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Experimental Evidence from a Large-Scale Recruitment Drive

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THE SELECTION EFFECTS OF PART-TIME WORK: EXPERIMENTAL EVIDENCE FROM A LARGE-SCALE RECRUITMENT DRIVE*

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Abstract

We implement a field experiment to examine how part-time work attracts applicants with different quality and productivity levels than full-time work. In a large-scale recruitment drive for a data-entry position in Ethiopia, either a part-time or full-time job opportunity was randomly offered across villages. We find that the part-time work attracts a less qualified pool of applicants with a stronger preference for short work hours, who in turn exhibit lower productivity, all relative to the full-time work. Our preferred estimates show that this selection effect on productivity may explain up to half of the typical part-time wage penalty. A simple conceptual framework demonstrates that a lack of high quality potential applicants with a strong preference for short work hours could explain the experimental evidence. The results have implications for the selection effects of alternative work arrangements and for the gender pay gap. JEL Codes: J22, J24, O15, M51

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

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1 Introduction

A growing fraction of the workforce is being employed under alternative work arrangements (Mas and Pallais (2017); Katz and Krueger (2019); and Abraham et al. (2021)). A key feature of these work arrangements is that the short or flexible work hours allow workers to more smoothly allocate their time between labor-market activities and non-market activities, such as household work. This suggests that workers who choose alternative work arrangements may differ from those choosing standard ones in their preferences, skills, and productivity. In turn, self-selection into different work arrangements may account for part of the variation in aggregate productivity across arrangements and types of occupations.

Part-time work is one of the most common alternative work arrangements (Mas and Pallais (2020); and Goldin (2021)), accounting for a substantial fraction of employment across developed and developing countries (e.g., Pagés et al. (2008); Dunn (2018); and OECD (2020)). Part-time work is associated with considerable wage penalties, implying that it may attract less productive workers than full-time work.[1] Part-time work is also associated with strong preferences for short working hours, however (e.g., proxied by the number of young children), especially for women.[2] This correlation implies that selection into part-time work may be primarily driven by household responsibilities rather than by worker productivity. However, little is known on whether and how self-selection on these dimensions leads to a productivity difference between part-time and full-time workers.

In this paper, we use a randomized field experiment to provide credible estimates of how part-time work attracts applicants with different quality and productivity relative to full-time work.[3] In a non-governmental organization's (NGO) large-scale recruitment

[1]See, e.g., Blank (1990); Aaronson and French (2004); and Manning and Petrongolo (2008). This line of research finds a part-time wage penalty of about one-fifth to one-quarter of full-time wages. A related literature finds generally positive relations between work hours and wages (e.g., Rosen (1976); and Simpson (1986)).

[2]See, e.g., Rosen (1976); Moffitt (1984); and Ermisch and Wright (1993).

[3]The human capital literature posits that individuals' performance on tasks (such as productivity) is

drive for a data-entry position in Ethiopia, either a part-time or full-time work opportunity was randomly offered by village group—a cluster of several nearby villages. The part-time and full-time jobs differed only in the hours required, four and eight hours per work day, respectively. This difference was made clear in job ads that were distributed during a census of households in the recruitment areas. Our experiment focuses on women, who typically value the flexibility between labor-market and non-market activities more than men (e.g., Blank (1990); and Wiswall and Zafar (2018)). Thus, the experiment offers an ideal setting to examine the selection effects of part-time work.

We first analyze the types of applicants part-time work attracts compared to full-time work by collecting information on each applicant's skills related to data-entry work as well as preferences for work hours from a survey and job aptitude tests. We find that there is a "part-time quality gap": Part-time applicants exhibit lower quality than full-time applicants. For example, the applicants in the part-time pool exhibit lower scores in data-entry and manual dexterity tests than those in the full-time pool. In addition, part-time applicants have stronger preferences for working short hours than full-time applicants.

Next, we analyze how part-time work affects labor productivity through selection by inviting job applicants to an internship in which we measure worker-level labor productivity using data-entry speed. *All* job applicants were invited to the internship, which allows us to measure the productivity difference between the part-time and full-time workers that is due to selection when the firm (i.e., NGO) is assumed to apply different *hypothetical* performance cutoffs for regular employment. We find that the productivity gap, as well as the quality gap, becomes more pronounced as the firm hypothetically applies a more stringent hiring cutoff. For example, assuming that the firm hires the interns

determined by multiple factors such as cognitive skills, noncognitive skills, and personality traits, as well as effort (e.g., Heckman, Stixrud, and Urzua (2006)). Heckman and Kautz (2012), in their survey of the literature, illustrate the difficulty in disentangling the effect of skills and traits from effort on performance. Thus, we use the term "quality" throughout this paper to capture these multiple aspects of ability as well as effort. The productivity measures we employ capture the effect of both ability and effort.

with above-the-median overall productivity, the productivity of those hired through the part-time arrangement is on average 0.46-standard deviation (or 13 percent) lower than the productivity of those hired through the otherwise identical full-time arrangement. This "part-time productivity gap" exists from the first day and persists throughout the internship, implying that self-selection on stable characteristics (such as quality), rather than differences in skill acquisition through the internship, drives the gap. In contrast, if the firm is assumed to hire all interns, the productivity difference between part-time and full-time recruited workers is smaller at 0.12 standard deviations (or 3 percent) and insignificant.

