Do Part-time Jobs Attract Less Productive Workers?

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Abstract

This paper examines how self-selection shapes the applicant pool for part-time work and affects labor productivity. In a recruitment drive for female data entry workers in Ethiopia, we implemented a field experiment that randomly offers either a part- or full-time job opportunity. We develop a theoretical model demonstrating how an individual's abilities and working hour preferences affect job application decisions, which in turn determine the ability of part- and full-time applicant pools. Consistent with the model, we find that offering part-time employment opportunities attracts less able applicants, who exhibit lower productivity as measured by data entry speed and accuracy during an internship. These differences are more pronounced for hireable candidates—applicants who show greater productivity in the internship. (JEL J24, O15, M51)

Keywords: Part-time work; alternative work arrangements; self-selection; ability; labor productivity; wage-hours relation

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1 Introduction

A growing fraction of the workforce is being employed under alternative work arrangements (Mas and Pallais (2017); Abraham et al. (2018); and Katz and Krueger (2019)). An important feature of these arrangements is the flexibility offered to workers between work and non-market activities. These trends in the labor market raise the question of whether the alternative arrangements attract different types of workers, and if so, how this self-selection affects the productivity of the workforce.

In this paper, we study the selection effects of part-time employment on productivity.[1] While existing research finds considerable wage penalties associated with part-time employment and attributes them in part to a productivity difference due to self-selection (e.g., Blank (1990); Ermisch and Wright (1993); Aaronson and French (2004); and Manning and Petrongolo (2008)),[2] there is no direct evidence on whether and how this selection works. We provide the first experimental evidence on the selection effects of part-time work on employee ability and ultimately productivity.

We use a randomized experiment in a real world setting to estimate the effect of offering part-time employment on the ability and productivity of the applicant pool and hired workers. We collaborate with Africa Future Foundation, a nongovernmental organization in Ethiopia, in its large-scale search for data entry clerks. We provide opportunities to apply for either a part- or full-time data entry clerk position to women with a secondary school diploma. The otherwise identical part- and full-time jobs require the employee to work, respectively, four and eight hours per day five days a week. Our experiment focuses on women because the flexibility between labor market and non-market activities is likely most relevant for them (e.g., Blank (1990); Wiswall and Zafar (2016)). The job offered is considered high-stakes to the potential applicants in the study areas with low formal sector employment rates.

[1] Part-time work is particularly common among women—it accounts for about a quarter of women's employment both in developed and developing countries (Census Bureau (2018); OECD (2020); and IDB (2008)).

[2] This line of research shows a wage penalty of about one-fifth to one-quarter of full-time wages. A related literature finds positive relations between working hours and wages (Rosen (1976); Moffitt (1984); and Simpson (1986)).

We first implement a district census of 20,595 households to collect information on individual and household characteristics and to advertise the job opportunities to 6,295 eligible women. 333 applicants completed the job aptitude tests and a survey measuring the job applicants' abilities related to data entry work, preferences regarding work hours and family, and sociodemographic conditions. We find that the part-time applicants are less able as measured by data entry test score, clerical ability, and manual dexterity, and are less likely to work in the formal sector. Differences in these skill measures are more pronounced among "hireable" applicants—those who demonstrated greater productivity during an initial internship period.

The applicants are then invited to an internship program for three weeks, during which we measured each applicant's productivity using accuracy-adjusted data entry speed. Focusing on the hireable internship participants (i.e., those with high productivity), we find that productivity of those recruited through the part-time work is lower by 0.46 standard deviations than that of those recruited through the full-time work. This productivity gap exists from the first day and persists throughout the training. These findings are consistent with self-selection on intrinsic characteristics (especially ability) rather than different effort levels during the internship driving the productivity gap. We show that this gap is largely explained by the ex-ante ability measures but not by other individual characteristics.

To illustrate the mechanism of how offering a part- versus full-time job affects the ability of the applicant pool, we build a simple theoretical model in which individuals decide whether to apply for otherwise identical part- and full-time jobs, given their ability and preference for short work hours: Holding preference for short work hours fixed, the greater an individual's ability, the less likely she is to apply for either job due to higher outside options; and holding ability fixed, the greater an individual's preference for short work hours, the more (less) likely she is to apply for the part-time (full-time) job. The model then shows that the average ability of the part-time applicant pool is lower than that of the full-time applicant pool, when individuals who both strongly prefer short work hours and have high ability are relatively rare. Intuitively, when there is a lack of high-ability individuals with strong preference for short work hours, the part-time applicant pool does not get the same boost in ability that the full-time applicant pool gets from the high-ability individuals with weak preference for short work hours.

We verify the assumption that individuals with high ability and strong preference for short work hours are relatively rare in our own census data and representative samples of individuals across countries. A plausible reason for this pattern is that preference for short work hours is due to non-market responsibilities such as child-rearing (e.g., Manning and Petrongolo (2005)), which make acquiring ability and outside options difficult (e.g., Jones and Long (1979)).

This paper relates to a line of research that studies individuals' selections into jobs based on job attributes, ability, and preferences.[3] Dohmen and Falk (2011) and Deserranno (2019) use controlled experiments to show how worker self-selection leads financial incentives (such as piece rates) to attract workers with different productivity and prosociality. Dal Bó, Finan, and Rossi (2013) and Ashraf et al. (2020) study how offering high wages and emphasizing the career aspect of public servant jobs affect the quality of applicant pools in terms of both ability and proclivity for public service in field experiments.[4] Our paper is the first to provide experimental estimates of the selection effect of offering part-time employment on the quality of applicant pools and productivity of the workforce.

More broadly, the results in our paper have implications for the selection effect of alternative work arrangements that provide flexibility in scheduling the worker's labor market and non-market activities. In particular, to the extent that alternative arrangements attract workers who have high valuation of flexible work (and non-work) hours (e.g., Mas and Pallais (2017); and Mas and Pallais (2020)) and those workers rarely have high ability in the population, our results imply that the average recruited workers would be less able than those recruited through more traditional arrangements.

[3]See Roy (1951) and Borjas (1984) for classical contributions to this literature.

[4]A related literature shows how financial incentives affect labor productivity through an incentive effect (e.g., Lazear (2000); Shearer (2004); and Guiteras and Jack (2018)). A recent paper by Kim, Kim, and Kim (2020) attempts to disentangle the selection and incentive effects of financial and non-financial incentives on productivity.

In addition, our finding that part-time work attracts on average less able workers shows that the wage penalty associated with part-time employment is in part due to differences in the underlying productivity of workers. While previous research consistently finds significant wage penalties in the cross-section of workers across countries and time (Blank (1990); Ermisch and Wright (1993); Aaronson and French (2004); Manning and Petrongolo (2008)), no research we are aware of shows direct evidence that workers' self-selection explains this wage gap.[5]

2 Study Setting

We conducted our study in the Holeta and Ejerie areas of Ethiopia. Ethiopia is one of the least developed countries in the world, with GDP per capita of US$936 in 2020 (World Bank 2021). 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 is relatively high: 87 percent of women aged 15 or above are employed, according to the World Bank.[6]

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 rate is 70 percent in Holeta and 43 percent in Ejerie.

In the study areas, the data entry clerk position offers an attractive opportunity for women as one of the few formal sector jobs available. Data entry involves reading information from documents and entering it as a data field on a computer. The job requires

[5]Papers examining the effect of part-time work on productivity present mixed evidence largely relying on observational data. For example, Künn-Nelen, De Grip, and Fouarge (2013) find that employing part-time workers could increase productivity by allowing firms to allocate their workforce more efficiently. Garnero, Kampelmann, and Rycx (2014) find that women working part-time are as productive as those working full-time. In contrast, Specchia and Vandenberghe (2013) and Devicienti, Grinza, and Vannoni (2015) find a negative relationship between the fraction of part-time employees and firm-level productivity.

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

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. Outside options for data entry clerks include household farming and other formal sector jobs. At the time of the baseline survey for job applicants, 13.2 percent of applicants were working for their family and 19.5 percent were working for pay in formal sectors.

3 Experimental Design

Africa Future Foundation (AFF) established its data entry unit with plans to hire women as data entry clerks from the catchment areas. In May–June 2016, AFF conducted a census of Holeta and Ejerie gathering information on 20,595 households. During the census, job flyers with a job description, working conditions, and expected pay were distributed to 6,295 resident women with a secondary school diploma. 71 village groups—clusters of several villages— were randomly assigned into 35 part-time and 36 full-time groups and job flyers were distributed accordingly.[7] These village groups included 234 villages in our sample.

Figure A1 shows job flyers for the part-time (Panel A) and full-time (Panel B) positions. Applicants are required to submit a résumé and a copy of their secondary school graduation exam report at the AFF office located in the Holeta city center. The part-time (full-time) job requires four (eight) hours of work per day. The monthly pay offered ranges from 1,000 to 1,250 (2,000 to 2,500) Ethiopian Birrs for part-time (full-time) employees with the variation depending on their performance. The pay offered is in line with pay at other data entry firms in Ethiopia.[8] It is worth noting that there is no wage discount for

[7] The experimental 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, because AFF had to evacuate from the study area due to political turmoils, during which more than 500 people are estimated to have been killed, it was not able to proceed as planned. See https://www.theguardian.com/world/2016/oct/02/ethiopia-many-dead-anti-government-protest-religious-festival.

[8] According to the authors' market survey in 2016, a typical data entry firm in Ethiopia paid the average full-time worker a baseline wage of 80 Ethiopian Birrs (ETBs) per day (or 1,600 ETBs per

the part-time job offered. Therefore, the difference in ability and productivity between part- and full-time applicants observed in our setting is likely a lower bound estimate, relative to a setting with a part-time wage discount.[9]

One advantage of our recruitment strategy is that we observe the entire population of potential job applicants through the census of the catchment areas. Our approach allows us to characterize the distribution of potential applicants along key dimensions such as socioeconomic (e.g., ability) and family characteristics, which could be important to understanding how the self-selection to part-time work operates. This approach contrasts with existing studies, which typically observe actual (i.e., ex-post) job applicants only. We find that those who are not married, have less children, and do not currently have a job are more likely to apply for the position (see Table A1). These results imply that family status and outside option are important determinants of the employment decisions and plausibly of the decision to work part- and full-time, as our model shows below.

Table 1 shows the stages in our experiment and the number of individuals who joined in each stage. We first identified 6,295 eligible women through the census and distributed part- and full-time job flyers to 3,202 and 3,093 women according to our randomization at the village group level from May through July 2016. Among the eligible women, 230 (7.2 percent) and 226 (7.3 percent) in the part- and full-time village groups submitted applications and supporting documents within the following month. Those who applied for the job (referred to as "job applicants" hereafter) were asked to join baseline job survey and aptitude tests at the AFF office in Holeta in December 2016. 162 (5.1 percent) and 171 (5.5 percent) job applicants in the part- and full-time village groups completed the job survey and aptitude tests (referred to as "job survey participants" hereafter). Last, AFF invited all job survey participants to an internship program, to which 61 (1.9 percent) in the part-time group and 61 (2.0 percent) in the full-time group participated (referred to

month) plus two ETBs per additional accurate entry over 30 entries per day as an incentive. 100 ETBs are approximately US$3 as of the timing of the experiment.

[9] Fixed costs of employment could explain part of the wage penalty (e.g., Rosen (1976)). Compensating differentials frameworks (e.g., Rosen (1986)) suggest that to the extent that flexibility in scheduling provided by part-time work is valuable to workers, the part-time job could offer lower wages conditional on productivity.

as "interns" hereafter).[10] AFF allowed the participants to attend either the morning (9:00 a.m.–12:00 p.m.) or afternoon (2:00 p.m.–5:00 p.m.) session to ensure that they could participate regardless of their working hour preferences. The three-week-long internship program entailed basic computer training, and importantly data entry practice and tests (see Figure A2 for details). Thus, the administrative data collected during the internship allow us to measure each intern's productivity. It is worth noting that AFF invited all job survey participants to the internship, as opposed to those with high measured ability only, such as top performers in the aptitude tests. This setting allows us to gauge the productivity difference between part-time and full-time applicant pools with various potential cutoffs applied for hiring employees. The last row in the table shows that the top 50 percent performers during the internship are similarly distributed across the part- and full-time pools.

