Are Part-Time Workers Less Productive than Full-Time Workers? Evidence from a Field Experiment in Ethiopia

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Abstract

We use a randomized field experiment to estimate a causal effect of part-time recruitment on labor productivity by identifying worker selection as a mechanism and using worker-level productivity data. In recruiting for data entry work in Ethiopia, we identify 6,236 eligible women and randomly assign them to part-time or full-time job opportunities. We find that applicants with lower ability are more likely to select into part-time arrangements. Other observable characteristics capturing demographics, socioeconomic status, and attitudes toward work and family barely explain the selection. Those recruited through part-time job opportunities exhibit significantly lower productivity as measured by data entry speed. (*JEL* J24, O15, M51)

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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 particular, many workers are employed part-time. 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 even more common, comprising up to 60 percent of employment, with the fraction being higher among women (IDB 2008). Even though part-time employment is widespread, it is associated with a considerable wage discount in both developed and developing countries (e.g., IDB 2008; Manning and Petrongolo 2008; Matteazzi, Pailhe, and Solaz 2014). Despite this wage penalty, relatively little is known about how part-time employment influences worker selection and productivity.[2]

The effects of part-time work on labor productivity, particularly through worker selection, is theoretically ambiguous. If workers who are more productive prefer to take full-time jobs (e.g., Mas and Pallaise 2017), workers for part-time positions (and, in turn, firms hiring them) may be less productive because of such adverse selection. However, the effect of part-time employment on employee quality and productivity may be more positive if workers choose part-time work because they value work-hour flexibility. In particular, women on average value flexibility in work hours in comparison to men (e.g., Goldin 2014; Goldin and Katz 2016; Wiswall and Zafar 2016). It is thus possible to observe a positive selection effect of part-time employment for women, who tend to have greater family-related responsibilities, such as child-rearing, in addition to their paid work. Part-time workers might also be more productive because they suffer less of the stress and fatigue associated with working full time (e.g., Brewster, Hegewisch, and Mayne 1994).

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

[2] For example, Garnero (2016) concludes that evidence for the effect of part-time jobs on productivity is largely inconclusive. Moreover, little research examines the implication of part-time employment for workers' self-selection.

Given that women are more likely to work part time than men, how part-time recruitment affects worker selection could explain the gender wage gap. On the one hand, if part-time arrangements attract less productive workers, the gender wage gap would be partly explained by productivity. On the other hand, if women select part-time work largely because of their marital or motherhood status, then part-time arrangements could mitigate the wage gap because they allow productive women to participate in the labor market.

In this paper, we investigate the selection and productivity effects of part-time (versus full-time) work arrangements using a randomized field experiment offering full- and part-time job opportunities to women in Ethiopia in an actual data entry work setting. The experiment focuses on women (who, relative to men, value the temporal flexibility provided by part-time work), which allows us to study whether this flexibility affects worker selection into part-time arrangements.

We conducted a large-scale search for job applicants in a data entry unit at the Africa Future Foundation (AFF), an international nongovernmental organization (NGO). In 2016, AFF advertised job vacancies to 6,236 women during a census of more than 20,000 households in AFF's catchment areas, Holeta and Ejere. We randomly assigned 71 village groups to either full- or part-time jobs and handed out flyers describing either full-time or part-time data entry work to women with a high school certificate ("eligible women").

The full- and part-time jobs were described as involving either eight or four hours of data entry work per day, five days a week. Both jobs had identical task descriptions (see Figure A1). 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 three hours a day, five days a week, for three weeks. We measured workers' productivity during this training period using error-adjusted typing and data entry speed.

Our paper shows a causal effect of part-time job recruitment on the selection and productivity of workers through a large-scale randomized field experiment conducted in a real-world setting. We thus offer credible experimental evidence on the effects of recruiting for part-time work. Further, we collect detailed information on individual characteristics from a census of population and administer a survey and aptitude tests to job applicants. We also collect data on worker-level productivity daily.

First, we examine whether individual and family characteristics (collected from the applicants' job survey and aptitude tests) are associated with women's decision to apply for either part-time or full-time work. We find that individuals who have lower ability to perform the data entry work and who place less value on pay are more likely to select into part-time as opposed to full-time work arrangements. Moreover, women who have a spouse who supports her desire to work are more likely to apply to the full-time job. We do not find evidence that selection is significantly explained by other observable characteristics capturing demographics, socioeconomic status, and attitudes toward work and family.

Second, during the job training, we find that applicants who were recruited through the part-time job announcement exhibit significantly lower productivity by 0.09 to 0.40 of the standard deviation than those recruited through the full-time flyer. This productivity gap exists in the first week of training, suggesting that the gap is driven by such (intrinsic) characteristics as ability and preferences for work as opposed to differential skill investments during training. Our results imply that productive workers prefer to work full time, in line with Mas and Palliais's (2017) finding that job applicants place little value on the option to work part time despite the flexibility it offers.

This paper is related to three strands of literature. The first strand examines how job attributes (e.g., compensation schemes and 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). We depart from this literature by showing the causal effect of part-time work arrangements on worker selection and productivity using a randomized experiment for the first time.

The second strand examines the influence of part-time job arrangements on workers and firms. While previous research finds a negative correlation between part-time employment and wages (e.g., Manning and Petrongolo 2008; Matteazzi, Pailhe, and Solaz 2014), the effect on productivity is largely mixed and is based on firm-level, as opposed to individual-level, productivity measures. Using Dutch data on the pharmacy sector, Kunn-Nelen, de Grip, and Fourage (2013) find that part-time employees increase firm 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 relation between the fraction of part-time employees and firm-level productivity.[3] We estimate a causal effect of part-time recruitment on labor productivity using worker-level productivity data and identify worker selection as a mechanism.

Last, our paper is related to the literature on female labor markets, especially the gender pay gap (see, e.g., Goldin 2006, 2014; Goldin and Katz 2016; and Blau and Kahn 2006, 2017). Our finding that part-time arrangements attract less productive workers, combined with the fact that women are more likely to work part time, in part explains the gender wage gap.

I. Study Setting and Design

[3] 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.