We demonstrate that a standard self-selection model with a relative lack of potential applicants in the population who both strongly prefer short work hours and have high quality could explain the observed differences in quality between the full-time and part-time applicant pools.[4] In the framework, a worker is offered a job opportunity – either part-time or full-time – to which she applies when the payoff from the job offered exceeds her outside option. An increase in a worker's preference for working short hours increases (decreases) the payoff from the part-time (full-time) job, and her outside option increases in her quality. We show that high-quality applicants in the part-time (full-time) pool have strong (weak) preferences for short hours, whereas low-quality applicants in the two pools have similar preferences. Therefore, the selection effect of part-time work, relative to full-time work, on the quality of hired workers depends on the firm's ability to distinguish quality and hire higher quality employees from the applicant pool. If the firm cannot distinguish quality and hires randomly from the applicant pool, the average quality of part-time employees is still lower than that of full-time employees. However, the gap widens when the firm can distinguish quality and hires only the highest quality

[4]We verify the assumption on the distribution of potential applicants by quality and short working hour preference in both our own census data of the recruitment areas and representative samples of workers across dozens of countries. Specifically, we use years of education and the number of children living in the household as proxies for quality and preference for short work hours, respectively.

applicants, such as those above a threshold.

This paper relates to the growing literature that studies individuals' selection into jobs based on job attributes, ability, and preferences.[5] Dohmen and Falk (2011), Dal Bó, Finan, and Rossi (2013), Guiteras and Jack (2018), and Deserranno (2019) show how financial incentives (such as piece rates and higher salary) attract workers with different productivity and prosociality. Ashraf et al. (2020) show that salient career incentives (compared to public service motivation) attract more productive public health workers without sacrificing pro-social preference. Kim, Kim, and Kim (2020) show that career incentives could attract higher-performing workers than wage incentives through self-selection. Our paper is the first to provide experimental evidence on how part-time employment attracts applicants with markedly different quality than full-time employment.[6]

Moreover, our finding that part-time work attracts less productive workers implies that the wage penalties associated with short work hours are in part due to underlying differences in worker productivity.[7] In fact, the part-time productivity differentials we estimate are of comparable magnitudes to typical part-time wage differentials in existing research. More broadly, given that alternative work arrangements would generally attract workers with high valuations of flexible work and non-work hours (e.g., Mas and Pallais (2017); and Mas and Pallais (2020)), our results imply that the average worker recruited through alternative arrangements might also be less productive than one recruited through standard work arrangements.

Lastly, this paper adds to the current debate on the causes of, and solutions to, the gender pay gap observed in both developed and developing countries (e.g., Morton et al. (2014)). Mas and Pallais (2020) argue that the hours dimension of flexibility that

[5] See Roy (1951) and Borjas (1987) for classical contributions to this literature.

[6] Bick, Blandin, and Rogerson (2022) employ a structural estimation approach to show that part-time (full-time) workers are more likely to be low (high)-productivity.

[7] Existing papers examining the effect of part-time work on productivity largely rely on observational data, hence do not distinguish the selection from other effects, and find mixed evidence. See, e.g., Künn-Nelen, De Grip, and Fouarge (2013); Garnero, Kampelmann, and Rycx (2014); and Devicienti, Grinza, and Vannoni (2017).

we examine is particularly promising in explaining gender gaps in pay and employment. Goldin (2021) argues that the positive wage-hour relation, exemplified by so-called "greedy jobs"—high-paying jobs that require long work hours—are a key reason for the persistent gender pay gap: Women who juggle work and family choose, more often than men, to work short hours (i.e., part-time) thereby suffering a wage penalty (e.g., Juhn and McCue (2017); and Kleven, Landais, and Søgaard (2019)). However, our findings suggest that the positive relation between (hourly) wages and hours reflects, at least in part, positive relations between productivity and work hours. Therefore, future discussions of the gender pay gap should account for the productivity difference across work hours we identify.

2 Context and Experimental Design

2.1 Context: Recruitment Drive for a Data-Entry Position

In 2016, Africa Future Foundation (AFF), a non-governmental organization, sought to hire up to 100 women for a data-entry position from the Holeta and Ejere areas of Ethiopia. Holeta is an urban town of approximately 28,000 people, located about 31 miles west of the capital, Addis Ababa. Ejere is a mostly rural district near Holeta with a population of approximately 59,000. The data-entry industry in Ethiopia largely employs women. Access to early childhood care and education, which would mitigate women's preference for short working hours, is generally limited in the recruitment areas. For instance, at the time of the experiment, there were only three certified private kindergartens across Holeta and Ejere. As a result, grandparents, other relatives, or personally hired nannies typically provided childcare to working mothers. These characteristics of the industry and region make it an ideal setting to examine the selection effects of part-time work because the flexibility that part-time work offers would be an important consideration for the potential applicants who are women.

The data-entry position for which AFF recruited involves reading documents that contains census information of households in the areas and entering it as data fields on a computer. Therefore, the job requires basic computer skills, clerical ability to read paper surveys and input the information on a computer, fine motor skills to control hands and fingers, and perseverance to perform tedious work. We measure the quality of applicants on these dimensions using aptitude tests (see Section 3.2). The key job eligibility criterion is to have a high school diploma. The level of education is generally high in the recruitment areas with 60 percent and 38 percent of women holding high school diplomas in Holeta and Ejere, respectively, while the corresponding number across Ethiopia is only 4 percent (CSACE (2016)).

2.2 Experimental Design

Table I summarizes the stages in our experiment, reporting the number of women who participated in each stage by the posted job. In May to July 2016, AFF conducted a census of Holeta and Ejere, gathering information on 20,595 households with approximately 87,000 individuals in the areas. During the census, enumerators distributed job ads to 6,295 resident women with a secondary school diploma (or their family members in case they were absent at the time of census visits). These eligible women represent potential applicants in our experiment.