4 Data

4.1 Data Sources

The primary data sources for our study are the census of the study area, baseline survey and job aptitude tests, and administrative data collected during the job application and internship. The census data cover approximately 87,000 individuals in 20,595 households, including the 6,295 women eligible for the job. We draw from the census data variables capturing demographic and socioeconomic status and family structure, including age, marital status, education, employment, and numbers of household members and children.

The baseline survey collected comprehensive information on 333 applicants including (i) demographics and socioeconomic status; (ii) attitude and expectation toward work (e.g., factors affecting job selection, intrinsic and extrinsic motivation, career expectations); and (iii) preference about working hours. The applicants also completed job aptitude tests that measure data entry speed, computer literacy, clerical and computa-

[10] The survey participants were invited to the internship in five batches, each of which consists of 22 to 32 people.

tion abilities based on the O*NET and Bruininks-Oseretsky Test of Motor Proficiency. Data Appendix B provides details of the survey modules and aptitude tests we employ.

4.2 Study Population Characteristics and Randomization Balance

Table A2 presents descriptive statistics of individual-, household-, and village-level characteristics for the population of eligible women. In particular, columns 2 to 5 show the average characteristics of all eligible women, those in the part- and full- time village groups, and the difference between the two. First, the table confirms that the randomization was successful: only one (working within household) out of 27 characteristics differs significantly at the 10 percent level between the part- and full-time groups. As shown in Panel A, the average age of job-eligible women in the area is 26 years, about 74 percent of them belong to the Oromo ethnic group (the majority ethnicity in Ethiopia), and 69 percent are Orthodox Christians. The fraction of eligible women who have attained postsecondary education is 39 percent. Panel B shows that the average eligible woman's household has 4.2 members, and Panel C shows that about one-third of the villages in the sample are in Holeta, the more urban area, with the balance in Ejerie, the more rural area.

4.3 Distribution of Ability and Work Hour Preference in Study Population

We focus on individuals' ability and preference for working hours as two key dimensions that affect self-selection into part- and full-time jobs. As we show in our theoretical model in Section 5, the impact of this selection on the quality of applicant pools crucially hinges on the distribution of potential applicants along these dimensions. Thus, we examine the distribution of variables that capture these dimensions among the population of potential job applicants using our census data. We use the level of education as a proxy for an individual's ability and the number of children living in the same household as a proxy for the preference for short working hours driven by child-rearing responsibilities (Rosen (1976); Moffitt (1984); and Ermisch and Wright (1993)).

Figure 1 graphically shows that the density of individuals who have both higher level of education and more children living with them (i.e., those in the north-east corner) is particularly low relative to the rest of population in our study area. Moreover, Figure A3 shows similar distributional patterns across 24 African countries using the Demographic and Health Survey (DHS) data on women: There are fewer women who have both high level of education and large number of children in the household. A plausible reason for this common pattern is that preference for short work hours is due to child-rearing responsibilities, which make acquiring ability difficult (Jones and Long (1979)).

4.4 Outcome Variables

The primary outcomes for this study are error-adjusted typing and data entry speeds during the internship. First, we measure the number of total words correctly entered per minute (typing speed) using Mavis Beacon, a computer application designed for typing training. Each task involves the intern typing in a series of words or sentences shown on the computer screen for seven to 15 minutes depending on specific sessions in Mavis Beacon. The interns performed the task twice a day over the three week internship period.

Second, we measure the number of census data fields correctly entered scaled by the number of minutes spent (data entry speed). For this task, we gave the same set of census forms with identical information to all interns on a given day and asked them to type in the information using the computer within 15 minutes.[11] The interns performed the data entry task during the last two weeks of the internship. To ensure accurate measurement of performance, two supervisors independently recorded the number of words or fields that each intern correctly entered per minute. Our empirical analysis uses these measures of individual productivity standardized by subtracting the respective mean and scaling by the standard deviation (see, e.g., Kling, Liebman, and Katz (2007)).

[11] We define a "correctly entered field" as a non-missing value in a census data field (e.g., a person's name) that is entered without an error or a missing value that is not supposed to be entered. All other entries are considered incorrect.

5 Conceptual framework

We illustrate how offering a part- or full-time job affects the ability of the applicant pool by building a theoretical model of individuals' selection into jobs with differing work hours. To this end, we consider a population of potential applicants, parameterized by two variables: preference for short working hours (γ) and ability (θ). γ takes values in $[0,1]$ and measures the strength of a worker's preference for part-time work over full-time work. The higher γ is, the more the worker prefers part-time work (4 hours per day) over full-time work (8 hours per day). θ takes values in $[0,1]$ and measures both the worker's ability and her outside option value – for simplicity, we assume they are perfectly correlated. The higher θ is, the greater the worker's ability and outside option. Thus, the entire population of workers can be represented as a measure μ over the unit square $[0,1] \times [0,1]$. For example, for $0 \leqslant a < b \leqslant 1$ and $0 \leqslant c < d \leqslant 1$, $\mu([a,b] \times [c,d])$ is the measure of workers with γ between a and b, and θ between c and d.

Given a part-time job $j = PT$, a worker's payoff is $W^{PT}(\gamma,\theta) = \gamma$. Given a full-time job $j = FT$, a worker's payoff is $W^{FT}(\gamma,\theta) = 1-\gamma$. Thus, the greater a worker's preference is for part-time work over full-time work, the greater her payoff is from having a part-time job, and the lower her payoff is from having a full-time job. A worker with type (γ,θ) applies to a job j if and only if her payoff from having job j is weakly greater than her outside option – that is, if $W^j(\gamma,\theta) \geqslant \theta$ for $j \in \{PT, FT\}$. For example, a worker with type $(0.75, 0.5)$ will apply to a part-time job, because $W^{PT}(0.75, 0.5) = 0.75 > 0.5$. However, this same worker will not apply to a full-time job, because $W^{FT}(0.75, 0.5) = 0.25 < 0.5$. In contrast, a worker with type $(0.5, 0.25)$ will apply to both kinds of jobs, and a worker with type $(0.5, 0.75)$ will not apply to either kind of job. Let S^j denote the subset of worker types that apply to job $j \in \{PT, FT\}$.

S^{PT} is the *part-time applicant pool* that corresponds to those women who applied in the villages with the part-time job posting. S^{FT} is the *full-time applicant pool* that corresponds to those women who applied in the villages with the full-time job posting. Obviously, the statistical properties of S^{PT} and S^{FT} depend on the statistical properties of the population – i.e., μ. We make the following assumption about μ:

μ has a density. There is a parameter $x \in (0, 1)$ and a value $l > 0$, such that the density of μ on the subset, $[x, 1] \times [x, 1]$, of worker types is 0, while the density of μ outside that subset is l.

See Figure 2 for a depiction of the unit square of worker types, S^{PT}, S^{FT}, and μ. The motivation for this assumption is as follows: We posit that the preference for part-time work is driven by non-market responsibilities such as child-rearing which also make acquiring ability and outside options difficult (see, e.g., Manning and Petrongolo (2005); and Jones and Long (1979)). Thus, we expect that workers who both strongly prefer part-time work and have very high ability and outside options are relatively rare. The assumption above reflects this position. The specific functional form we have chosen is not crucial for our results, and is made largely for computational tractability and conceptual clarity.

Our main result is that what kind of job is being posted – part-time or full-time – affects the type of applicant that the job attracts, in particular, the statistical properties of the applicant pool's ability.

Proposition 1. *The average ability of the full-time applicant pool S^{FT} is greater than the average ability of the part-time applicant pool S^{PT}.*

Proof. The result can be easily seen geometrically. Fix an ability level $\tilde{\theta} \in [0, x)$. Notice, the (marginal) measure of part-time and full-time applicants with ability $= \tilde{\theta}$ is the same: $l \cdot (1 - \tilde{\theta})$. This means, below the ability level x, the distribution of ability within S^{PT} and S^{FT} is identical. Above the ability level x, there are no applicants in S^{PT}, while there is a strictly positive measure of applicants in S^{FT}. Thus, the average ability of S^{FT} is greater than the average ability of S^{PT}. $\square$

Of course, the applicant pool is not the same as the pool of workers that are eventually hired by the firm. First, let us consider the extreme case when the firm cannot screen θ or γ.[12] Then the average ability of those workers the firm hires from the j-applicant pool is exactly the average ability of the j-applicant pool. We now immediately have the following result:

Corollary 1. *Suppose the firm cannot screen θ or γ. Then, the average ability of the hired full-time workers is greater than the average ability of the hired part-time workers.*

Next, let us consider the opposite extreme and suppose the firm can perfectly screen θ. We posit there is an ability cutoff $\theta^* < x$ such that a worker is worth hiring if and only if her ability is at or above θ^*. Consequently, the *part-time hiring pool* is $S^{PT}(\theta^*)$ defined to be the subset of S^{PT} consisting of those workers with ability $\geqslant \theta^*$. The *full-time hiring pool* $S^{FT}(\theta^*)$ is defined similarly.

Proposition 2. *The average ability of the full-time hiring pool $S^{FT}(\theta^*)$ is greater than the average ability of the part-time hiring pool $S^{PT}(\theta^*)$. Moreover, when $x \geqslant 0.5$, the difference – call it the average ability gap – is increasing in $\theta^* \in [0, x)$.*

Proof. The proof of the first part is virtually identical to the proof of Proposition 1. To prove the second part, assume $x \geqslant 0.5$. The average ability of the full-time hiring pool is

$$\frac{1 + 2\theta^*}{3},$$

which means that the average ability of the full-time hiring pool increases at rate $\frac{2}{3}$ with respect to θ^*. A simple calculation shows that the average ability of the part-time hiring pool increases at a variable rate $< \frac{2}{3}$ with respect to θ^*. This implies the gap is increasing. $\square$

[12] We do not presume that the firm's utility function depends on γ, only θ. However, since γ and θ are correlated in the applicant pools, even if the firm cannot screen θ, if it could screen γ, it would do so. For example, in the full-time applicant pool, it would try to hire those with the weakest preference for part-time work, since they are more likely to have higher ability.

6 Empirical Results

6.1 Treatment Effect of Offering Part-time Employment Opportunities on the Applicant Pool

We first study the effect of offering part-time employment opportunities on the applicant pool, relative to offering full-time opportunities, by estimating the following equation on a sample of job applicants:

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

where y_{ij} is a characteristic of applicant i in village group j measured in the job survey or an aptitude test; $Part_{ij}$ is an indicator equal to one if applicant i in village group j was given a part-time opportunity, and zero if given a full-time opportunity; and ε_{ij} is a random error clustered at the village group level.

Proposition 1 of the theoretical model shows that the average ability of the part-time applicant pool is lower than that of the full-time applicant pool, when workers who both strongly prefer part-time work and have very high ability are *relatively* rare (see Figures 1 and A3). Further, Proposition 2 implies that this difference in ability would be more pronounced in a subset of applicants that satisfies a minimum ability threshold. Thus, we estimate equation (1) on the following samples: (i) all applicants, (ii) applicants who participated in the internship with average performance greater than or equal to the 50$^{\text{th}}$ percentile and (iii) below the 50$^{\text{th}}$ percentile. The sample with top 50 percent performance in the internship likely represents a subset of high-quality applicants the firm would consider hiring ("hireable"), for which the ability difference is expected to be more pronounced.[13] We examine the robustness of our results to varying the hiring

[13]The median words per minute (WPM) of the internship participants is 12. A study by Karat et al. (1999) finds that a group of IBM employees in the US who are experienced computer users and native speakers of English exhibit an average WPM of 33. Naturally, AFF found applicants with below-the-

cutoff in Section 6.3.