A. *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, which is our context, largely employ women. Our study is conducted in Holeta and Ijere. Holeta is an urban town of approximately 28,000 people located about 31 miles west of the capital, Addis Ababa. Ijere 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 Ijere, respectively. The literacy rates are 70 percent in Holeta and 43 percent in Ijere.

In the study area, the data entry clerk is an attractive job for women because it is one of the few official sector jobs available in the area 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 the computer. The job requires basic computer skills, clerical ability to read a paper survey (in English) and input the information on a computer, fine motor ability to control hands and fingers, and perseverance to perform tedious work. 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

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

(65 of 345) of applicants were working for their family, and 5.8 percent (20 of 345) were working for pay in formal sectors.

B. *Study Design*

AFF established its data entry unit with plans to hire a maximum of 100 full-time equivalent (i.e., 70 full-time and 60 part-time) women workers from the catchment area. In May–June 2016, we conducted a census in Holeta and Ijere, gathering information on 20,595 households. During the census, we distributed job flyers with a job description, working conditions, and expected salary and benefits to resident women with a high school diploma. We focus on women in our experiment because of prior research showing that women prefer part-time arrangements that offer temporal flexibility (Goldin 2014; Wiswall and Zafar 2016).

We randomly assigned 71 village groups—clusters of several villages—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. The full-time (part-time) job requires eight (four) hours of work per day with a monthly pay of 1,200 (600) Birr (approximately US$60 (US$30)). Both jobs require three weeks of training.[6] 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.

An important advantage of this recruitment strategy is that we observe the population of eligible women in the catchment area who are interested in the jobs. This contrasts with most

[5] The original study design included 81 village groups. However, because of security concerns, some village groups in Ijere were excluded from the sample. The original design also included long-term employment and further randomization. However, AFF was forced to give up the plan for the data entry unit 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 Birr (approximately US$4) per day as a baseline wage plus 2 Birr per additional accurate entry over 30 entries per day as an incentive.

existing studies in the literature, which only observe job applicants. Our approach increases the external validity of our findings by allowing us to compare the characteristics of applicants with nonapplicants in the population.

As shown in Table 1, we identified 6,236 eligible women and provided flyers to them or to 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 in the part-time group villages and 226 in the full-time group villages submitted applications and supporting documents. Those who applied for the job ("job applicants," hereafter) were asked to complete a baseline job survey and take aptitude tests ("job survey," hereafter) in December 2016. Among the job applicants, 162 (70.4 percent) and 171 (75.7 percent) women in the part- and full-time village groups, respectively, completed the job survey.[7]

AFF invited those who completed the baseline job survey ("survey participants," hereafter) to three weeks of training, which entailed basic computer training (such as Excel) and data entry practice and tests. To ensure that the participants could attend training independent of preferences for working hours, we offered the option of attending the training sessions either in the morning (9:00 a.m.–12:00 p.m.) or in the afternoon (1:00 p.m.–4:00 p.m.). Among the survey participants, 75 (46.3 percent) in the part-time group and 78 (45.6 percent) in the full-time group participated in the training ("trainees," hereafter). AFF invited the survey participants to training in five batches of 22 to 32 people. The administrative data collected during the training allowed us to track the

[7] Throughout this paper, *eligible women* refer to women who meet the data entry job criteria; *job applicants* refer to the 456 individuals who submitted application documents; *survey participants* refer to the 333 individuals who participated in the baseline job survey and ability tests; and *trainees* refer to the 153 individuals who participated in the job training.

trainees' labor productivity. The study design and the outcome variables considered in this study are pre-specified in the pre-analysis plan at the AEA RCT Registry.[8]

C. *Data and Measurements*

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 21,000 households in the study area and include such demographic and socioeconomic variables as age, marital status, language, education and employment, household assets, and mother's birth history.

In Table A1, we present descriptive statistics for observable characteristics and balance tests between the part-time and full-time village groups. Column 2 shows statistics for the entire sample, and columns 3 and 4 show statistics for each of the two groups. As shown in Panel A, the average age of job-eligible women is 24.3 years, about 76 percent of the women belong to the Oromo ethnic group (the majority ethnicity in Ethiopia), and 60 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, Table A1 confirms that the randomization is reasonable: only 1 out of 27 characteristics (3.7 percent) differs significantly at the 10 percent level (column 5).

Next, the baseline job survey collected (i) demographics and socioeconomic information, including educational background, employment history, household income, and assets; (ii) work and family orientation; and (iii) attitude toward work, including intrinsic and extrinsic motivation, career expectations, accomplishment-seeking, status-seeking, and career concerns. The applicants also completed job aptitude tests that measure data entry ability (speed), computer literacy, clerical

[8] https://www.socialscienceregistry.org/trials/1829/history/12246.

and computation abilities based on the O*NET, and manual dexterity ability in the Bruininks-Oseretsky Test of Motor Proficiency, 2nd edition (BOT™-2). Data Appendix B provides the specific survey modules and ability tests.[9]

AFF collected data on workers' performance during the job training from August to December 2017. Figure A2 shows details of the three-week-long training program. We employ two measures of labor productivity. First, we measure the number of total words correctly entered per minute (typing speed) using Mavis Beacon, a computer application designed to teach typing, two times per training day.[10] Second, we measure the number of census 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.[11] To ensure accurate measurement of performance, two supervisors independently recorded each trainee's number of correct words or 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).

II. Empirical Framework

A. *Worker Selection*

We first study worker selection into 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:

[9] 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 A2).
[10] 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_Beacon_Teaches_Typing for a description of the application.
[11] 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.

$$Characteristic_i = \alpha_0 + \alpha_1 Part_i + \varepsilon_i, \quad (1)$$

where $Characteristic_i$ includes applicant characteristics measured in the baseline job survey; $Part_i$ is an indicator equal to one if a part-time job opportunity was given to individual i, and zero if a full-time opportunity was given; and ε_i is an error term clustered at the village group level.