The part-time and full-time jobs were randomly assigned across 71 village groups—clusters of several villages—with 35 and 36 village groups posting part-time and full-time jobs, respectively.[8] We randomized treatment at the village group level by combining nearby

[8]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. Although the original study design included 81 village groups, 10 village groups in Ejere were excluded from the final study sample due to safety concerns from political turmoils during which more than 500 people are estimated to have been killed. See, e.g., https://www.theguardian.com/world/2016/oct/02/ethiopia-many-dead-anti-government-protest-religious-festival. The original design also included long-term employment and further randomization at the data-entry unit but AFF evacuated from the study areas for the same

villages with frequent contacts to minimize potential information spillovers between the treatment and control villages.

The job ads we distributed (see Appendix Figure A1) make it clear that the part-time and full-time jobs differ only in the hours required per day, four and eight hours. Other aspects of the position such as the application requirements, task, and wage (per hour) are identical. The monthly pay offered ranged from 1,000 to 1,250 (2,000 to 2,500) Ethiopian Birrs for part-time (full-time) employees depending on their performance, which was in line with pay at other data-entry firms in Ethiopia.[9] Because there was no wage discount for the part-time job offered, the quality and productivity gaps between part- and full-time applicants observed in our experiment are likely lower bound estimates (in absolute value), relative to a setting with a part-time wage discount.[10]

Among the 6,295 potential applicants, 456 individuals submitted a résumé and a copy of their high school graduation exam report at the AFF office located in the Holeta city center by August 2016. Those who submitted application materials were subsequently asked to join a baseline job survey and to take aptitude tests, which were administered at the AFF office in December 2016. We refer to those who both submitted application materials and participated in the job survey and aptitude tests as "applicants" ($N = 333$).

Finally, AFF invited applicants to an internship program to assess their productivity as data-entry workers. The AFF staff contacted each applicant by phone; if the person was not available immediately, the staff made multiple contact attempts. 122 out of of 333 applicants took up the internship (referred to as "interns") across August to December 2017. Interns were grouped into five waves, and those with higher scores in a data-entry

reason.

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

[10] In addition to the worker selection effects we focus on, fixed costs of employment could explain part of the wage penalty (e.g., Rosen (1976)). Compensating differentials (e.g., Rosen (1986)) suggest that to the extent that schedule flexibility that part-time work provides is valuable to workers, the part-time job could offer lower wages conditional on productivity.

test (conducted as part of the aptitude tests) were invited earlier. The internship for each wave consisted of 22 to 32 interns and lasted for three weeks. The program entailed typing and data-entry tests as well as basic computer training (see Appendix Figure A2 for details). The interns were allowed to attend either the morning (9 a.m.–noon) or afternoon (2 p.m.–5 p.m.) session with an identical program, which ensured that they could participate regardless of their working hour preferences. They were paid a daily wage of 30 ETBs and were told that tenured workers would be hired based on productivity in the internship.

It is worth noting that AFF attempted to invite all job applicants to the internship, as opposed to those with high measured ability only, such as top performers in the aptitude tests. This feature allows us to gauge the productivity difference between part-time and full-time workers that is due to selection when the firm (i.e., AFF) is assumed to apply different hypothetical performance cutoffs to hire workers.

3 Data

Our primary data sources are the job survey, aptitude tests, administrative data collected during the job application and internship, and the census of the recruitment areas. The census data provide variables capturing basic demographic and socioeconomic status and family structure, including age, education, employment status, and the number of household members, including children.

3.1 Study Population and Randomization Balance

Appendix Table A1 presents randomization balance tests on individual, household, and village characteristics for our sample of potential applicants. The table confirms that the randomization was successful: Only one out of 20 characteristics differs significantly at the 10 percent level between the village groups with part- and full-time job postings.

In addition to showing the balance, it provides useful information to understand labor markets in the study areas. First, the fraction of potential applicants with post-secondary education is 39 percent. Second, 19.5 percent of applicants were working in formal sectors and 13.2 percent were working for their family business. This low formal-sector employment rate in the areas, even for those with high school education, implies that the data-entry position should offer them an attractive labor-market opportunity. Third, the average potential applicant's household has 4.2 members among whom are 2.5 children. Lastly, about one-third of the villages in the areas are in Holeta, the urban area, with the rest in Ejere, the more rural area.

Further, Appendix Table A2 compares characteristics of job applicants with non-applicants among the potential applicants. We find that those who are younger, more educated, not married, have fewer children, and do not currently have an (official) job are more likely to apply for the position. All of these differences are significant at the 1 percent level. The results show that outside option and family status are important determinants of application decisions in general.

3.2 Measuring Applicant Quality and Work Hour Preference

We employ two types of applicant quality measures. First, we conducted job aptitude tests that measure each applicant's skills related to data-entry work. The most direct measure of job-specific ability is data-entry speed, defined as the number of correct data entries made within 15 minutes. We also measure applicants' clerical and computation abilities based on the O*NET Ability Profiler (O*NET Resource Center (2010)) and manual dexterity based on the Bruininks-Oseretsky Test of Motor Proficiency, 2nd edition (BOT-2, Deitz, Kartin, and Kopp (2007)). The clerical ability test mainly involves noticing if there are mistakes in the text and numbers. The computation test measures an individual's ability to apply arithmetic operations to calculate solutions to mathematical problems. To measure manual dexterity, we counted how many small coins (out of 20) the applicant moves using fingers from a table to a small box in 15 seconds. Second, we employ years of education and whether the applicant currently works for an official job as measures of general quality valued by the labor market (e.g., Dal Bó, Finan, and Rossi (2013)).

For preference regarding work hours, we conducted surveys that directly ask the applicant's preferences between (i) non-work, working part-time and full-time and (ii) family and work, as well as how supportive the spouse is for the applicant's work. We also collected information on the number of children living in the same household as a proxy for preference for working short hours driven by child-rearing responsibilities (see, e.g., Rosen (1976); Moffitt (1984); and Ermisch and Wright (1993)). The Data Appendix provides details of the aptitude tests and survey modules we employ.