Table 2 presents the results of estimating equation (1). First, columns 1-3 of Panel A show that for the full sample of applicants, the part-time pool is significantly less able than the full-time pool, as measured by data entry speed (significant at the 5 percent level) and manual dexterity (at the 10 percent level). The gaps in typing speed and dexterity between the part- and full-time pools amount to 0.22 and 0.24 standard deviations (SDs). The part- and full-time pools exhibit insignificant differences along the other ability measures, rendering the difference in the standardized score combining all ability measures insignificant (last row in Panel A).

Importantly, consistent with the theoretical prediction (Proposition 2), the difference in ability between the part- and full-time pools is larger in magnitude and statistically more significant when conditioning on top 50 percent internship performance (columns 4–6): in six out of seven ability measures employed (i.e., data entry speed, clerical ability, computer literacy, manual dexterity, education, and official sector work status), the part-time pool shows a significantly lower level (at a 5 percent or less level) than the full-time pool. As a result, the part-time pool is 0.44 SDs lower in the standardized score combining the six ability measures, which is significant at the 1 percent level. In contrast, among interns with performance in the bottom 50 percent (columns 7–9), there is no significant difference in any of the ability measures between the part- and full-time pools.

Panel B shows that the part-time applicants are, not surprisingly, less likely to prefer full-time work and more likely to prefer family over work. Moreover, the part-time applicants exhibit weaker spousal support for working (significant at the 1 to 5 percent level) and have a larger number of children who live with them, indicating their stronger preferences for short work hours. The difference between the part- and full-time applicants in the standardized score that combines the five variables capturing preferences for shorter

median performance largely unemployable.

work hours is on average 0.17 SDs and significant at the 1% level (column 1). The difference is larger at 0.29 SDs among those in the top 50 percent internship performance (column 6, significant at the 1% level) while it is 0.16 SDs (column 9, insignificant) for those in the bottom 50 percent performance. Overall, the results in Panel B are consistent with job applicants self-selecting to a part- or full-time job according to their preferences for working hours, as the model presumes.

Unlike the above two panels, Panels C and D show that the part- and full-time applicant pools are little different in terms of other demographic and socioeconomic variables, as well as motivations for choosing jobs. One exception is that part-time applicants with top 50 percent internship performance have lower career- and compensation-related motivations for choosing jobs (significant at the 10 percent level).

6.2 Treatment Effect of Offering Part-time Opportunities on Labor Productivity

The analysis in the previous section shows that part-time job applicants have significantly lower ability than full-time applicants, particularly among those with higher ability level. These findings suggest that part-time workers would exhibit lower productivity at work. We test this implication by comparing the labor productivity of the interns in the part- and full-time groups (see Section 3 for details of the internship). Specifically, we estimate the following equation on a sample of interns:

$$Productivity_{ijslt} = \gamma_0 + \gamma_1 Part_{ij} + \mu_s + \upsilon_l + \lambda_t + \varepsilon_{ijslt}, \quad (2)$$

where $Productivity_{ijslt}$ represents the following productivity measures with their respective means subtracted and scaled by standard deviations: (i) typing speed (number of correctly entered words per minute) and (ii) data entry speed (number of correctly entered census data fields per minute) for individual i from village group j in internship batch s in trial l on day t; $Part_{ij}$ is an indicator equal to one if worker i in village group j is offered a part-time opportunity, and zero if full-time, and μ_s, υ_l, and λ_t are internship batch, trial, and working day fixed effects. ε_{ijslt} is an error term clustered at the village group level.

We argue that the productivity difference between part- and full-time recruited interns, captured by γ_1, is driven by self-selection of applicants. A key identifying assumption for this interpretation is that any incentive effect of the job opportunity offered is negligible. For example, those recruited through the part-time offer might have less incentives to invest in human capital during the internship given lower returns on their investment once they are hired. We test the plausibility of the identifying assumption in the next section by examining the attendance and productivity trends during the internship.[14]

We first visually present trends in labor productivity for part- and full-time recruited interns over the three-week internship period in Figure 3. To do so, we estimate a variant of equation (2) which replaces the $Part$ indicator with the interaction terms between the indicators for part- and full-time groups and a series of indicators for internship days (from 1 through 15) on the sample including both productivity measures.[15] The figure shows increasing productivity over time both for the part-time (red dashed line) and full-time (blue solid line) groups, consistent with the interns being generally at a steep portion of the learning curve. Importantly, Panel A shows that among the interns with top 50 percent average performance, those recruited through the part-time opportunity perform worse than those recruited through the full-time opportunity from the beginning. This finding is consistent with theoretical and empirical results on the ability difference

[14]The causal effects of the actual part- or full-time work arrangement (such as fatigue from long work hour) do not play a role in our study, given that all interns worked for the same three hours a day regardless of the opportunity offered.

[15]Figure A4 plots productivity trends over time for the part-time and full-time groups by task (i.e., typing and data entry).

between applicant pools. Panel B makes it clear that a significant productivity gap exists through most of the days in the internship. In contrast, Panels C and D show that, again in line with theoretical and empirical results above, the productivity difference between the part- and full-time groups is small and insignificant for the bottom 50 percent performers.[16]

Table 3 formally presents results of estimating equation (2) for the full sample (column 1), top 50 percent and bottom 50 percent performers (columns 2 and 3). Panel A confirms that the productivity difference is significant among the top 50 percent interns but not in the bottom 50 percent. In Panel B, we include the variable *Day* representing the number of days in the internship and its interaction with the *Part* indicator, which allows us to estimate differential time trends in productivity between interns recruited through part- and full-time opportunities. The panel shows that the initial productivity differences between the part-time and full-time groups are 0.498 ($= -0.509 + 0.011 \times 1$ day) and 0.291 ($= -0.313 + 0.022 \times 1$ day) standard deviations for top 50 percent performers (column 2) and all interns (column 1). By the end of the internship, the productivity gap remains at 0.344 ($= -0.509 + 0.011 \times 15$ days) and significant at the 5 percent level for the top 50 percent interns, whereas it becomes 0.017 ($= -0.313 + 0.022 \times 15$ days) for all interns. Column 3 shows that this convergence in labor productivity difference between the part- and full-time groups is driven by the bottom 50 percent interns.

We further examine sources of the difference in the effect of offering part-time employment on productivity between the top and bottom performer samples by estimating a quantile regression version of equation (2). Table A3 shows that the productivity difference is generally increasing in the percentile and becomes statistically and economically significant above the top decile.

[16]Similarly, the cumulative distribution functions in Figure A5 show that the productivity of full-time recruited interns first-order stochastic dominates that of part-time recruited interns among the top 50 percent performers but not in the bottom 50 percent.

Taken together, the findings in this and previous sections on ability and productivity differences are consistent with the theoretical prediction that the ability of the part-time applicant pool is on average lower than that of the full-time pool; and this difference is driven by higher-quality applicants who are more hireable.

6.3 Further Results

Employment cutoffs. Our main results show that the productivity difference is larger among the hireable applicants with top 50 percent internship performance, consistent with the theoretical model (Proposition 2). We generalize this analysis by varying the cutoff to define hireable applicants. The analysis would have important implications for practice because firms likely want to hire a varying fraction of job applicants as their labor demand changes, which in turn affects their labor productivity. Specifically, we estimate equation (2) by varying the performance cutoff for hiring. We apply cutoffs ranging from no restriction (i.e., 100 percent) to top 45 percent in 5 percent increments.

Figure 4 presents the result of the analysis. The x-axis shows the percentile that defines hireable candidates and the y-axis shows the average productivity difference between part- and full-time recruited interns with 95 percent confidence intervals. We find that the productivity gap is generally larger in a subset of interns with tighter performance (i.e., proxy for ability) cutoffs. In particular, the productivity difference is economically and statistically significant for all subsamples from top 75 percent to 45 percent performers. This finding is consistent with our model and suggests that when a firm selects top performers based on pre-employment training programs (such as internship) or tests, the productivity gap between the part- and full-time recruited applicants would become more pronounced.

Incentive effects. One might argue that the productivity difference we observe in the internship is driven by incentive effects, in addition to our proposed selection effects. For example, interns who expect to work full-time might have a stronger incentive to make an effort because their future return on the human capital investment would be higher once they are hired. However, this incentive effect is unlikely to explain the observed productivity difference for several reasons. First, it cannot explain the significant initial difference in productivity. Second, the productivity of part-time recruits increases faster than or at least on par with the productivity of full-time recruits. Third, the rate of internship participation, an important investment for their human capital, does not differ between the part- and full-time applicants among the top 50 percent performance sample, where the significant productivity difference exists (Table A4).

What explains the productivity difference? In this subsection, we examine the extent to which ex-ante measures of ability explain the productivity gap. To this end, we reestimate equation (2) by explicitly including the variables from Table 2, Panels A and B as controls for (i) ability; (ii) preference for short working hours; and (iii) both. Table A5 presents the estimation results.

Columns 1, 5, and 9 show the baseline estimates excluding the control variables for the full intern, top 50 percent, and bottom 50 percent samples. In the second, third, and fourth columns for each sample, we present coefficients controlling for measures of ability only, preference about working hours only, and both. We find that ability is in fact most important in explaining the productivity difference due to offering a part- or full-time opportunity, particularly for the hireable intern sample (columns 5–8). The ability proxies explain 72 percent ($= [0.411 - 0.117]/0.411$) of the productivity difference, whereas the measures of working hour preferences explain only 19 percent ($= [0.411 - 0.332]/0.411$) of the gap.[17] This result is consistent with individuals' ability differentials being a key source of productivity differentials between part- and full-time applicant pools.

[17] Following Gelbach (2016), we also formally decompose the effect of offering part-time employment opportunities that is explained by covariates capturing ability and preference for short working hours. We find that the portion explained by the former is -0.314 (significant at the 1 percent level), whereas that by the latter is insignificant at -0.030.

7 Conclusion

How part-time work arrangements affect employee selection and productivity of the workforce is an important question, given the high prevalence of part-time work across economies. More generally, the recent rise of alternative work arrangements, whose often-argued advantage is to offer flexibility in workers' labor market and non-market activities, raises the question of which workers self-select into these flexible work arrangements and why. We explore these questions by implementing a randomized experiment that provides a part- or full-time data entry job opportunity to women. We also develop a theoretical model of job application given ability and preference for short work hours to explain the mechanism.

The experimental results show that part-time work attracts applicants with lower job-specific ability, relative to full-time work. This "part-time ability gap" is more pronounced among applicants with top initial performance, who are plausibly more hireable. Our model shows that the lack of potential applicants who have both strong preference for short working hours and high ability, combined with ability driving workers' outside option, leads to this selection effect. The part-time applicants also exhibit lower initial productivity at work as measured by data entry speed during an internship, which is again more pronounced for more hireable, higher-performance applicants.

These findings have important implications for part-time work and alternative work arrangements in general. First, the wage penalty associated with part-time employment shown in previous research (e.g., Blank (1990); and Manning and Petrongolo (2008)) is at least in part explained by the lower average ability of workers who self-select into part-time work. Second, to the extent that alternative work arrangements attract workers who have high valuation of flexible schedule (e.g., Mas and Pallais (2017); and Mas and Pallais (2020)) yet rarely have high ability, the workers recruited under these alternative arrangements would be less productive than those hired through standard arrangements.

Of course, if workers who both highly value flexibility and have high ability are relatively common in certain labor markets (e.g., perhaps for high-skill independent contractors and freelancers), the self-selection effects of offering nonstandard work arrangement in those markets might differ from our findings. Investigating potentially differing selection effects of alternative arrangements across labor markets and types of jobs appears an important avenue for future research.

This paper also offers implications for women's labor market issues, particularly the relation between the gender pay gap and short (or flexible) work hours (see, e.g., Goldin (2014); Goldin and Katz (2016); and Blau and Kahn (2017)). Our findings imply that pay structures that are nonlinear (e.g., increasing) in work hours may reflect workers' self-selection on ability and value of short work hours. Thus, future research that investigates the role of work-hour flexibility—such as the part-time option we examine—for mitigating the gender pay gap should take into account a negative selection effect on the ability of applicant pools those arrangements could entail.