We provide additional 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:

$$Applied_{ijk} = \beta_0 + \beta_1 Part_{ijk} + \beta_2 Characteristic_{ijk} + \beta_3 Part_{ijk} \times Characteristic_{ijk} + \mu_k + \varepsilon_{ijk}, \quad (2)$$

where $Applied_{ijk}$ is an indicator equal to one if individual i in village group j and district k (i.e., Holeta or Ejere) applied to a (full- or part-time) job, and $Part_{ijk}$ is an indicator equal to one for individual i who resides in part-time village group j, and zero in a full-time village group. $Characteristic_{ijk}$ includes individual characteristics measured in the census, and μ_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 between the part- and full-time villages by an individual characteristic. 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), work preferences, and attitudes, which are potentially important determinants of job choices not measured in the census.

B. *Effects of Part-Time Worker Recruitment on 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:

$$Productivity_{ijtsl} = \gamma_0 + \gamma_1 Part_i + \nu_j + \lambda_t + \mu_s + \varepsilon_{ijtsl}, \quad (3)$$

where $Productivity_{ijts}$ is either (i) typing speed (words per minute from Mavis Beacon) or (ii) data entry speed for individual i at trial j in day t in training batch s from village group l; ν_j, λ_t, and μ_s are trial, working day, and worker batch fixed effects, and $Part_i$ is an indicator variable equal to one if worker i is recruited as part time, and zero otherwise. ε_{ijtsl} 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 group 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 have lower incentives. 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 III.C.

III. Results

A. *Job Application Decision*

We begin our empirical analysis 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 ("trainees"); and (iii) trainees with average performance in the top 50 percent. The third 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 could hire in practice.[12] Indeed, AFF found that productivity of applicants with average performance in the lower 50 percent is below an employable level.[13] In Section III.B, we examine the robustness of our results by varying the cutoff to define a top performer group.

Table 2 presents the results of estimating equation (1), which compares the characteristics of women who applied to part- and full-time jobs. Panel A shows that the part-time applicants have 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: 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 training participation (columns 4–6) and top training performance (columns 7–9); the absolute difference in standardized score combining the five ability tests increases to 0.18 and 0.46 standard deviations for trainees and top 50 percent performers, respectively.

However, as shown in Panels B and C, we find little evidence that demographic, socioeconomic variables, family orientation, and attitude and expectations toward work drive selection between part- and full-time jobs. One exception is that part-time job applicants place less value on pay when choosing jobs compared to full-time job applicants (Panel B). In addition, part-

[12] We identify the top performers using individual-level average standardized productivity in the last two weeks of the training.

[13] For example, the median words per minute (WPM) for the training participants is 12. Karat et al. (1999) find that the average typing speed is 33 WPM for experienced computer users who are native speakers of English and employees of IBM. Given the low wages offered in Ethiopia, AFF finds that a relatively lower level of productivity is acceptable.

time applicants prefer jobs paying less but with an option to work part time over jobs paying more but without the option, consistent with our experiment design. This difference is statistically significant among the trainees with top 50 percent performance. Another notable finding is that full-time recruited women have a spouse who is more supportive of her work (Panel C). Overall, the results in Table 2 suggest that ability, importance of pay, and spousal support determine an applicant's preference for part- or full-time 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 estimates of the coefficient on *Part* × *Characteristic* (β_3) are statistically 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 either part or full time tend to apply more to full-time jobs (columns 12 and 13), which is significant at the 5 percent level. This result is consistent with a similar finding in Table 2, Panel C.

B. *Productivity during Job Training*

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 I.B, 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 over the duration of training. Panel A shows that productivity increases over time both for the part-time (solid line) and full-time (dashed line) trainees in the full sample. As expected from the selection result in Section III.A, we find that trainees recruited through the part-time arrangement perform worse than those recruited through

the full-time process, especially in the beginning. However, the difference largely disappears by the last week of training. In contrast, Panel B shows that, for the top performers, the initial difference between the part- and full-time groups is larger and the productivity of part-time trainees does not converge to that of full-time trainees over time.[14] Panel C shows the difference in productivity between the part- and full-time groups and confirms the patterns in the earlier panels.

Now we turn to Table 3, which presents corresponding results from the regression in equation (3) for the full trainee sample (columns 1–4) and top 50 percent performer sample (columns 5–8) during training. 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 trends in productivity over time between trainees recruited through part- and full-time job opportunities.

Estimates in column 4 confirm the patterns shown in Figure 1 for the full sample. On day 1, the productivity of the part-time group is 0.28 standard deviations (= -0.297 + 0.022 × 1 day) lower than that of the full-time group. However, the part-time group catches up in productivity with the full-time group by 0.022 standard deviations per day, with a difference in productivity becoming economically insignificant by the end of the training (i.e., 0.033 of SD = −0.297 + 0.022 × 15 days). Column 8, however, shows different patterns among the top 50 percent performers. The initial productivity difference is 0.43 standard deviations (= −0.436 + 0.005 × 1 day), which is larger than the initial difference for the full sample (0.28 standard deviations). Further, the part- and full-time groups do not converge on productivity over time. Panels B and C show that results

[14] Figure A3 presents CDFs of part- and full-time trainees' productivity for the full sample (left) and top 50 percent performers (right). It shows the first-order stochastic dominance of CDF of full-time trainees over part-time trainees among the top 50 percent performers.

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.

C. *Further Results*

Employment cutoffs. Given the larger productivity difference between part- and full-time recruited trainees among the top 50 percent subsample relative to the full sample, a natural question is how the difference would vary as we change the cutoff to define a top-performer subsample. This question has important implications for practice because firms could decide to hire different fractions of job applicants depending on their (changing) labor demands. By observing labor productivity across all training participants, we can estimate the effect of part-time recruiting on employee productivity by varying the cutoff performance to hire employees. We apply cutoffs ranging from no restriction (i.e., 100 percent) to top 25 percent in 5 percent increments.

Figure 2 shows the estimation 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 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 25 percent performers. This finding suggests that when a firm hires top performers among applicants (which would naturally occur), the negative 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.

What explains the productivity difference? Next, we examine the extent to which measurable ability, preferences for family versus work, and attitudes 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 for work and family and attitudes toward work; and (iii) both. Table A4 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). These findings are consistent with the result in Table 2 that the part- and full-time applicants are significantly different in observable ability, whereas they are similar in variables capturing family and work preferences and attitudes toward work. 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.