In the empirical analysis, we standardize these measures by subtracting the respective mean and scaling by the standard deviation – as z-scores (Kling, Liebman, and Katz (2007)). In addition, we stack the z-scores within the quality (preference) dimension and analyze them as an overall measure of quality (preference) in a single pooled OLS regression with standard errors clustered at the village group level. To mitigate the influence of outliers, we winsorize data-entry speed and manual dexterity at the 1 percent tails.

3.3 Measuring Labor Productivity

We employ two measures of labor productivity for the interns. First, we measure error-adjusted typing speed as the number of words the intern correctly entered per minute using Mavis Beacon, a computer application designed for typing training. Each typing task involves the intern typing in a series of words or sentences shown on the computer screen for seven to 15 minutes. The interns performed two typing tasks a day over the three-week internship period.

Second, we measure error-adjusted data-entry speed as the number of correctly entered census data fields, scaled by the number of minutes spent.[11] We gave all interns the same set of census forms with identical information on a given day and asked them to type in the information using the computer within 15 minutes. The interns performed the data-entry task in the last two weeks of the internship, once a day in the second week and twice a day in the third week. In the empirical analysis, we employ standardized measures of labor productivity as z-scores. To mitigate the influence of outliers, we winsorize the productivity measures at the 1 percent tails.

4 Conceptual Framework: Part-Time and Full-Time Job Application and the Quality of Applicant Pools

We illustrate how offering a part-time job opportunity versus a full-time job opportunity affects the quality of the applicant pool through selection by modeling workers' selection into jobs with differing hours.

4.1 Set Up

We consider a population of potential applicants, parameterized by two variables: preference for short working hours (γ) and quality (θ). γ takes values in $[0, 1]$ and measures the strength of a worker's preference for part-time work over full-time work, quoted in hourly terms. The higher γ is, the more the worker prefers part-time work (four hours per day) over full-time work (eight hours per day). θ takes values in $[0, 1]$ and measures

[11] We define a "correctly entered field" as a non-missing value in a census data field (such as 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.

both the worker's quality and her hourly outside option value – for simplicity, we assume they are perfectly correlated. The higher θ is, the greater is the worker's quality and hourly outside option value. Thus, the entire population of potential applicants 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.

We then offer this population of potential applicants a job opportunity j. We consider two cases, when $j = PT$ is a part-time job and when $j = FT$ is a full-time job.

A worker's hourly payoff from a part-time job is assumed to be

$$W^{PT}(\gamma, \theta) = w + \gamma = \gamma.$$

Here, w denotes the hourly wage, which we normalize to zero. Notice, the worker's hourly payoff from working a part-time job is her hourly wage plus an hourly benefit she derives from the part-time job. For a worker with children, this benefit can be utility derived from being able to spend more time with their children, or the cost savings from not having to procure childcare. Or, it can simply represent preference for leisure. Naturally, the benefit is increasing in γ.

A worker's hourly payoff from a full-time job is assumed to be

$$W^{FT}(\gamma, \theta) = w + (1 - \gamma) = 1 - \gamma.$$

Similar to before, the worker's hourly payoff from working a full-time job is her hourly wage plus an hourly benefit she derives from the full-time job. This benefit can be a sense of pride from working full-time or could represent the cost savings from not having to find, train for, and travel to multiple part-time jobs in order to fill up the work day. Naturally, the benefit is decreasing in γ. The per-hour wage (w) is identical between the part-time and full-time jobs, consistent with our experimental design.

4.2 Workers' Application Decision, Distribution of Workers, and the Quality of Applicant Pools

Let $j \in \{PT, FT\}$ be the job opportunity that is being offered. Since θ is a worker's hourly outside option value, a (γ, θ) worker will apply for the job if and only if her hourly payoff from having job j is weakly greater than θ. Let S^j denote the subset of worker types that apply. Then we have,

$$(\gamma, \theta) \in S^j \Leftrightarrow W^j(\gamma, \theta) \geqslant \theta \quad \text{for } j \in \{PT, FT\}.$$

Within the unit square of all possible worker types, S^{PT} consists of the set of points located on or below the diagonal running from $(0, 0)$ to $(1, 1)$, while S^{FT} consists of the set of points located on or below the diagonal running from $(0, 1)$ to $(1, 0)$. For example, a worker with type $(0.75, 0.5)$ will apply when the job opportunity being offered is a part-time job because $W^{PT}(0.75, 0.5) = 0.75 > 0.5$. However, this same worker will not apply when the job opportunity being offered is 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 in both cases, and a worker with type $(0.5, 0.75)$ will not apply in either case.

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 $x \in (0.5, 1)$ 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 I for a depiction of the unit square of worker types, applicant pools S^{PT} and S^{FT}, and density μ. The specific functional form we have chosen is not crucial for our results, and is made largely for computational tractability and conceptual clarity. What matters is that there is a relative lack of workers who have both high quality and strong preference for short working hours. 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, that also make acquiring high quality and outside options difficult. Thus, we expect that workers who both strongly prefer part-time work and have high quality and outside options are relatively rare.[12]

The empirical distribution of potential applicants in our recruitment areas along proxies for these dimensions provides evidence for this assumption. Specifically, we employ years of education as a proxy for worker quality and the number of children living in the same household as a proxy for preference for short working hours. Figure II shows that the density of potential applicants who have both higher levels 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. Appendix Figure A3 shows similar distributional patterns across 24 African countries using the Demographic and Health Surveys (DHS) data on women. Bick, Blandin, and Rogerson (2022) provide further empirical support by documenting a negative correlation between worker productivity and preference for fewer working hours.

Our main theoretical result is that what kind of job opportunity is being offered – part-time or full-time – affects the type of applicants that the job attracts, in particular, the statistical properties of the applicants' quality.