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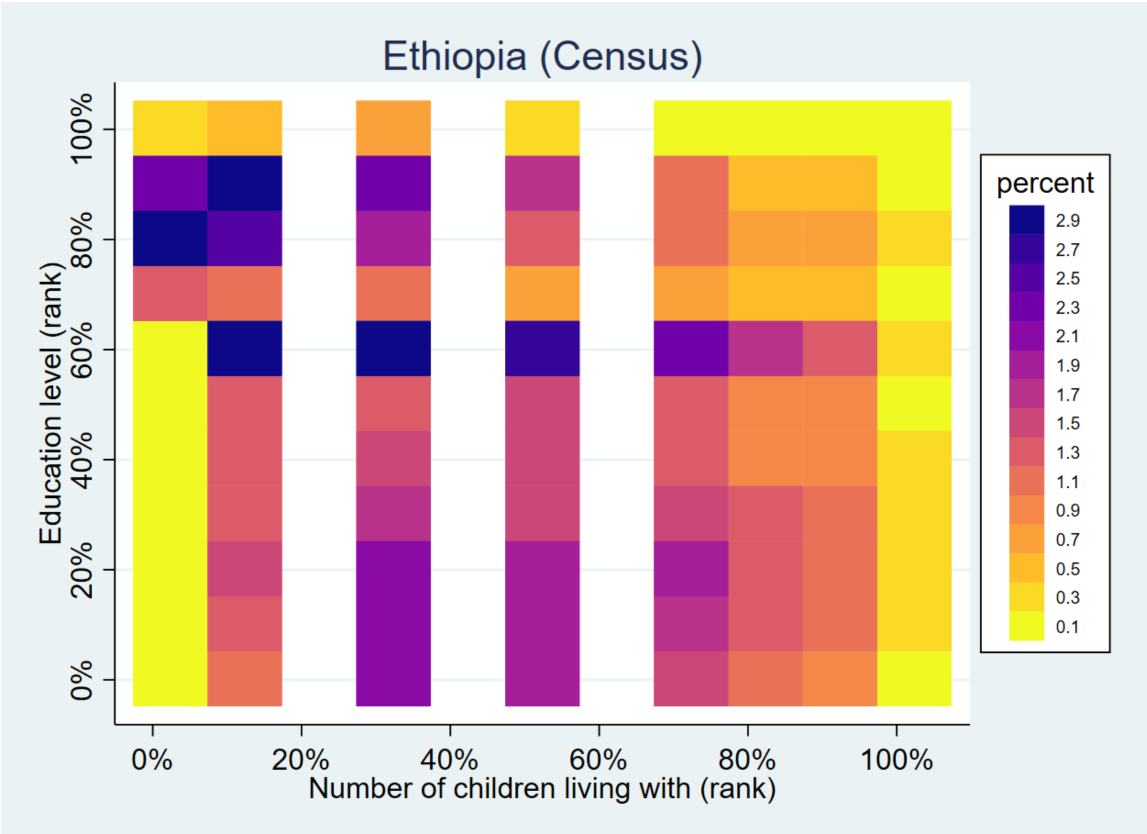
Figure 1: Number of Children Living with (Preference) and Years of Education (Ability), Census of Holeta and Ijerie



Note: The figure presents the distribution of the number of children living with (x-axis) and year of education (y-axis) in rank for job-eligible women in Holeta and Ijerie, the catchment areas. The data are collected in the Census.

Figure 2: Applicant pools for part-time and full-time jobs in the ability-preference for short working hour space

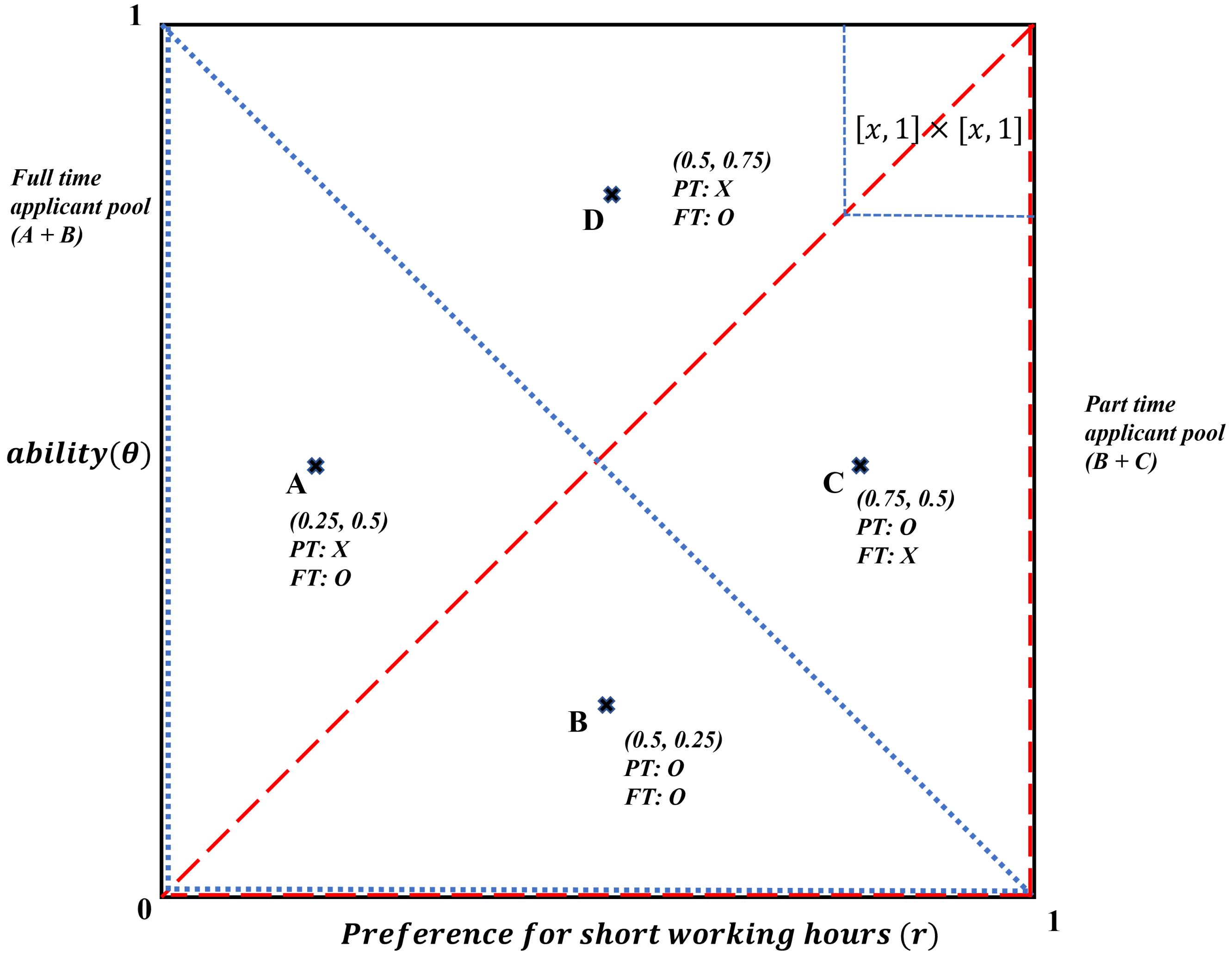
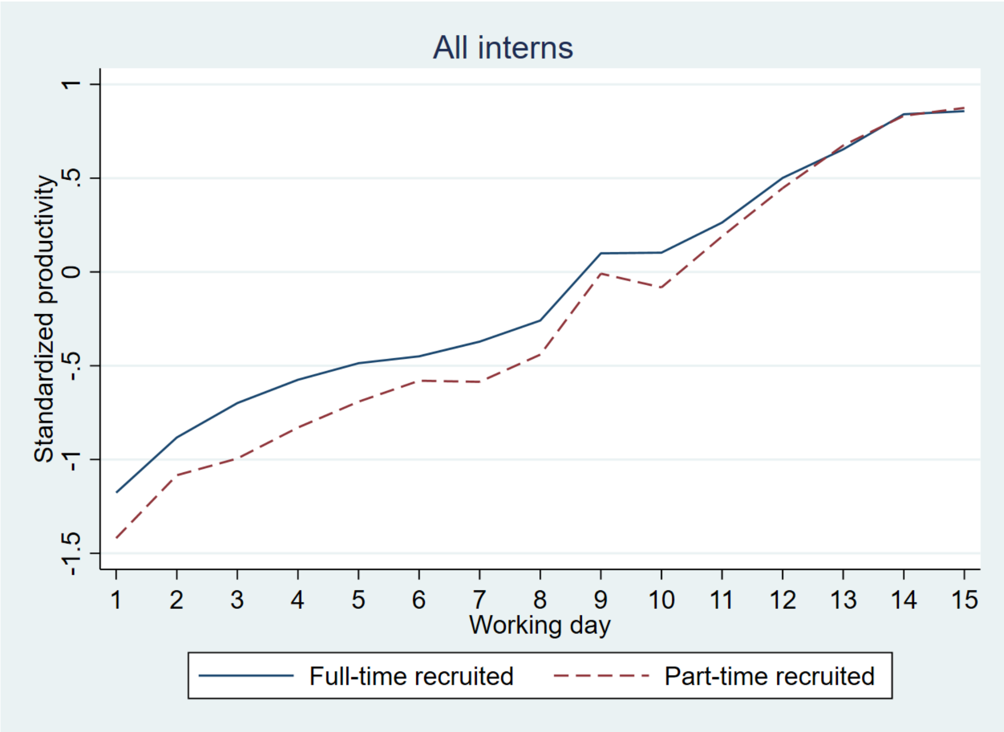
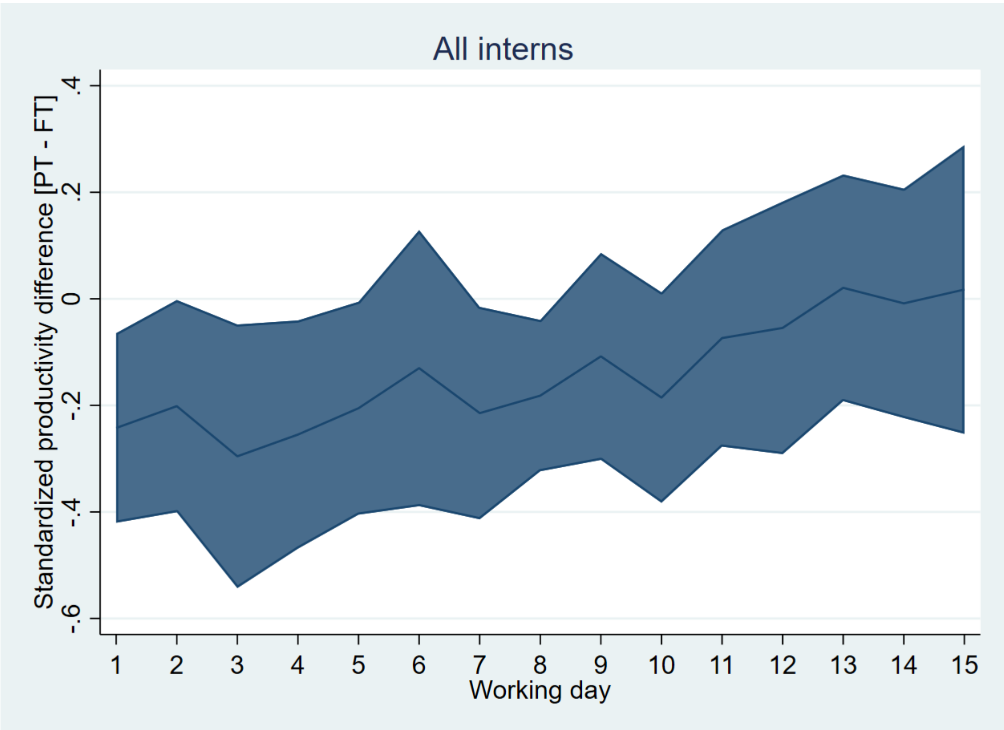