IV. 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 implement a randomized field experiment that provides part- and full-time data entry job opportunities to women. We find that applicants with lower ability are more likely to select into part-time relative to full-time arrangements and that those recruited through part-time announcements exhibit lower productivity at work. Other observable characteristics capturing demographics, socioeconomic status, and attitudes toward work and family barely explain the selection and productivity effects. We also find suggestive evidence that having low ability initially explains a substantial portion of the productivity deficit for part-time recruited applicants.

Our findings imply that the wage penalty associated with part-time employment found in previous research could be explained, at least in part, by lower ability and productivity of part-time employees (e.g., Manning and Petrongolo 2008). Future research could investigate whether firms may wish to mitigate the negative effects of part-time recruiting by applying stricter hiring standards for part-time relative to full-time jobs. In addition, we find that more productive workers prefer full-time jobs, consistent with Mas and Palliais's (2017) finding that job applicants (in a similar phone survey and data entry position context) place little value on the option to work part time. However, our findings are inconsistent with the argument that the effect of part-time employment on the quality of the workforce may be positive because workers, and women in particular, value temporal flexibility in the form of part-time work (e.g., Goldin 2014 and Wiswall and Zafar 2016).

There are several limitations to our study. First, we measure productivity only during job training. Indeed, 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 horizon. Relatedly, the current experimental design does not allow us to examine how part-

time arrangements affect worker retention, another important aspect of productivity. Second, we do not measure (e.g., in the job survey) how applicants value the time flexibility offered by a part-time arrangement. Hence, we are not able to tell whether workers choose part-time employment because they value temporal flexibility. Nonetheless, we do not find that applicants' job preferences such as career concerns are correlated with their choice of part-time versus full-time positions (Table 2, Panel B), which suggests that the flexibility benefit of part-time employment might affect their choice.

In this investigation of part-time employment and productivity, we focus on women workers, and by doing so we offer implications for women's labor market issues, in particular the gender pay gap. If women recruited for part-time work tend to be adversely selected on job-specific ability, as we show, offering temporal flexibility may not fully mitigate the gender pay gap caused by a part-time wage penalty. Our results suggest that a further convergence in gender pay may be possible by having (equally) productive women work part time (or more flexibly) relative to full time (or less flexibly) (Goldin 2014; Goldin and Katz 2016).

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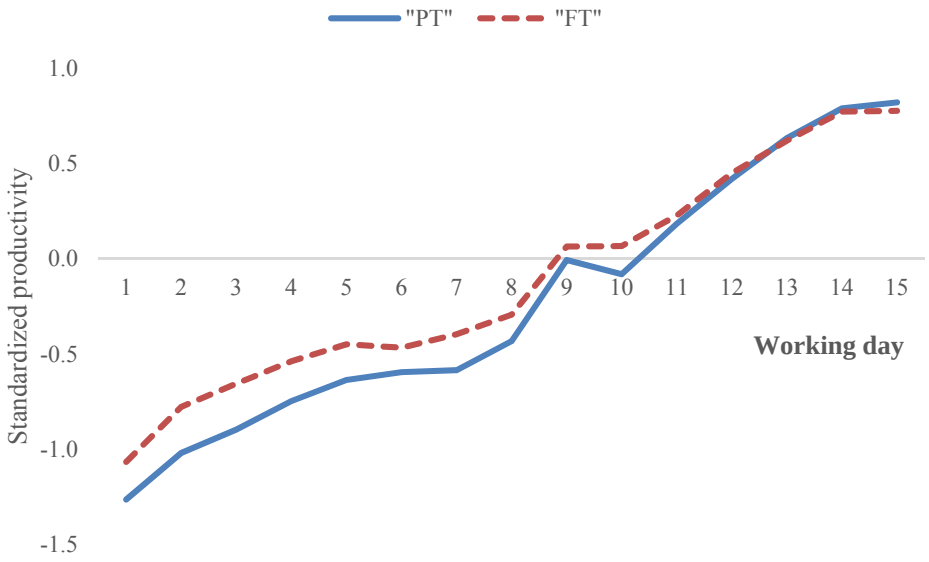
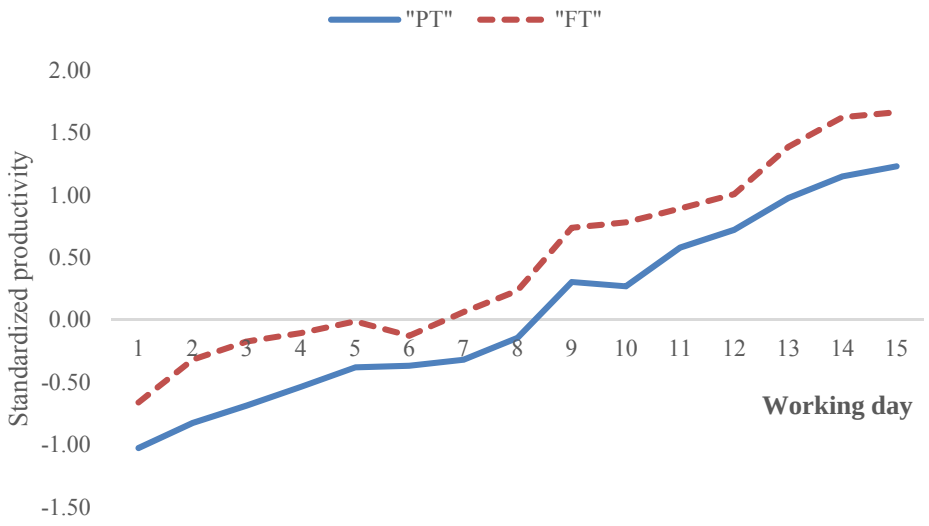
Panel A. All workers



Panel B. Top 50 percent performers



Panel C. Productivity difference between part-time and full-time workers among all trainees and top 50 percent trainees