[12] The assumption is consistent with negative correlations between women's education and fertility shown in existing research. The mechanisms include education delaying or reducing fertility (Keats (2018); and Lavy and Zablotsky (2015)) and early pregnancy preventing mothers from having further educational opportunities (Becker, Cinnirella, and Woessmann (2010)). We are agnostic about the direction of causality for the purpose of the model predictions. Beyond schooling, see Jones and Long (1979) for evidence that women with more children tend to receive less on-the-job training from the employer.

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

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

4.3 Firm's Hiring from Applicant Pools and the Quality of Hired Workers

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.[13] Then the average quality of workers the firm hires when a job opportunity j is being offered is exactly the average quality 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 quality of the hired workers is lower when the job opportunity being offered is part-time.*

Next, let us consider the opposite extreme and suppose the firm can perfectly screen θ. We posit that there is a quality cutoff $\theta^* < x$ such that a worker is worth hiring if and only if her quality is at or above θ^*. Consequently, the set of *hired workers* when the job opportunity being offered is part-time is $S^{PT}(\theta^*)$, defined to be the subset of S^{PT}

[13] 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 short working hours, since they are more likely to have higher quality.

consisting of those workers with quality $\geqslant \theta^*$. The set of hired workers when the job opportunity being offered is full-time, $S^{FT}(\theta^*)$, is defined analogously.

Proposition 2. *The average quality of the hired workers when the job opportunity being offered is part-time,* $S^{PT}(\theta^*)$*, is less than the average quality of the hired workers when the job opportunity being offered is full-time,* $S^{FT}(\theta^*)$*. Moreover, the magnitude of the difference – call it the average quality 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 $\theta^* < x$. The average quality of the hired workers when the job opportunity being offered is full-time is

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

which means that the average quality of this group increases at rate $\frac{2}{3}$ with respect to θ^*. A simple calculation shows that the average quality of the hired workers when the job opportunity being offered is part-time increases at a variable rate $< \frac{2}{3}$ with respect to θ^*. This implies the gap is increasing in θ^*. □

5 The Effect of Part-Time Work on Applicant Characteristics through Selection

We examine the effect of part-time employment on the applicant pool, relative to otherwise identical full-time employment, by estimating the following equation on an applicant pool:

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

where y_{ij} is a characteristic of applicant i in village group j measured in the job survey, aptitude test, or census; $Part_{ij}$ is an indicator equal to one if applicant i was in village group j with the part-time job posting, and zero with the full-time job posting; and ε_{ij} is a random error clustered at the level of randomization, village groups. The coefficient of interest is α_1, which captures the causal effect of part-time employment opportunities on the applicant pool through selection.

To analyze the selection effect on applicant pools with differing ex ante likelihoods of being hired, we estimate equation (1) on the following three applicant pools: (i) all applicants, (ii) applicants who participated in the internship with average performance greater than or equal to the median intern's (referred to as "above-the-median performance"), and (iii) interns with average performance below the median.[14] That is, we employ internship participation and above-the-median performance as approximate criteria for AFF to hire from the overall applicant pool.[15]

Table II presents the results of estimating equation (1). Column 3 of Panel A shows that among all applicants, the part-time applicant pool has significantly lower average quality than the full-time pool as measured by data-entry test score (significant at the 5 percent level) and manual dexterity (significant at the 10 percent level). The gaps in data-entry test score and dexterity between the part- and full-time pools amount to -0.22 and -0.24 standard deviations (SDs), respectively. The differences in the other quality measures however are economically smaller and insignificant. The difference in overall applicant quality is -0.07 SDs yet insignificant.[16]

Importantly, column 6 in Panel A shows that the differences in quality measures are larger in economic magnitude and largely significant when conditioning on above-the-

[14] We employ the average performance in the internship as a proxy for the applicant's quality in splitting into the subsamples, given that internship participation is an important criterion for AFF's hiring decision and the internship performance likely represents a more direct and precise measure of job-specific skills than the results of aptitude tests or other baseline proxies such as education.

[15] The median words per minute (WPM) of the interns is 12. Karat et al. (1999) find 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. AFF found applicants with below-the-median performance largely unemployable.

[16] Given that our analysis focuses on the overall quality of applicants rather than individual quality measures, we employ the "stacking" approach rather than adjust the p-value for each quality measure to account for multiple hypotheses testing.

median internship performance: The part-time pool shows significantly lower quality (at a 10 percent or less level) than the full-time pool as measured by six out of seven variables. As a result, the part-time pool is lower by 0.44 SDs in overall quality than the full-time pool with the difference being significant at the 1 percent level. In contrast, none of the quality measures is significantly different between the part- and full-time pools among interns with below-the-median performance, who are unlikely to be hired (column 9). Also consistent with the pronounced quality difference among more hireable applicants, Panel A of Appendix Figure A4 shows that the distribution of overall quality for part-time applicants left-shifts relative to that for full-time applicants among the above-the-median performers, but not among the below-the-median performers.

The results above imply that the part-time quality gap will be more pronounced among hired workers, under the assumption that the firm hires applicants who are above a common performance threshold, such as the median. While this threshold was considered reasonable by AFF, firms in general may want to apply different cutoffs depending on their production functions, labor demand, and other factors. Therefore, we generalize the analysis by varying the hypothetical cutoff to hire from the applicant pool. Specifically, we estimate equation (1) with overall quality as the dependent variable on a series of subsamples consisting of all interns (i.e., hiring 100 percent of them) up to the top 35 percent in 5 percent increments in terms of average performance in the internship.[17]

Figure III shows that the magnitude of quality gap increases monotonically as a more stringent quality cutoff is applied: The gap begins at -0.17 SDs when all interns are assumed to be hired and expands to -0.30 SDs when the top 75 percent interns are assumed to be hired. As a greater performance cutoff is applied, the productivity gap continues to increase, reaching -0.54 SDs for the top 35 percent threshold. All of these estimates are significantly different from zero at a 5 percent or less level. This result suggests that once

[17]We stop at the top 35 percent subsample since the sample size becomes too small beyond this point to allow for precise estimation (e.g., less than 20 interns in each of the part- and full-time pools).

the firm hires from applicants based on performance in pre-employment programs (such as internships and tests), the quality gap between the part- and full-time employees will be more pronounced than the gap that exists for underlying applicant pools.