Figure 3: Productivity of part-time and full-time recruited interns over time

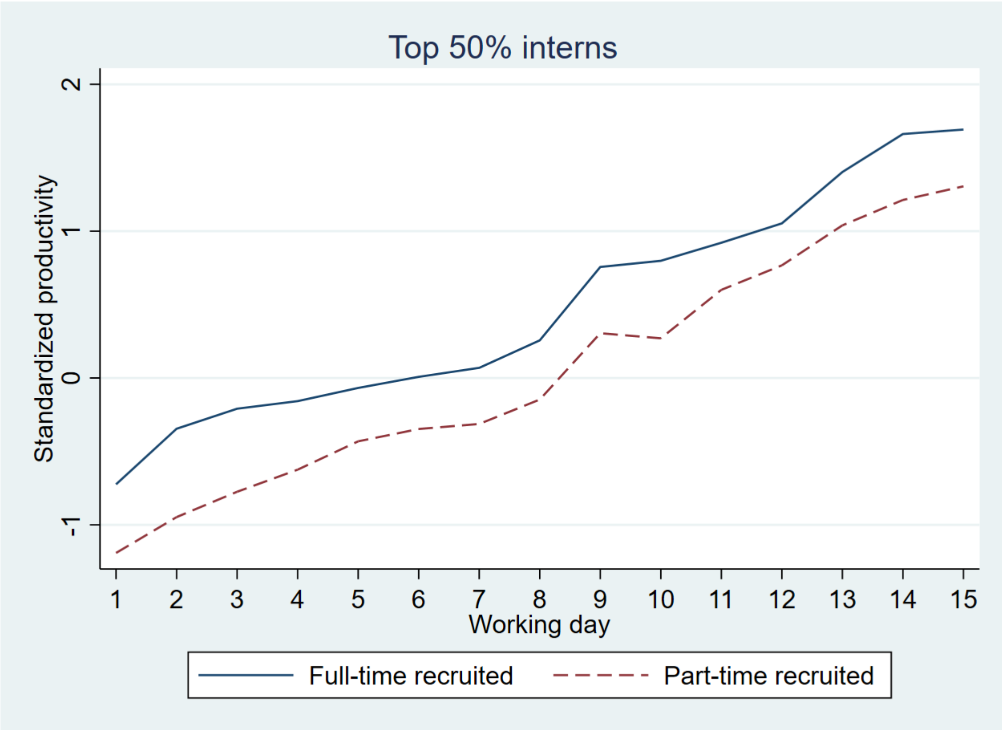
Panel A. All interns



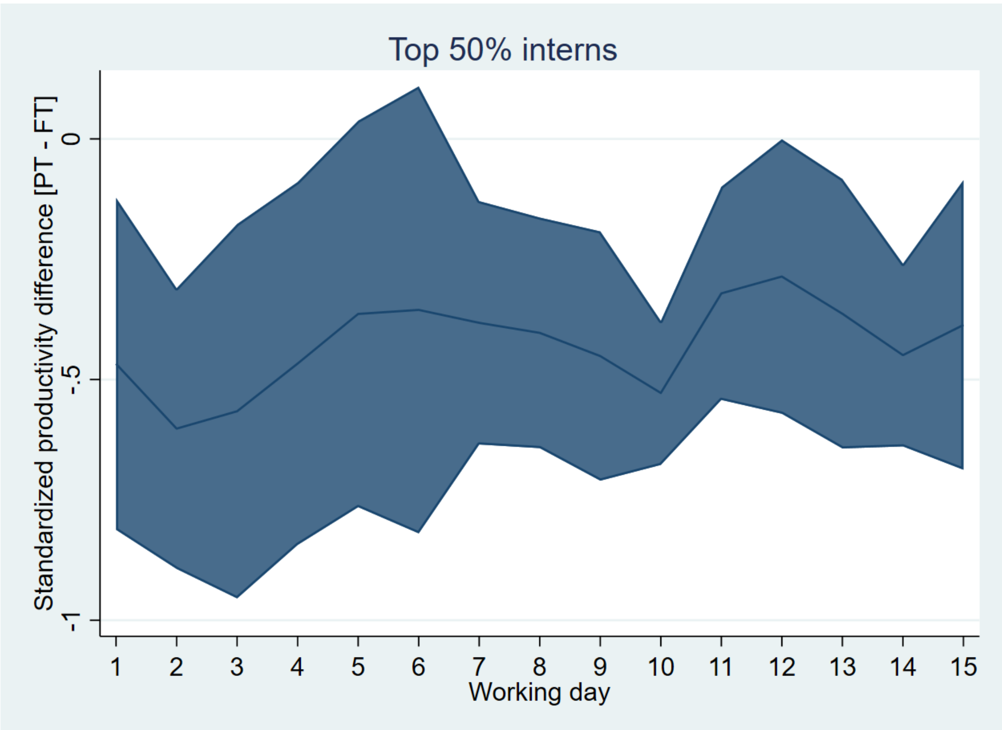
Panel B. All interns – difference



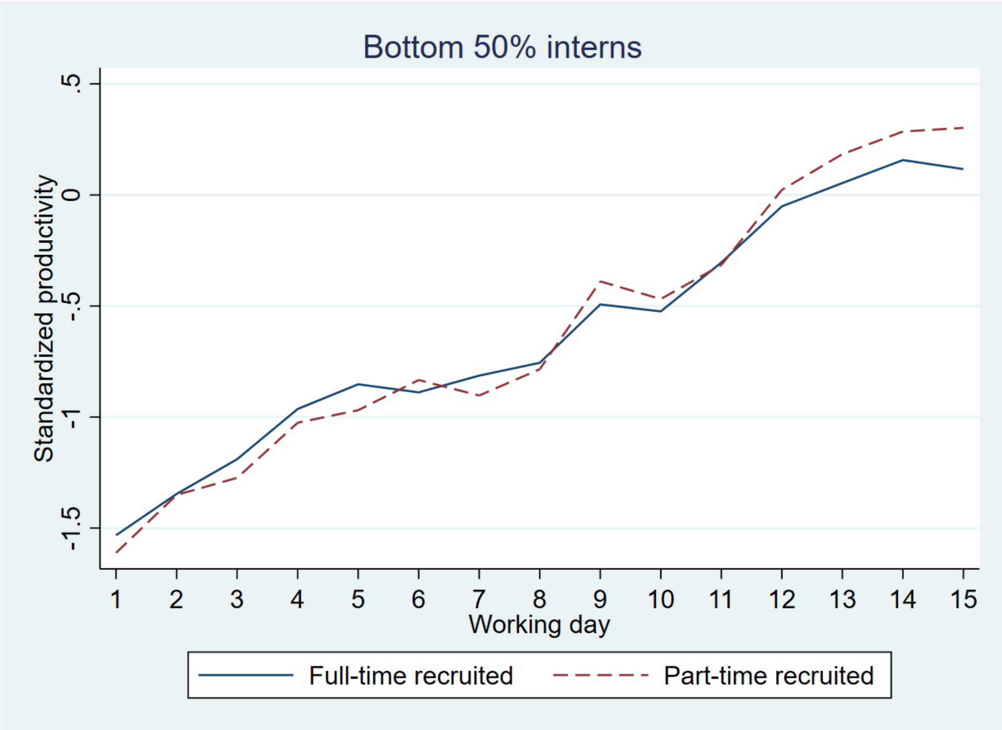
Panel C. Top 50 percent interns



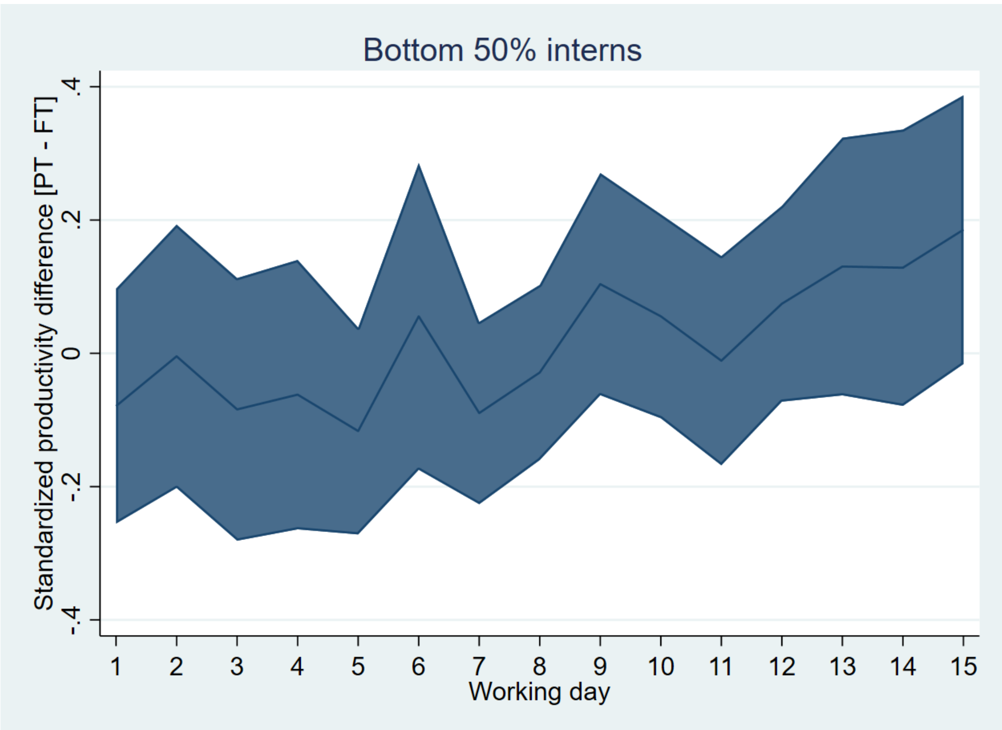
Panel D. Top 50 percent interns – difference



Panel E. Bottom 50 percent interns

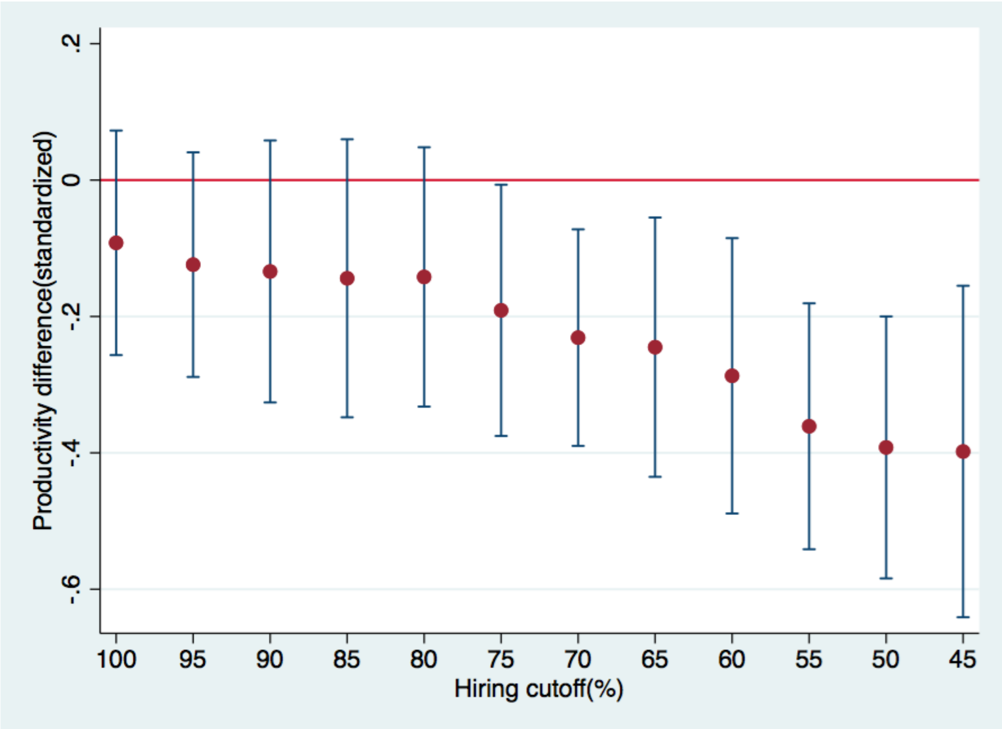


Panel F. Bottom 50 percent interns – difference



Note: The figure presents coefficient estimates and robust 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 recruited interns, interacted with indicators for training days (from 1 through 15).