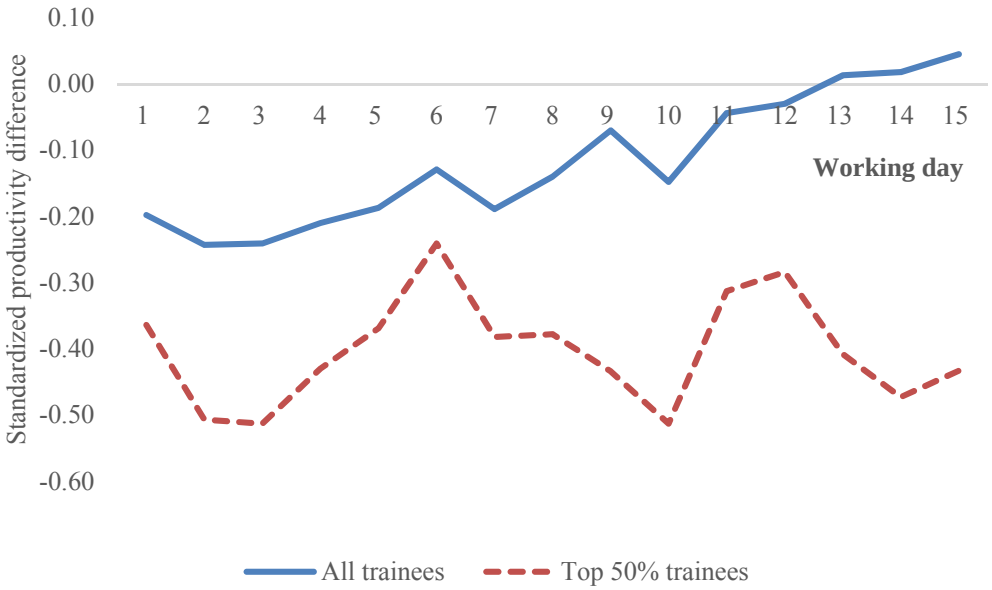


FIGURE 1. PRODUCTIVITY OF PART-TIME (PT) AND FULL-TIME (FT) WORKERS OVER TIME

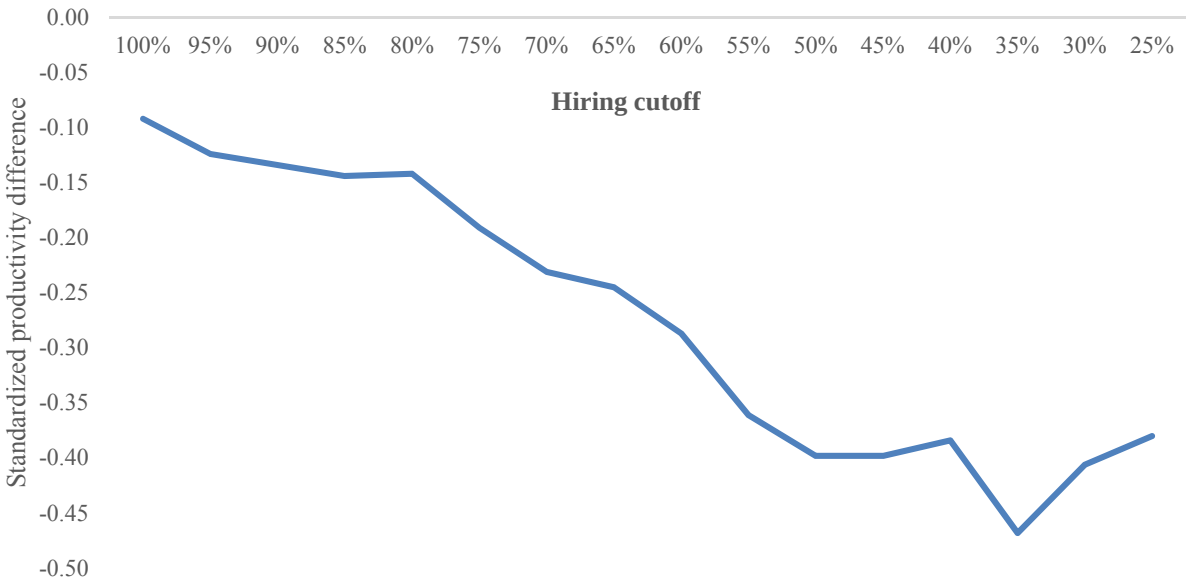


FIGURE 2. AVERAGE PRODUCTIVITY DIFFERENCE BETWEEN PART-TIME AND FULL-TIME WORKERS CONDITIONAL ON HYPOTHETICAL HIRING CUTOFFS

TABLE 1—EXPERIMENT STAGES

Time	Experimental stage	Number and percentage of individuals				
		Part-time		Full-time		Total
May–July 2016	A. Census (job flyers distributed)	3,171		3,065		6,236
July–August 2016	B. Submitted job application	230	(7.3%)	226	(7.4%)	456
December 2016	C. Participated in job survey and aptitude tests	162	(5.1%)	171	(5.6%)	333
August–December 2017	D. Participated in job training (performance measured)	75	(2.4%)	78	(2.5%)	153

