage?	1	2	3	99
412	After marrying but before having children?	1	2	3	99
413	When there is a child under school age?	1	2	3	99
414	After the youngest child starts school?	1	2	3	99
415	After all children leave home?	1	2	3	99

Third, we measure preference for part-time work through monetary compensation, and (work you like). We assign zero when individual prefer part-time work assignment (B in Q509-1 and Q509-2), otherwise 1. We also use composite score by adding scores from two questions. A lower score implies stronger preference for part-time work.

Q509. For each question, choose one that you agree with the most (circle either A or B).

1. Which job would you prefer?	A	A job that offers good chances for making more money and a raise but offers no chance to work part-time.
	B	A job that offers few chances for making more money and a raise but offers but offers a chance to work part-time.
2. Which job would you prefer?	A	A job that should be a full time work but you like the work.
	B	A job that offers a chance to work part time but you do not like the work.

B.3. Attitude and expectation toward work

<u>Relative importance for job choice</u>

We measure relative importance of job aspects. Survey participants were given 20 beans and asked to allocate them into five motivation categories: (i) good future career; (ii) earning respect and high status; (ii) paying well; (iv) interesting job; and (v) acquiring useful skills.

Q501. Suppose you have 20 beans in total. Please allocate your 20 beans between different potential motivations for choosing a job. The more beans mean the higher importance.

Potential Motivation	Beans (total 20)
a. Good future career	
b. Earns respect and high status in the community	
c. Pays well	
d. Interesting job	
e. Allows me to acquire useful skills	
Ensure that the sum of (a)-(e) is 20.	

<u>Intrinsic motivation</u>

Intrinsic motivation is an individual's trait that captures whether the individual is motivated to do things by intrinsic rewards such as his/her own desire to pursue goals or challenges. It is the opposite of extrinsic motivation, described below. We measure intrinsic motivation using a 15-item scale (Amabile et al. 1994). All items were answered using a 4-point Likert scale format ranging from *strongly agree* (1) to *strongly disagree* (4).

<u>Extrinsic motivation</u>

Extrinsic motivation is an individual's trait that captures whether the individual is motivated to act by external rewards, such as reputation and monetary rewards. We use a 15-item scale to measure the level of motivation triggered by extrinsic values (Amabile et al. 1994). All items were answered using a 4-point Likert scale format ranging from *strongly agree* (1) to *strongly disagree* (4).

Career expectations

The career expectation module measures what motivates the applicant to pursue her career. All items were answered using a 4-point Likert scale format ranging from *strongly disagree* (1) to *strongly agree* (4).

Q504. Below is a list of statements concerning career expectations. Please indicate how strongly you agree or disagree with each statement.

1 = Strongly disagree
2 = Disagree
3 = Agree
4 = Strongly agree

1	To be recognized for my expertise.	1	2	3	4
2	Knowing that I am respected for the specialist skills that I bring.	1	2	3	4
3	Knowing every year that I have further developed my expertise.	1	2	3	4
4	Being able to contribute new ideas which will help build the future.	1	2	3	4
5	Being given challenges which stretch me intellectually.	1	2	3	4
6	Promotion	1	2	3	4
7	Enough leisure time to travel, relax and be myself.	1	2	3	4
8	A balance between work and other areas of my life such as family.	1	2	3	4
9	Being able to put work in its place as an important, but not the only part of my life.	1	2	3	4
10	Control over how and when I work.	1	2	3	4
11	Being able to work when and where I want so long as I can deliver results.	1	2	3	4
12	To be able to see that I am doing better than those I am in competition with.	1	2	3	4

Accomplishment and status seeking

These modules, developed by Barrick, Stewart, and Piotrowski (2002), measure different types of motivation to work. The accomplishment-seeking module measures how much one cares about achievement in work. The status-seeking module measures how much one cares about what other people think of oneself and about one's status relative to other members of the group. All items were answered using a 4-point Likert scale format ranging from *strongly agree* (1) to *strongly disagree* (4).

Q505. Below is a list of statements concerning accomplishment seeking. Please indicate how strongly you agree or disagree with each statement.

1 = Strongly disagree
2 = Disagree
3 = Agree
4 = Strongly agree

1	I often think about getting my work done.	1	2	3	4
2	I focus my attention on completing work assignments	1	2	3	4
3	I set personal goals to get a lot of work accomplished.	1	2	3	4
4	I spend a lot of time thinking about finishing my work tasks.	1	2	3	4
5	I often consider how I can get more work done.	1	2	3	4
6	I try hard to get things done in my job.	1	2	3	4
7	I put a lot of effort into completing my work tasks.	1	2	3	4
8	I never give up trying to finish my work.	1	2	3	4
9	I spend a lot of effort completing work assignments.	1	2	3	4
10	I feel encouraged when I think about finishing my work tasks.	1	2	3	4
11	It is very important to me that I complete a lot of work.	1	2	3	4

Q506. Below is a list of statements concerning status seeking. Please indicate how strongly you agree or disagree with each statement.		**1 = Strongly disagree 2 = Disagree 3 = Agree 4 = Strongly agree**			
1	I frequently think about ways to advance and obtain better pay or working conditions.	1	2	3	4
2	I focus my attention on being the best sales representative in the office.	1	2	3	4
3	I set personal goals for obtaining more sales than anyone else.	1	2	3	4
4	I spend a lot of time thinking of ways to get ahead of my friends.	1	2	3	4
5	I often compare my work accomplishments against friends' accomplishments.	1	2	3	4
6	I never give up trying to perform at a level higher than others.	1	2	3	4
7	I always try to be the highest performer.	1	2	3	4
8	I get excited about the idea of being the most successful man in my area.	1	2	3	4
9	I feel happy when I think about getting a higher status position at work.	1	2	3	4

Career progress concern

This module measures how respondents view their career in the future. All items were answered using a 4-point Likert scale format ranging from *strongly disagree* (1) to *strongly agree* (4).

Q507. Below is a list of statements concerning career. Please indicate how strongly you agree or disagree with each statement.		**1 = Strongly disagree 2 = Disagree 3 = Agree 4 = Strongly agree**			
A	I expect to be in a higher level job in five years.	1	2	3	4
B	I view this job as a stepping stone to other subsequent jobs.	1	2	3	4
C	If I get this job, I expect to be doing the same work in three years.	1	2	3	4

Concern compensation and benefit

This module measures how much one cares about the compensation and benefits of jobs. All items were answered using a 4-point Likert scale format ranging from *strongly disagree* (1) to *strongly agree* (4).

Q508. Below is a list of statements concerning compensation and benefits offered by this job. Please indicate how strongly you agree or disagree with each statement.		**1 = Strongly disagree 2 = Disagree 3 = Agree 4 = Strongly agree**			
1	I like the overall pay and benefits package offered.	1	2	3	4
2	I think the pay and benefits offered are adequate for my responsibilities and qualifications.	1	2	3	4
3	I think the pay and benefits offered are appropriate for the work-related experience that I will have.	1	2	3	4
4	The current pay and benefit system will have a positive effect on my productivity.	1	2	3	4
5	The pay and benefits package that I am offered is as good as most available in other companies.	1	2	3	4

References for Data Appendix

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