Figure 4: Productivity difference between part-time and full-time recruited interns conditional on hypothetical hiring cutoffs



Note: The figure presents the average difference in standardized productivity between part-time and full-time recruited interns and the 95 percent confidence intervals, conditional on hypothetical hiring cutoffs from 100 percent (all) to top 45 percent of average internship performance. Confidence intervals are based on standard errors clustered at the village group level.

Table 1: Experiment stages

		Number and percentage of individuals						(4) - (6)
Approximate time	Experimental stage	Term	Part-time		Full-time		Total	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
May to July 2016	Census (job flyers distributed)	census participants	3,202	100.0%	3,093	100.0%	6,295	-
July to August 2016	Submitted job application	job applicants	230	7.2%	226	7.3%	456	0.92
December 2016	Participated in job survey and aptitude tests	job survey participants	162	5.1%	171	5.5%	333	0.68
August to December 2017	Participated in internship (for more than a week)	interns	61	1.9%	61	2.0%	122	0.90
August to December 2017	Performed in top 50% of interns	top 50% interns	34	1.1%	27	0.9%	61	0.11

Note: Columns (4) and (6) show the proportion of individuals continuing over experiment stages. For example, the second row shows the number of participants in the job application stage, divided by the number of participants in initial (Census) stage.

Table 2: Selection by part-time recruitment

Sample	All applicants			Top 50% interns			Bottom 50% interns		
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. Measures of Ability (Standardized)									
Data entry test	333	-0.115	-0.224**	61	0.167	-0.597**	61	-0.057	-0.206
Clerical ability	333	-0.015	-0.030	61	0.032	-0.502**	61	-0.240	-0.109
Computation ability	330	0.008	0.016	60	0.126	-0.111	60	-0.041	0.068
Computer literacy	329	-0.035	-0.069	61	-0.124	-0.632***	60	-0.120	0.054
Manual dexterity	332	-0.121	-0.236*	61	-0.107	-0.567**	60	0.073	0.073
Years of education	311	1.419	0.097	58	1.319	-0.331*	54	1.427	0.366*
Working in official sector	322	-0.218	-0.048	59	-0.415	-0.409**	59	-0.118	0.058
Overall ability (pooled)	2290	0.122	-0.072	421	0.140	-0.444***	415	0.118	0.047
Panel B. Measures of Preferences for Short Work Hours (Standardized)									
Preference for family to work	331	0.081	0.157	61	-0.038	0.122	59	0.226	0.154
Preference for non-work, working part- to full-time	325	0.063	0.123	60	-0.026	0.121	60	0.076	0.118
Preference for part-time to full-time work	330	0.051	0.099	61	0.091	0.273	61	0.015	0.081
(Inverse) Supportive spouse for work	280	-0.149	0.350***	49	0.107	0.721**	52	-0.158	0.332
Number of children living with	304	-1.130	0.129	57	-1.152	0.271	57	-1.211	0.065
Overall preference for short working hours (pooled)	924	0.081	0.167***	288	-0.200	0.293***	289	-0.194	0.160
Panel C. Individual Characteristics									
Age	286	22.576	-0.146	29	22.241	1.075	51	22.783	0.747
Married	323	0.269	-0.044	34	0.294	0.063	60	0.148	-0.155
Subjective health status [1-5]	330	4.506	0.077	34	4.529	0.233	61	4.333	-0.225
Asset score [1-10]	330	6.963	0.088	33	7.928	0.568	60	6.481	0.572
Panel D. Motivations Regarding Jobs									
Motivation for choosing a job [1-20]:									
a. Good future career	329	4.883	0.356	34	4.412	-0.281	61	4.63	-0.076
b. Earns respect and high status	311	3.807	-0.082	30	3.667	0.188	59	4.077	0.016
c. Pays well	313	3.450	-0.439**	33	3.545	-0.455	60	3.231	-0.446
d. Interesting job	322	4.170	0.170	33	4.000	-0.520	61	4.148	0.383
e. Acquire useful skills	322	4.962	0.114	33	5.182	0.404	57	4.680	-0.195
Importance in choosing a job [1-4]:									
Intrinsic motivation	333	3.421	0.033	34	3.465	0.175	61	3.449	0.030
Extrinsic motivation	333	2.947	-0.001	34	3.002	0.048	61	2.932	-0.040
Career expectation	333	3.248	0.001	34	3.316	-0.029	61	3.274	0.034
Accomplishment	333	3.535	0.007	34	3.566	-0.024	61	3.492	-0.024
Status	333	3.314	0.033	34	3.290	-0.080	61	3.427	0.087
Career progress	332	2.778	-0.087	34	2.696	-0.316	61	2.926	0.122
Compensation and benefits	332	3.212	0.015	34	3.063	-0.203**	61	3.274	0.098

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: Effect of part-time recruitment on labor productivity of interns

	All interns	**Top 50% interns**	**Bottom 50% interns**
	(1)	(2)	(3)
Panel A: Without time trend			
Part	-0.117	-0.411***	0.036
	(0.088)	(0.100)	(0.054)
Constant	0.058	0.682***	-0.477***
	(0.065)	(0.093)	(0.031)
Task type fixed effects	Y	Y	Y
Day fixed effects	Y	Y	Y
Batch fixed effects	Y	Y	Y
Trial fixed effects	Y	Y	Y
R^2	0.503	0.513	0.543
N	4890	2511	2310
Panel B: With time trend			
Part	-0.313***	-0.509**	-0.126
	(0.108)	(0.209)	(0.089)
Day	0.143***	0.172***	0.119***
	(0.004)	(0.011)	(0.006)
Part $\times$ Day	0.022**	0.011	0.017*
	(0.009)	(0.016)	(0.009)
Constant	-1.249***	-0.916***	-1.579***
	(0.067)	(0.177)	(0.042)
Task type fixed effects	Y	Y	Y
Batch fixed effects	Y	Y	Y
Trial fixed effects	Y	Y	Y
R^2	0.497	0.503	0.529
N	4890	2511	2310

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. Number of Children Living with (Preference) and Years of Education (Ability), Africa

Panel A. Whole Sample

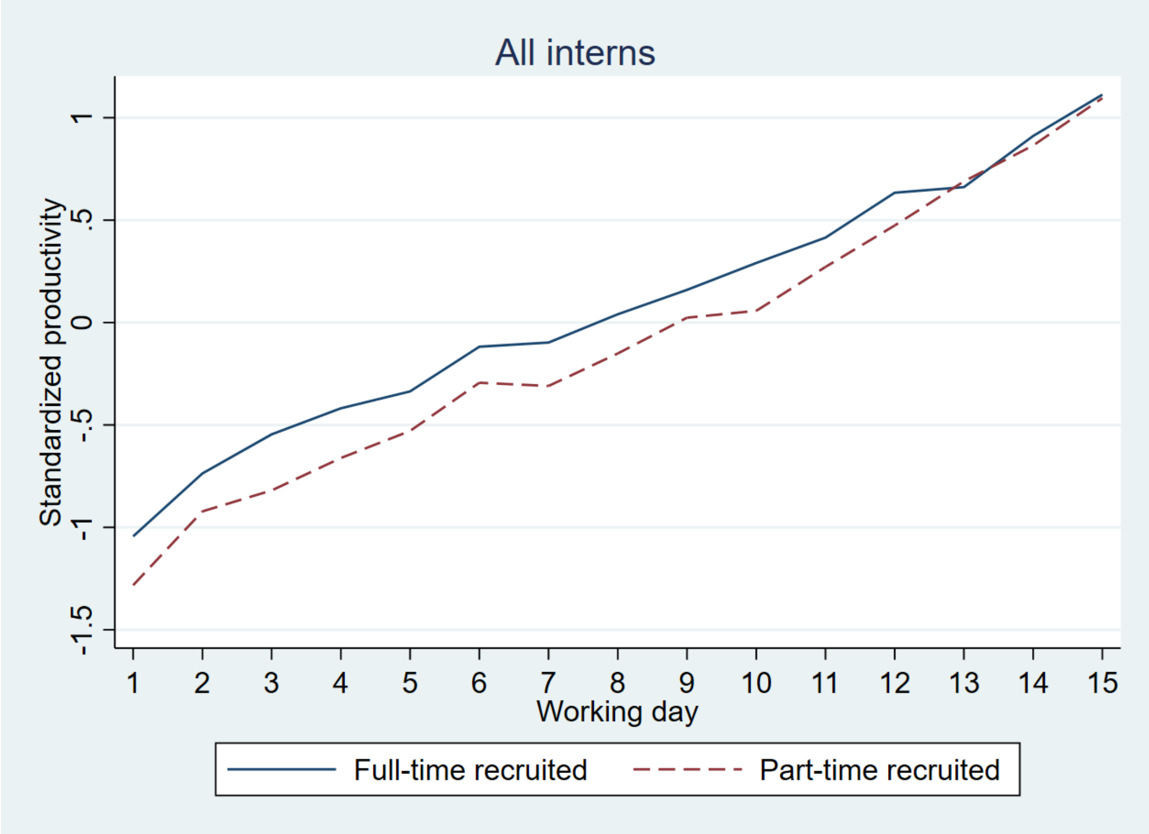
Note: The figure presents the distribution of the number of children living with (x-axis) and year of education (y-axis) in rank for women aged 20 and over. The data are based on Demographic and Health Survey (DHS).

Panel B. Urban Residents

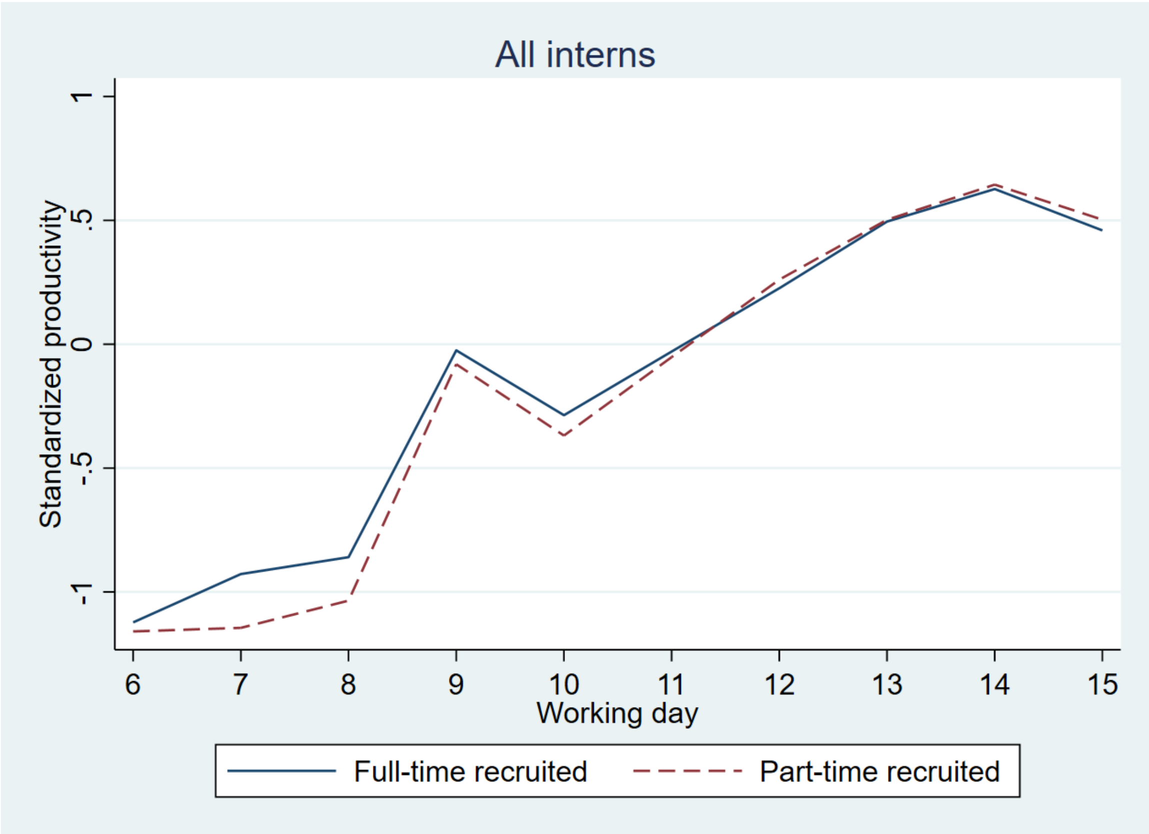
Note: The figure presents the distribution of the number of children living with (x-axis) and year of education (y-axis) in rank for women aged 20 and over. The data are based on Demographic and Health Survey (DHS).