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			All trainees			Top 50 percent		
Variable	Observations (N)	PT offered applicants	Mean difference (PT - FT)	Observations (N)	PT offered applicants	Mean difference	Number of Observations (N)	PT offered applicants	Mean difference (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**	123	0.057	-0.316*	63	0.134	-0.652***
Clerical ability	330	-0.032	-0.053	123	-0.094	-0.228	63	0.067	-0.464**
Computation ability	328	-0.011	0.01	122	0.067	0.041	62	0.140	-0.129
Computer literacy	326	-0.046	-0.105	122	-0.085	-0.235*	63	-0.090	-0.627***
Manual dexterity ability	329	-0.108	-0.232**	122	0.050	-0.142	63	0.053	-0.429*
Standardized Score	1643	-0.065	-0.126*	612	-0.089	-0.183	314	-0.196	-0.456***
Panel B. Work preference and attitude									
Family orientation (career vs. family) [1-10]	328	7.204	-0.108	121	7.271	-0.059	63	7.429	-0.17
Work preference over life (full–part–no work) [1-3]									
Before marriage	313	1.283	0.053	119	1.283	0.063	61	1.294	0.109
After marriage but no child	311	1.336	0.027	115	1.345	0.134	58	1.455	0.215
After marriage with child under school age	298	2.064	0.026	113	2.036	-0.033	59	1.938	-0.062
After marriage with child in school	302	1.448	0.077	116	1.456	0.1	58	1.355	0.059
After marriage with all children out of home	305	1.366	0.135**	116	1.362	0.052	59	1.485	0.254
Motivation for choosing job [1-20]									
a. Good future career	326	4.875	0.369*	122	4.476	-0.185	62	4.444	-0.287
b. Earns respect and high status	308	3.758	-0.173	113	3.741	-0.095	54	3.531	0.076
c. Pays well	310	3.416	-0.491**	117	3.311	-0.671**	58	3.286	-0.757*
d. Interesting job	320	4.146	0.171	120	4.063	-0.007	60	3.917	-0.625
e. Acquire useful skills	320	5.013	0.13	119	5.049	0.187	63	5.333	0.333
Intrinsic motivation [1-4]	309	3.420	0.019	118	3.459	0.081	61	3.490	0.182
Extrinsic motivation [1-4]	309	0.228	0.001	118	0.231	0.006	61	0.233	0.012
Career expectation [1-4]	315	3.260	-0.014	120	3.325	0	62	3.347	-0.031
Accomplishment seeking [1-4]	318	3.535	-0.012	120	3.541	-0.031	62	3.574	-0.008
Status seeking [1-4]	314	3.317	-0.009	118	3.356	-0.04	61	3.312	-0.069
Career progress concern [1-4]	329	2.785	-0.089	123	2.847	-0.092	63	2.778	-0.271
Concern compensation and benefit [1-4]	325	3.225	0.027	122	3.190	-0.023	62	3.120	-0.154
Working hour flexibility preference									

1: money, no PT (A=1) vs. no money, PT (B=0)	324	0.865	-0.034	121	0.871	-0.044	62	0.857	-0.106*
2: FT, like (A=1) vs. PT, don't like (B=0)	326	0.968	-0.02	123	0.968	-0.032*	63	0.972	-0.028
Panel C. Individual characteristics									
Age	284	22.525	-0.061	106	22.582	1.033	56	22.438	1.396
Married	322	0.288	-0.073	120	0.290	-0.072	60	0.371	0.091
Number of household members	313	4.000	0.288	114	3.966	0.341	58	4.394	0.314
Subjective health status [1-5]	327	4.475	0.002	123	4.429	-0.071	63	4.500	0.204
Have a child(ren)	330	0.237	-0.028	123	0.270	0.02	63	0.306	0.084
Number of children	330	0.313	-0.028	123	0.302	0.002	63	0.333	0
Currently in school	322	0.195	-0.069	121	0.286	0.01	61	0.306	-0.174
Working status	287	0.299	-0.028	109	0.278	-0.067	55	0.241	-0.028
Family business	286	0.234	0.019	109	0.185	-0.051	55	0.172	-0.02
Official sector	285	0.059	-0.022	109	0.093	0.002	55	0.069	0.031
Asset score [1-10]	280	5.124	-0.114	101	5.333	0.482	55	5.581	0.081
Supportive spouse for PT job [1-5]	267	4.115	-0.341**	96	3.959	-0.594**	48	3.852	-0.719**
Supportive spouse for FT job [1-5]	268	4.092	-0.339**	97	3.918	-0.603***	49	3.889	-0.702**

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

	All trainees				Top 50% trainees			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Standardized productivity								
Part	0.047	-0.092	-0.188	-0.297***	-0.354***	-0.392***	-0.436**	-0.431**
	(0.089)	(0.084)	(0.115)	(0.103)	(0.109)	(0.098)	(0.193)	(0.192)
Day	-	-	0.133***	0.132***	-	-	0.170***	0.166***
	-	-	(0.003)	(0.003)	-	-	(0.009)	(0.009)
Part × Day	-	-	0.025***	0.022***	-	-	0.005	0.005
	-	-	(0.008)	(0.008)	-	-	(0.013)	(0.013)
Constant	-0.018	0.051	-0.916***	-1.246***	0.634***	0.656***	-1.174***	-0.885***
	(0.073)	(0.058)	(0.161)	(0.082)	(0.097)	(0.095)	(0.061)	(0.163)
Task type fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.001	0.505	0.337	0.496	0.033	0.526	0.481	0.511
N	5066	5066	5066	5066	2638	2638	2638	2638
Panel B: Typing speed (Standardized)								
Part	-0.008	-0.134	-0.169	-0.273***	-0.466***	-0.443***	-0.414**	-0.357**
	(0.098)	(0.093)	(0.104)	(0.098)	(0.136)	(0.124)	(0.183)	(0.173)
Day	-	-	0.120***	0.122***	-	-	0.160***	0.159***
	-	-	(0.003)	(0.003)	-	-	(0.007)	(0.007)
Part × Day	-	-	0.019**	0.017**	-	-	-0.011	-0.010
	-	-	(0.007)	(0.007)	-	-	(0.010)	(0.010)
Constant	0.012	0.074	-0.582***	-0.975***	0.710***	0.696***	-0.927***	-0.610***
	(0.088)	(0.067)	(0.161)	(0.082)	(0.126)	(0.119)	(0.060)	(0.158)
R^2	0.000	0.554	0.355	0.552	0.063	0.587	0.549	0.584
N	3348	3348	3348	3348	1739	1739	1739	1739
Panel C: Data entry speed (Standardized)								
Part	0.154*	-0.008	-0.147	-0.266	-0.136	-0.286***	-0.037	-0.139
	(0.089)	(0.079)	(0.171)	(0.175)	(0.092)	(0.078)	(0.264)	(0.291)
Day	-	-	0.201***	0.196***	-	-	0.264***	0.257***
	-	-	(0.007)	(0.007)	-	-	(0.017)	(0.017)
Part × Day	-	-	0.026	0.022	-	-	-0.013	-0.013
	-	-	(0.016)	(0.015)	-	-	(0.024)	(0.024)
Constant	-0.076	0.005	-2.465***	-2.345***	0.485***	0.574***	-2.213***	-2.325***
	(0.047)	(0.049)	(0.206)	(0.117)	(0.054)	(0.062)	(0.112)	(0.220)
Day fixed effects		Y				Y		
Batch fixed effects		Y		Y		Y		Y
Trial fixed effects		Y		Y		Y		Y
R^2	0.006	0.525	0.353	0.489	0.004	0.573	0.458	0.531
N	1718	1718	1718	1718	899	899	899	899