Overall, these experimental results are consistent with the theoretical result that the average quality of part-time applicants is lower than that of full-time applicants, and this difference is driven by high-quality applicants.

We now turn to Panel B of Table II, which presents measures of preference for short working hours. Not surprisingly, the part-time applicants prefer non-work or working part-time to working full-time and prefer family over work more than the full-time applicants (first three measures). These differences range from 0.08 to 0.27 SDs across the three applicant pools (columns 3, 6, and 9), although they are not precisely estimated. In addition, the part-time applicants receive weaker spousal support for working (significant at the 1 and 5 percent levels among all applicants and interns with above-the-median performance, respectively) and have a larger number of children who live with them. The difference between the part- and full-time applicants in overall preference for short work hours is 0.17 SDs and significant at the 1 percent level (column 3). In addition, the overall preference differs by 0.29 SDs among interns with above-the-median performance (column 6, significant at the 1 percent level) and by 0.16 SDs among those with below-the-median performance (column 9, insignificant). Overall, the results in Panel B are consistent with applicants self-selecting to a part-time or full-time job according to their preferences for working hours.

Unlike the previous two panels, Panels C and D show that the part-time and full-time applicant pools are little different in terms of other demographic and socioeconomic variables, as well as motivations for choosing jobs.[18] This finding suggests that our conceptual framework that parsimoniously features worker quality and preference for working

[18] One exception is that part-time applicants with above-the-median internship performance have lower compensation-related motivations for choosing jobs than the corresponding full-time applicants (significant at the 5 percent level).

hours likely captures key economic forces behind the selection effects of part-time versus full-time work.

6 The Effect of Part-Time Work on Labor Productivity through Selection

The previous section shows that part-time job applicants have significantly lower quality than full-time applicants, measured by job-specific skills as well as education and official sector employment status, particularly among those with high internship performance. The findings imply that part-time workers would exhibit lower labor productivity at work through selection, other things held constant. We test this implication by comparing the labor productivity of interns from the part-time and full-time applicant pools. Specifically, we estimate the following equation on a sample of interns:

$$Productivity_{ijystl} = \beta_0 + \beta_1 Part_{ij} + \delta_y + \mu_s + \lambda_t + \upsilon_l + \varepsilon_{ijystl}, \tag{2}$$

where $Productivity_{ijystl}$ represents the following labor productivity measures (indexed by y): (i) error-adjusted typing speed and (ii) error-adjusted data-entry speed, with their respective means subtracted and scaled by standard deviations, for intern i from village group j in internship wave s on working day t in trial l (up to two on a given day); $Part_{ij}$ is an indicator equal to one if intern i was from village group j with the part-time job posting, and zero with the full-time job posting; and δ_y, μ_s, λ_t, and υ_l are productivity measure, internship wave, working day, and trial fixed effects. ε_{ijystl} is an error term clustered at the village group level.

We argue that the productivity difference between interns recruited through part-time and full-time opportunities, captured by β_1, is driven by self-selection of applicants.

A key identifying assumption is that there is no effect of the different job opportunities on (data-entry) skill acquisition during the internship.[19] We assess the plausibility of the identifying assumption by examining internship attendance and productivity dynamics.[20]

Table III presents the results of estimating equation (2). Column 1 of Panel A shows that typing and data-entry speeds are lower by 0.12 SDs for interns recruited through the part-time opportunity than those recruited through the full-time opportunity, although the difference is not significant. Column 2 shows a greater productivity difference of -0.41 SDs among the interns with above-the-median performance, significantly different from zero at the 1 percent level. In contrast, column 3 shows that the productivity difference is only 0.04 SDs and insignificant for the interns with below-the-median performance.[21] In fact, Panel B of Appendix Figure A4 reveals that the productivity distribution of part-time recruited interns left-shifts relative to that of full-time recruited interns among the above-the-median performers but not among the below-the-median performers. These results are consistent with theoretical and empirical results above on the quality gap between the part-time and full-time applicant pools, which we now show translates into a productivity gap for interns.

Next, Figure IV plots daily mean standardized labor productivity over the course of the three-week internship, separately for the part-time and full-time recruited interns, adjusted for fixed effects in equation (2).[22] Panel A makes it clear that the productivity gap for interns with above-the-median performance exists from the first day and persists

[19]Another identifying assumption is that $Part_{ij}$ is orthogonal to ε_{ijystl}, which is obtained via random assignment.

[20]The causal effect of actually working part- or full-time on productivity (due, e.g., to fatigue from working long hours) is not present in our setting, given that all interns worked for the same amount of time a day regardless of the job opportunity offered.

[21]We also examine the heterogeneity of effects by productivity level through a quantile regression version of equation (2). Appendix Table A3 shows that the productivity gap is generally increasing in the percentile and becomes economically and statistically significant above the top decile, consistent with the finding in Table III.