Figure A4. Productivity of part-time and full-time recruited interns over time by task

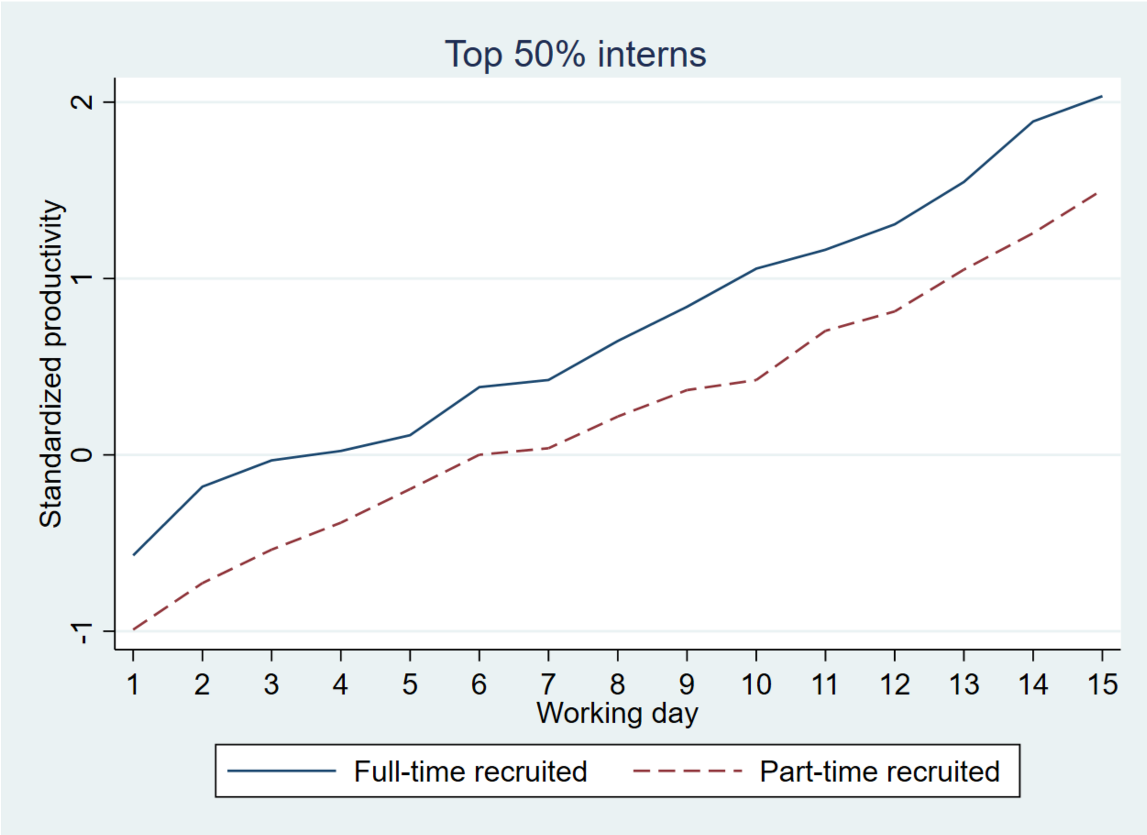
Panel A. All interns – typing speed



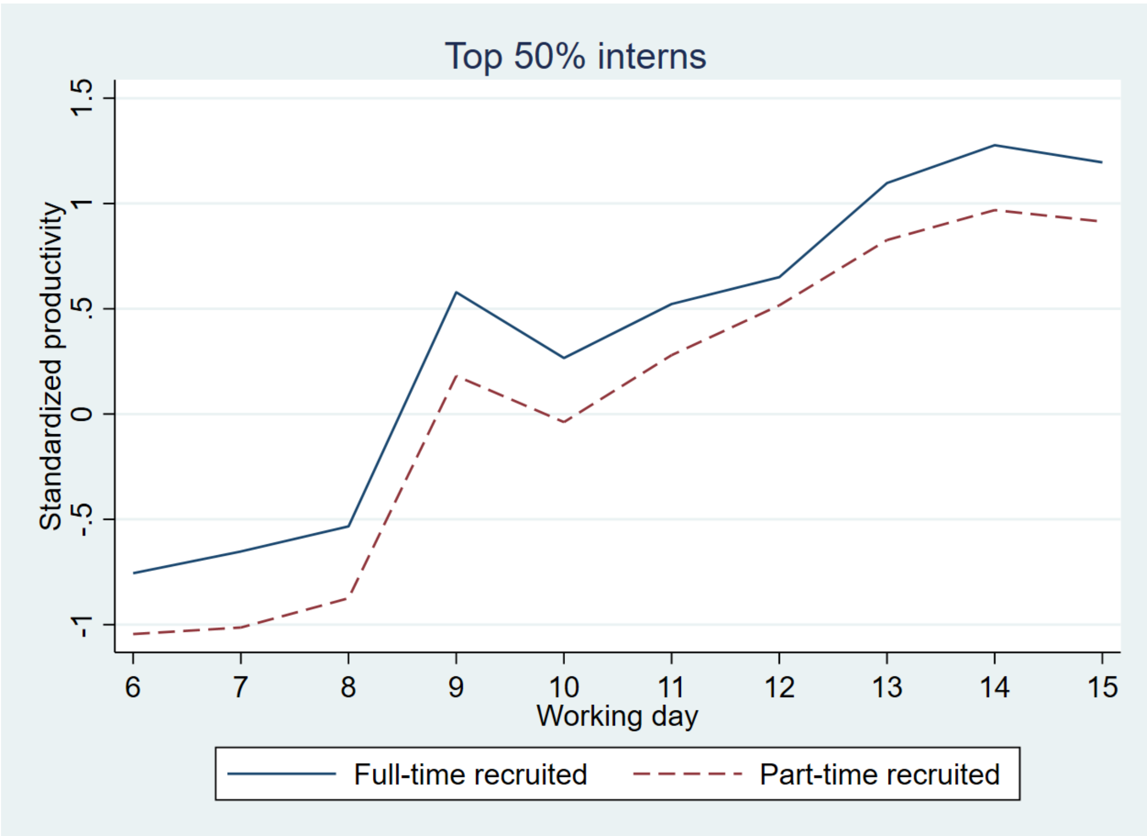
Panel B. All interns – data-entry speed



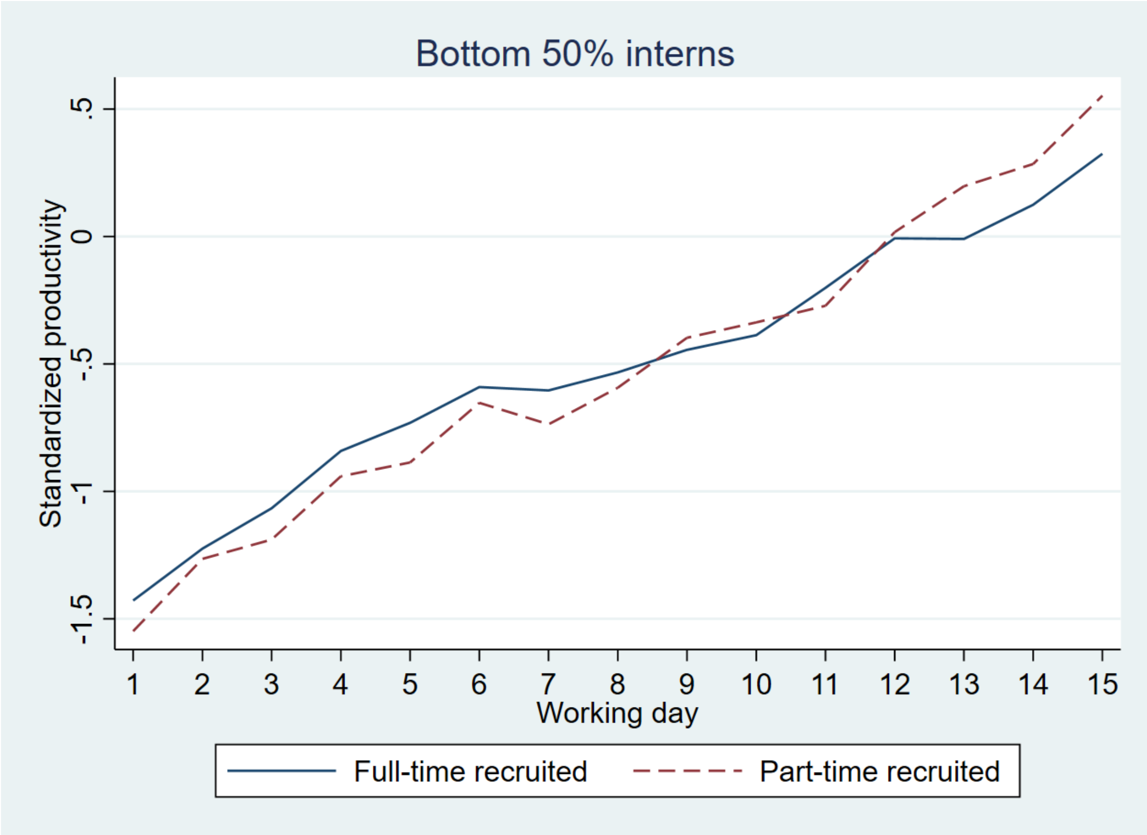
Panel C. Top 50 percent interns – typing speed



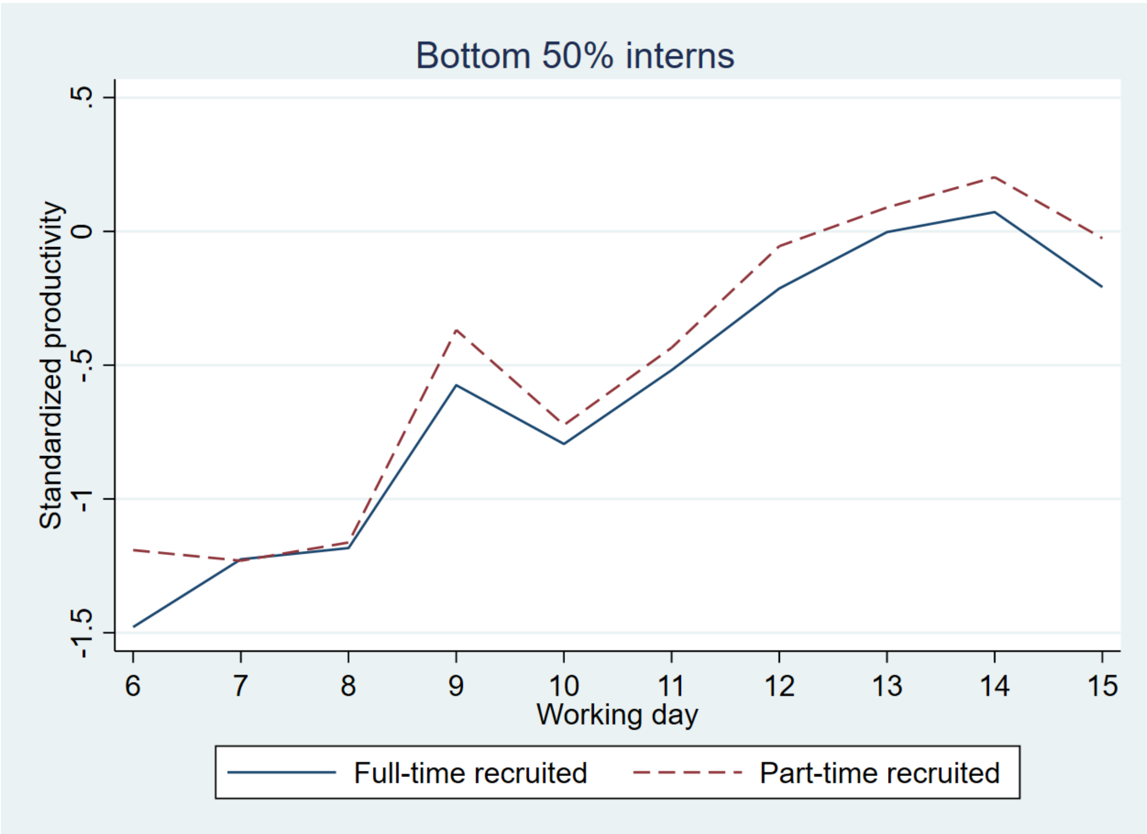
Panel D. Top 50 percent interns – data-entry speed