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

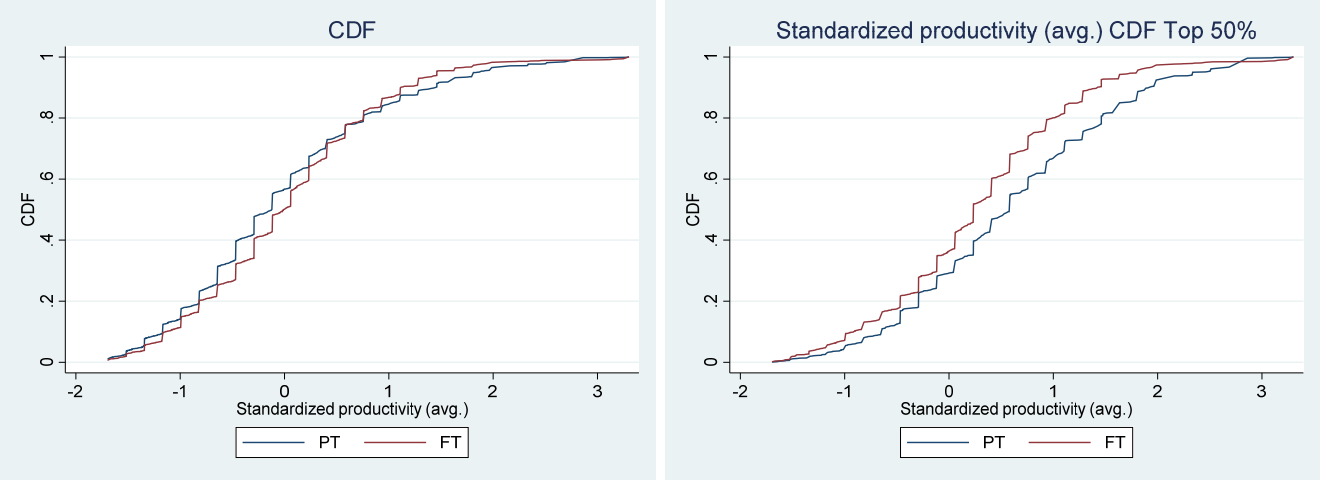
1st Week	1st	2nd	3rd	4th	5th
9:00-9:30	Introduction	Lecture 2: Microsoft Word - Saving + Opening + Editing + Typing + Copy & Paste	Lecture 3: Microsoft Word - Tables(Create + edit) + Inserting Pictures	Lecture 4: Microsoft Word - Spell Check + Printing and if time allows to create a document	Final Quiz
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	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		Typing Test (14minutes) + Gumball Gambit(15 Minutes) + Lesson (Rest of Time)	Typing Test (14minutes) + Shark Attack (15 Minutes) + Lesson (Rest of Time)	Typing Test (14minutes) + Road Trip (15 Minutes) + Lesson (Rest of Time)	
10:30-11:00	Typing 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)				

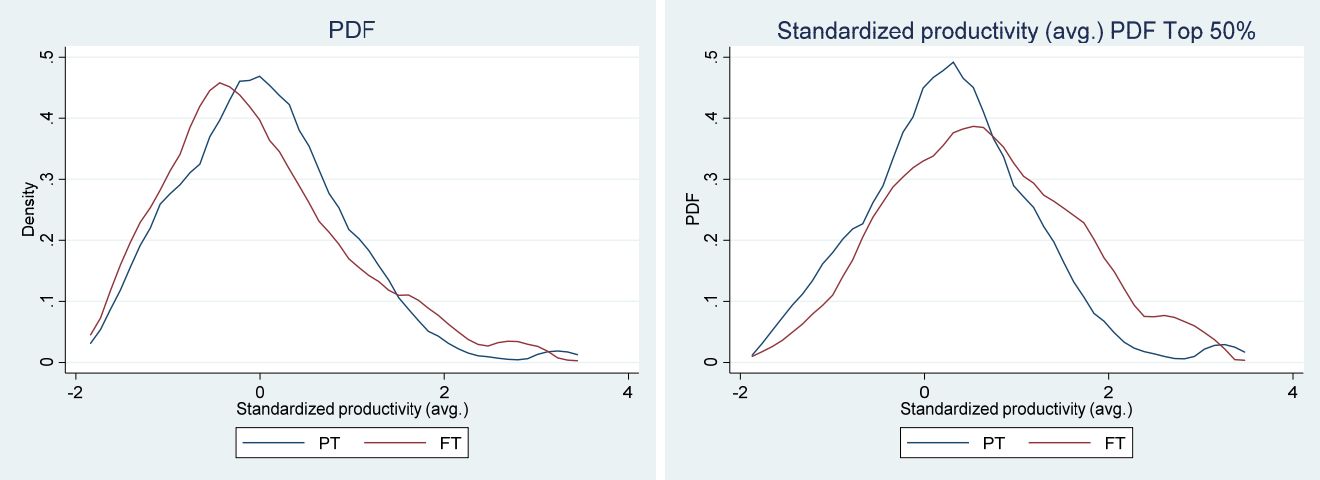
3rd Week	1st	2nd	3rd	4th	5th
9:00-9:30	Typing Test (14minutes) + Road Race Game (15 Minutes) + Lesson (Rest of Time)	Typing Test (14minutes) + Gumball Gambit (15 Minutes) + Lesson (Rest of Time)	Typing Test (14minutes) + Shark Attack (15 Minutes) + Lesson (Rest of Time)	Typing Test (14minutes) + Road Trip (15 Minutes) + Lesson (Rest of Time)	Typing 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. 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—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
Postsecondary 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 [1-10]	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	0.500
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 A2—COMPARISON OF JOB SURVEY PARTICIPANTS VS. NONPARTICIPANTS