[22]Specifically, we estimate a variant of equation (2) that replaces the *Part* indicator with the interactions between the indicators for whether part- and full-time jobs were posted and a set of indicators for working days (from 1 through 15).

throughout the internship. Panel B shows that the productivity gap hovers around -0.4 SDs, which is significant on most work days including the first. In contrast, Panels C and D show that there is virtually no productivity difference throughout among interns with below-the-median performance. For both above- and below-the-median performing interns, the labor productivity of part-time recruited interns increases over time at least on par with the productivity of full-time recruits.[23]

These productivity dynamics cast doubt on the alternative explanation that interns who have applied to the part-time job have weaker incentives to invest in skills during the internship given lower returns on their investment once they are hired. First, the alternative story cannot explain the significant initial productivity difference, which by construction is unaffected by skills acquired in the internship.[24] Second, the productivity improvement over time for part-time recruited interns is not slower than the improvement for full-time recruits, which appears inconsistent with part-time recruits having weaker incentives to acquire skills. Further, we test whether internship attendance, an important human capital investment for the job and related careers, differs between the part- and full-time recruited interns. Appendix Table A4 shows that the attendance rate is not significantly different among the above-the-median performing interns, for which a significant productivity gap exists. Therefore, the overall evidence does not support differences in skill acquisition as a main explanation for the productivity differential, hence supporting the key identifying assumption.[25]

Analogous to the analysis of worker quality that varies hypothetical hiring cutoffs in the previous section, Figure V presents the corresponding result for productivity. It

[23] Appendix Figure A5 plots productivity trends by productivity measure (i.e., typing or data-entry speed) and finds similar results with those from Figure IV.

[24] Estimates in Panel B of Table III imply that the initial productivity difference between the part-time and full-time recruited interns with above-the-median performance is -0.498 SDs ($= -0.509 + 0.011 \times 1$ day), which is significant at the 1 percent level.

[25] Our experimental setting does not allows us to observe labor productivity in the long run. Nonetheless, given the generally steep productivity increase we observe over the course of the internship, any differences in skill acquisition would have shown up as differential productivity trends.

shows that, as for the quality gap, the magnitude of the productivity gap generally increases as the firm is assumed to apply a more stringent hiring cutoff. The differences are significantly different from zero at a 5 percent or less level when the top 75 percent interns or above are assumed to be hired. This similarity in results for quality and productivity points toward the productivity gap being driven by worker quality.

As a final analysis, we examine the extent to which the productivity differences are due to selection on observable measures of quality or preference for short work hours. We estimate a variant of equation (2) that further includes the variables that capture applicants' (i) quality, (ii) preference for short working hours, and (iii) both (from Table II). Appendix Table A5 presents the estimation results. We find that variables capturing applicant quality explain most of the productivity difference due to offering a part-time or full-time job opportunity, particularly for interns with above-the-median performance (columns 5–8). For these interns, the quality measures explain 80 percent ($= [-0.411 - (-0.081) = -0.330]/-0.411$) of the raw productivity gap, whereas the preference measures explain 19 percent ($= [-0.411 - (-0.332) = -0.079]/-0.411$).[26] This finding is consistent with individuals' quality differentials, rather than differences in work hour preference, being a key source of productivity gaps between part-time and full-time applicants.

7 Conclusion and Discussion

How part-time and other alternative work arrangements affect employee selection and workforce productivity are important questions, given their rising prevalence across labor markets. We explore these questions by implementing a randomized field experiment that provides a part-time or full-time data-entry job opportunity to women in Ethiopia.

[26] In addition, we follow Gelbach (2016) and formally decompose the effect of offering part-time, relative to full-time, employment opportunities on productivity that is explained by covariates capturing quality and preference. We find that the former explains -0.314 SDs (significant at the 1 percent level) whereas the latter explains -0.030 SDs (insignificant) among interns with above-the-median performance.

We also develop a conceptual framework for job application given worker quality and preference for work hours to explain the mechanism underlying the selection effects of part-time work.

The experimental results show that part-time work attracts lower-quality applicants with a stronger preference for short work hours relative to full-time work. This "part-time quality gap" is more pronounced among applicants with top performance in the internship, who are ex ante more likely to be hired by the firm. Our conceptual framework demonstrates that the lack of potential applicants who have both a strong preference for short working hours and high quality is key to this selection effect. The part-time applicants also exhibit lower productivity as measured by data-entry speed during the internship, which is again more pronounced for higher-performing and thus more hireable interns.

These findings have several important implications for part-time work and, more generally, alternative work arrangements. First, the wage penalty associated with working short hours is, in part, explained by the lower average productivity of workers who self-select to work shorter hours.[27] Second, suppose our finding that there is a lack of high quality workers who also highly value short work hours generalizes to a lack of high quality workers who highly value alternative work arrangements (e.g., for flexibility in work hours). Then our results suggest that workers recruited under other alternative arrangements may also be less productive on average than those hired through standard arrangements. Third, if quality is more evenly distributed across workers with different preferences for short or flexible work hours, the self-selection effects of offering alternative work arrangements would be weaker than the results in this paper.[28] Investigating how

[27] To shed light on the quantitative importance of the part-time productivity gap due to selection in explaining the associated wage gap, we estimate a version of equation (2) that uses the log of labor productivity as the dependent variable. We find a part-time productivity gap of about 14 log points or 13 percent for interns with above-the-median performance, which is of comparable magnitude with a typical part-time wage penalty of 20 to 25 percent.

[28] For example, occupations with relatively low variability in productivity across workers are candidates for those with muted selection effects of alternative work arrangements.

the selection effects of alternative arrangements, including part-time work, differ across types of occupations appears an important avenue for future research.[29]

This paper also offers implications for the relation between the gender pay gap and wage-work hour relation. The literature argues that wages that increase in hours are a key reason for the persistent gender pay gap (see, e.g., Goldin (2014); Goldin and Katz (2016); and Goldin (2021)) – when faced with an increased burden from the household, especially the arrival of a young child, it is more often women than men who choose to work short hours, thereby suffering a wage penalty (Juhn and McCue (2017); and Kleven, Landais, and Søgaard (2019)). Our findings imply that the positive relation between (hourly) wages and hours is due, in part, to firms rationally using longer hours as a selection mechanism for more productive workers. Therefore, future discussions of the gender pay gap should account for the productivity difference across work hours we identify.