Panel E. Bottom 50 percent interns – typing speed



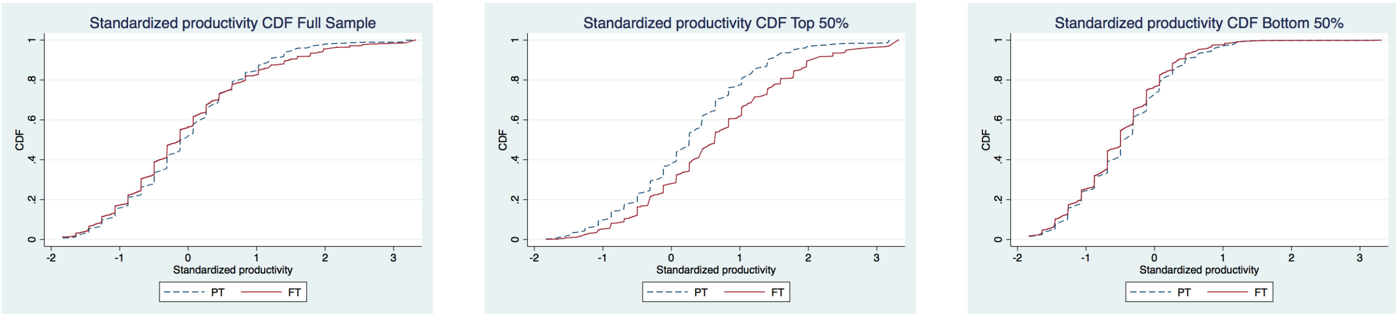
Panel F. Bottom 50 percent interns – data-entry speed



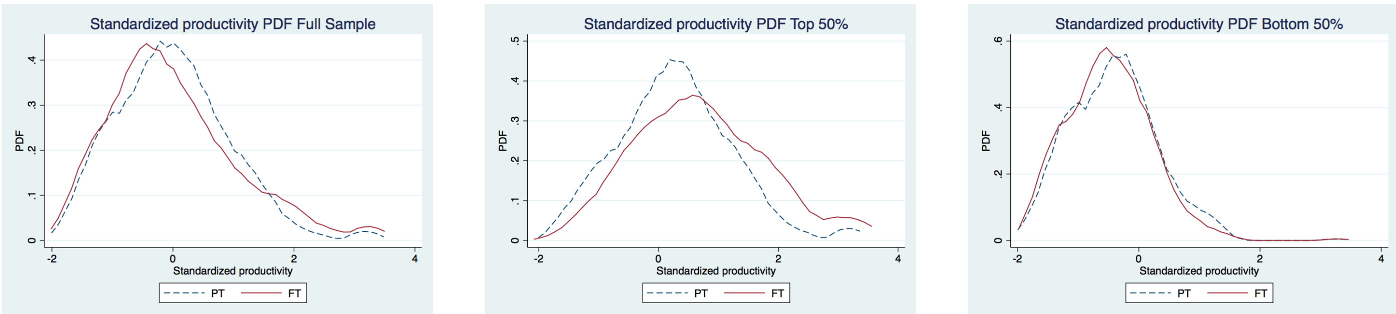
Note: The figure presents coefficient estimates from a variant of equation (3) which replaces the *Part* indicator with the indicators for part-time and full-time recruited interns, interacted with indicators for training days (from 1 through 15) by task.

Figure A5. CDF and PDF of standardized productivity for part-time and full-time recruited interns

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 internship for the full sample (left), top 50% (middle), and bottom 50% performers (right).

Table A1. Comparison of job applicants vs. non-applicants

Variable / Sample	(1) Job non-applicants N	(2) Job non-applicants Mean	(3) Job applicants N	(4) Job applicants Mean	(5) Difference (4)-(2)
Age (/100)	5844	0.262	316	0.231	-0.031***
Married	5844	0.426	323	0.291	-0.135***
Ever birth	4601	0.494	276	0.330	-0.165***
Number of children living with	5340	1.367	304	0.819	-0.548***
Working	5848	0.299	324	0.182	-0.117***
Official sector work	5756	0.199	322	0.118	-0.081***
Post-Secondary+	5950	0.380	315	0.556	0.175***
Asset score	5934	7.013	330	6.918	-0.095
Supportive spouse for work	5227	3.958	280	4.259	0.301***

Note: *** denotes the significance level at 1%.

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	6160	26.032	25.74	26.329	0.588	0.339
Married	6167	0.419	0.441	0.397	-0.044	0.160
Ethnicity						
Amhara	6234	0.202	0.177	0.227	0.05	0.201
Oromo	6234	0.735	0.754	0.716	-0.038	0.430
Language						
Amharic	6236	0.415	0.372	0.460	0.088	0.235
Oromigna	6236	0.581	0.623	0.538	-0.085	0.256
Religion						
Orthodox	6225	0.694	0.66	0.729	0.068	0.205
Protestant	6225	0.251	0.275	0.226	-0.049	0.312
Muslim	6225	0.021	0.026	0.016	-0.01	0.176
Post-secondary education	6265	0.389	0.376	0.402	0.026	0.516
Working						
Within household	6115	0.132	0.09	0.175	0.085*	0.074
Official Sector	6078	0.195	0.193	0.196	0.003	0.952
Panel B. Household Characteristics						
Number of household members	20255	4.216	4.166	4.267	0.101	0.499
Asset score	20383	4.582	4.474	4.693	0.219	0.679
Number of children living with	16159	2.501	2.496	2.505	0.009	0.695
Having saving account	20382	0.278	0.266	0.292	0.026	0.695
Receiving government subsidy	20371	0.016	0.018	0.013	-0.004	0.307
Panel C. Village Characteristics						
Ijerie (=0) vs. Holeta (=1)	233	0.350	0.397	0.301	-0.096	0.450
Population	233	359.6	356.2	363.1	6.817	0.859
Gender ratio (F/M)	233	0.510	0.505	0.515	0.010	0.591
Number of household members	233	4.396	4.417	4.375	-0.041	0.834

Note: * denotes the significance level at 10%.

Table A3. Quantile regression of standardized productivity on part-time recruitment status

	(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	-0.123	-0.042	-0.014	-0.046	-0.042	-0.064	-0.333	-0.575***
	(0.089)	(0.058)	(0.072)	(0.060)	(0.058)	(0.130)	(0.210)	(0.180)
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	0.5	0.494	0.479	0.484	0.494	0.494	0.454	0.389
N	4,821	4,821	4,821	4,821	4,821	4,821	4,821	4,821

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 A4. Internship participation for part- and full-time recruited applicants

	All interns		Top 50% interns		Bottom 50% interns	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	1(Participate)					
Part	-0.023	-0.032	0.018	0.004	-0.077**	-0.075**
	(0.024)	(0.024)	(0.032)	(0.036)	(0.037)	(0.030)
Constant	0.914***	0.918***	0.912***	0.920***	0.914***	0.913***
	(0.013)	(0.014)	(0.023)	(0.023)	(0.013)	(0.016)
Batch fixed effects	N	Y	N	Y	N	Y
Trial fixed effects	N	Y	N	Y	N	Y
R^2	0.002	0.044	0.001	0.042	0.014	0.079
N	3538	3538	1769	1769	1769	1769

Note: This table shows estimates of linear probability models that explain job applicants' participation in the internship. 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 A5. Productivity difference with controls for ability and work hour preference

	All interns				Top 50% interns				Bottom 50% interns			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var.:	Standardized productivity											
Part	-0.117	0.056	-0.068	0.054	-0.411***	-0.081	-0.332***	-0.066	0.036	0.053	0.061	0.049
	(0.088)	(0.055)	(0.088)	(0.054)	(0.100)	(0.094)	(0.118)	(0.091)	(0.054)	(0.048)	(0.053)	(0.050)
Ability controls		Y		Y		Y		Y		Y		Y
Work preference controls			Y	Y			Y	Y			Y	Y
Task type fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Batch fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Trial fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.503	0.627	0.528	0.631	0.513	0.636	0.547	0.645	0.543	0.592	0.550	0.595
N	4890	4890	4890	4890	2511	2511	2511	2511	2310	2310	2310	2310

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, manual dexterity, and official sector working status. Columns 3 and 7 include variables capturing preferences for work hours shown in Panel B of Table 2, including preference for work over life, spousal support for work, and number of children living with. 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

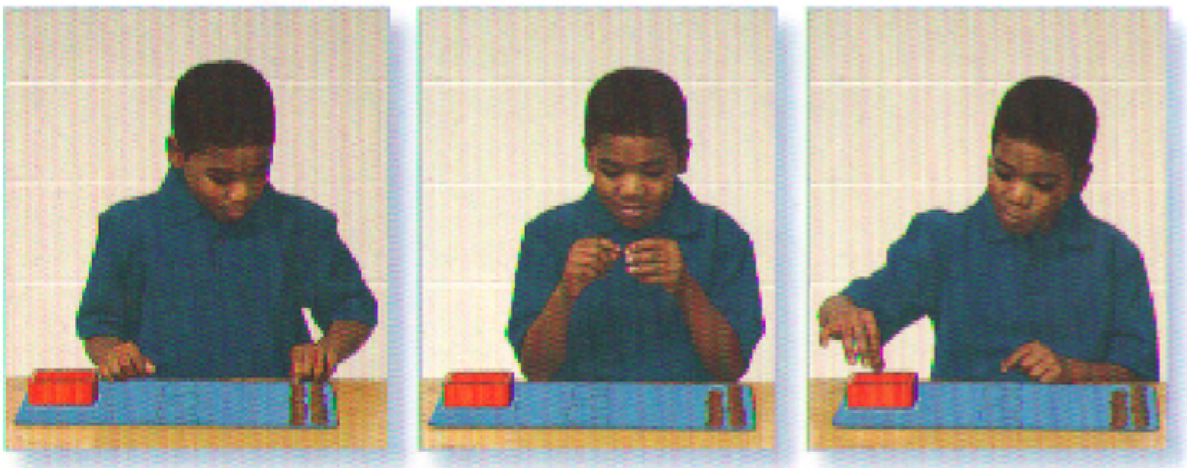
	A. 32,822
	B. 32,932
	C. 34,932
8,733	D. 35,932
x 4	E. none of these

16. Divide

	A. 2,116
	B. 2,121
	C. 2,131
14 ⟌ 29,554	D. 2,146
	E. none of these

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

The BOT^{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

Relative importance for job choice 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.		**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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Barrick, Murray R., Greg L. Stewart, and Mike Piotrowski. 2002. "Personality and Job Performance: Test of the Mediating Effects of Motivation among Sales Representatives." *Journal of Applied Psychology* 87 (1): 43–51.

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