Variable / Sample	(1) Application only (N)	(2) Application only (Mean)	(3) Job survey participation (N)	(4) Job survey participation (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
Postsecondary+	101	0.475	323	0.474	0.001
Asset score	98	7.031	314	6.927	0.104
Number of household members	100	4.450	317	3.855	0.595*
Number 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 A3. JOB APPLICATION BY FULL-TIME OFFER AND INDIVIDUAL CHARACTERISTICS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:				1 (Apply to job)			
Characteristic:		Age (/100)	Married	Ever birth	Working	Working in official sector	College+
Characteristic	-	-0.230***	-0.030***	-0.043***	-0.028*	-0.024**	0.050***
	-	(0.032)	(0.010)	(0.008)	(0.014)	(0.010)	(0.012)
Part	-0.003	-0.006	0.005	0.001	-0.002	-0.000	-0.011
	(0.011)	(0.019)	(0.013)	(0.015)	(0.014)	(0.014)	(0.009)
Part × Characteristic	-	0.009	-0.010	-0.005	-0.007	-0.008	0.041*
	-	(0.045)	(0.014)	(0.013)	(0.019)	(0.018)	(0.021)
Constant	0.065***	0.125***	0.075***	0.089***	0.074***	0.070***	0.051***
	(0.009)	(0.015)	(0.010)	(0.011)	(0.010)	(0.010)	(0.007)
R^2	0.000	0.008	0.005	0.008	0.004	0.002	0.017
N	6236	6082	6123	4839	6136	6076	6236
Control group mean	-	0.26	0.40	0.48	0.32	0.20	0.27

	(8)	(9)	(10)	(11)	(12)	(13)
Dependent Variable:				1 (Apply to job)		
Characteristic:	Post-Secondary+	Asset score	N. of HH members	N. of Children	Supportive spouse for PT job	Supportive spouse for FT job
Characteristic	0.035***	-0.003	-0.011***	-0.021***	0.022***	0.025***
	(0.010)	(0.002)	(0.003)	(0.005)	(0.005)	(0.005)
Part	-0.008	-0.034	-0.030	-0.024	0.057***	0.059***
	(0.010)	(0.027)	(0.023)	(0.022)	(0.021)	(0.020)
Part × Characteristic	0.016	0.004	0.006*	0.010	-0.015**	-0.015**
	(0.017)	(0.003)	(0.004)	(0.006)	(0.007)	(0.006)
Constant	0.051***	0.086***	0.115***	0.086***	-0.046***	-0.054***
	(0.008)	(0.022)	(0.021)	(0.018)	(0.011)	(0.012)
R^2	0.008	0.001	0.006	0.013	0.008	0.010
N	6236	6140	6173	2325	2385	2383
Control group mean	0.40	7.32	4.62	0.99	3.99	3.96

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 A4—STANDARDIZED PRODUCTIVITY WITH CONTROLS INCLUDED

	All trainees				Top 50% trainees			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable:	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, work preference over life, intrinsic motivation, extrinsic motivation, career expectation, accomplishment seeking, status seeking, career progress concern, and concern about compensation and benefits. Columns 4 and 8 include both the ability and work preference variables.

Data Appendix

B.1 Survey questions to measure preferences for work versus family

We measure the applicants' preferences for work versus family using 10 survey questions regarding the importance of work (5) and family (5). We calculate a composite score for work preference (over family) by subtracting the average score for family (Q401–Q405) from that for work (Q406–Q410). We also measure women's preference for work arrangements, such as full- and part-time jobs, in each stage of life (Q411–Q415).

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.						
408	Both the husband and wife should contribute to the household income.						
409	A husband's job is to earn money; a wife's job is to look after the home and family.						
410	I would enjoy having a job even if I didn't need the money.						

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

B.2 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:

On the line in the middle, write S if the two names are exactly the same and write D if they are different.

1.	Paramore & Co.	—	Paramore & Co.
2.	Bimler	—	Binler
3.	E-Z Neon	—	E-Z Neon
4.	Blackstone	—	Blackstone
5.	Chris Brasch	—	Chris Grasch

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

```
   8,733
x      4
```

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

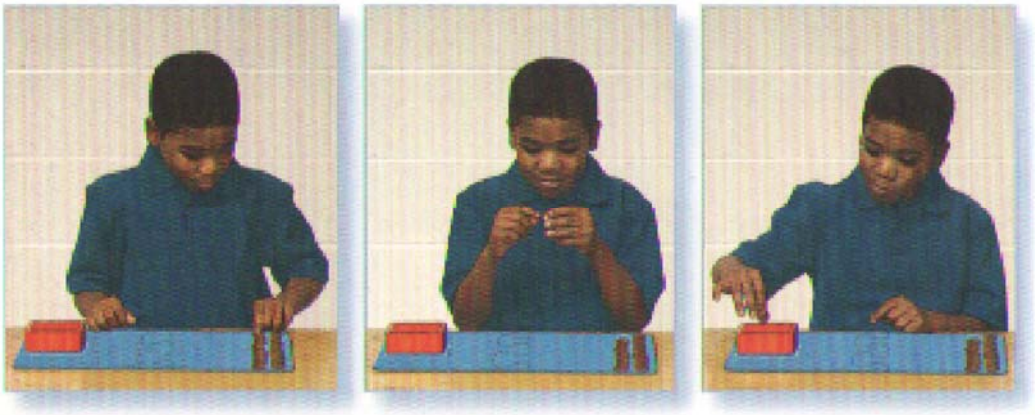
16. Divide

```
14 | 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™-2)

The BOT™-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.3. Attitude and expectation toward work

Relative importance for job decision

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.	

Intrinsic motivation

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).

Extrinsic motivation

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. "It is important for me…."		**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
10	I want to perform my job better than my friends.	1	2	3	4
11	I get worked up thinking about ways to become the highest performing man in my area.	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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