Lastly, our findings speak to the efficacy of policies that reduce work hours at an economy level, as have been implemented in both developed and developing economies (see, e.g., Hunt (1999); Chemin and Wasmer (2009); and Park and Park (2019)). If only a subset of firms in the economy were to introduce shorter working hours, there may be a negative consequence for the adopting firms' productivity due to the selection effect we identify (e.g., productive workers may go to firms offering long-hour jobs). This negative selection effect would dampen their incentives to offer jobs with shorter hours ex ante, even when doing so would improve the welfare of both firms and workers (see Rebitzer and Taylor (1995) for a similar result based on an efficient-wage model). Thus, policies that reduce work hours across firms in the economy, as opposed to a subset of firms, may be preferred to mitigate the potentially negative effect on productivity.[30]

[29] Another topic for future research is whether varying the quantity (e.g., short) of hours worked, which this paper focuses on, and varying the pattern of hours (e.g., flexible) have a similar (or different) effect on the quality of workers. See Chen et al. (2019) for the valuation of flexible work using Uber drivers.

[30] As of this writing, several governments are implementing or considering work hour reductions. Colombia will reduce weekly work hours from 48 to 42 essentially for all workers by 2026. California is considering reducing work hours from 40 to 32 per week only for private-sector firms with more than 500 employees. Meanwhile, Spain is piloting a 32-hour work week for volunteering firms. Our results suggest that the

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negative selection effect on productivity of participating firms is more likely for the cases of California and Spain than Colombia.

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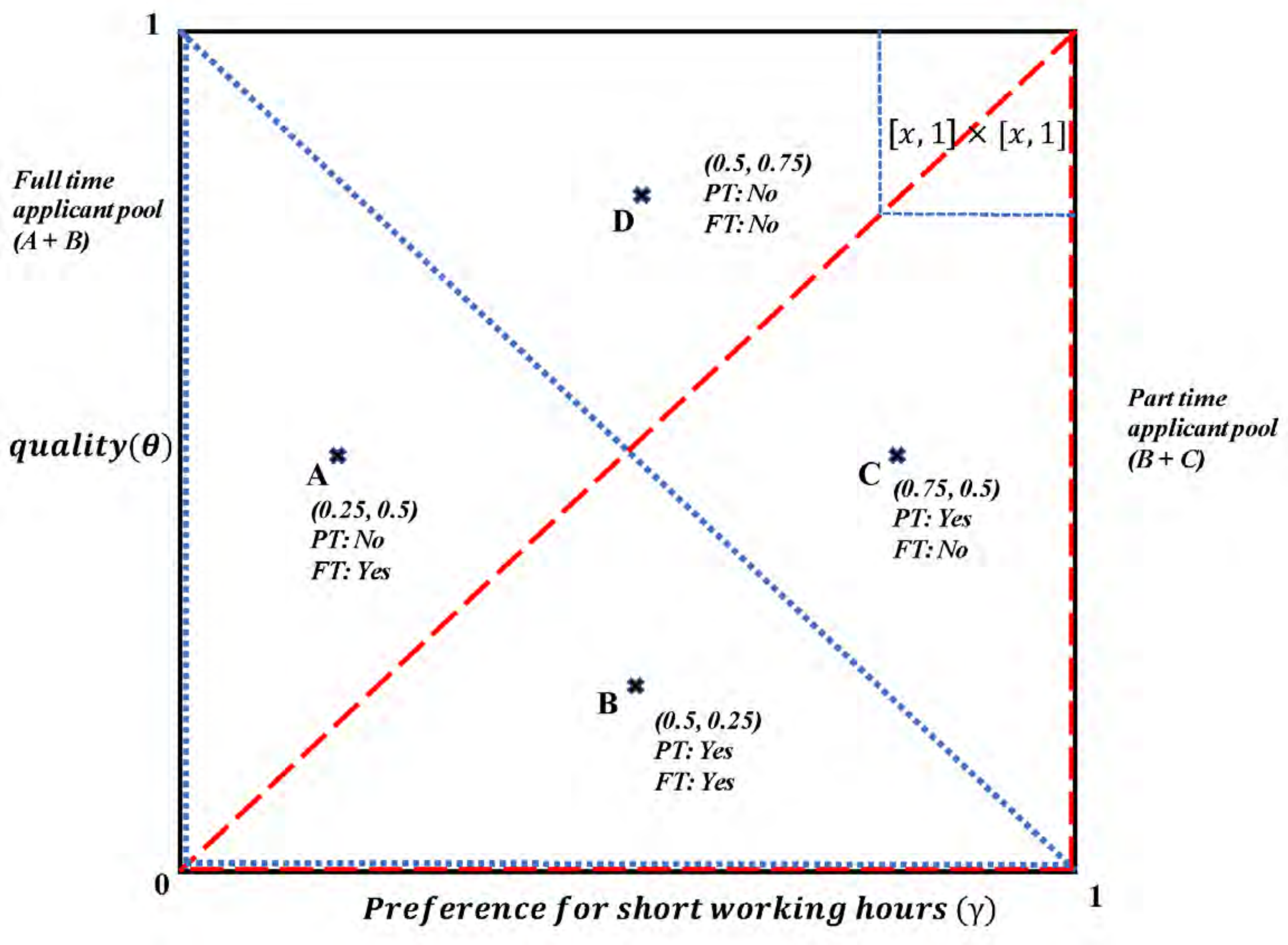
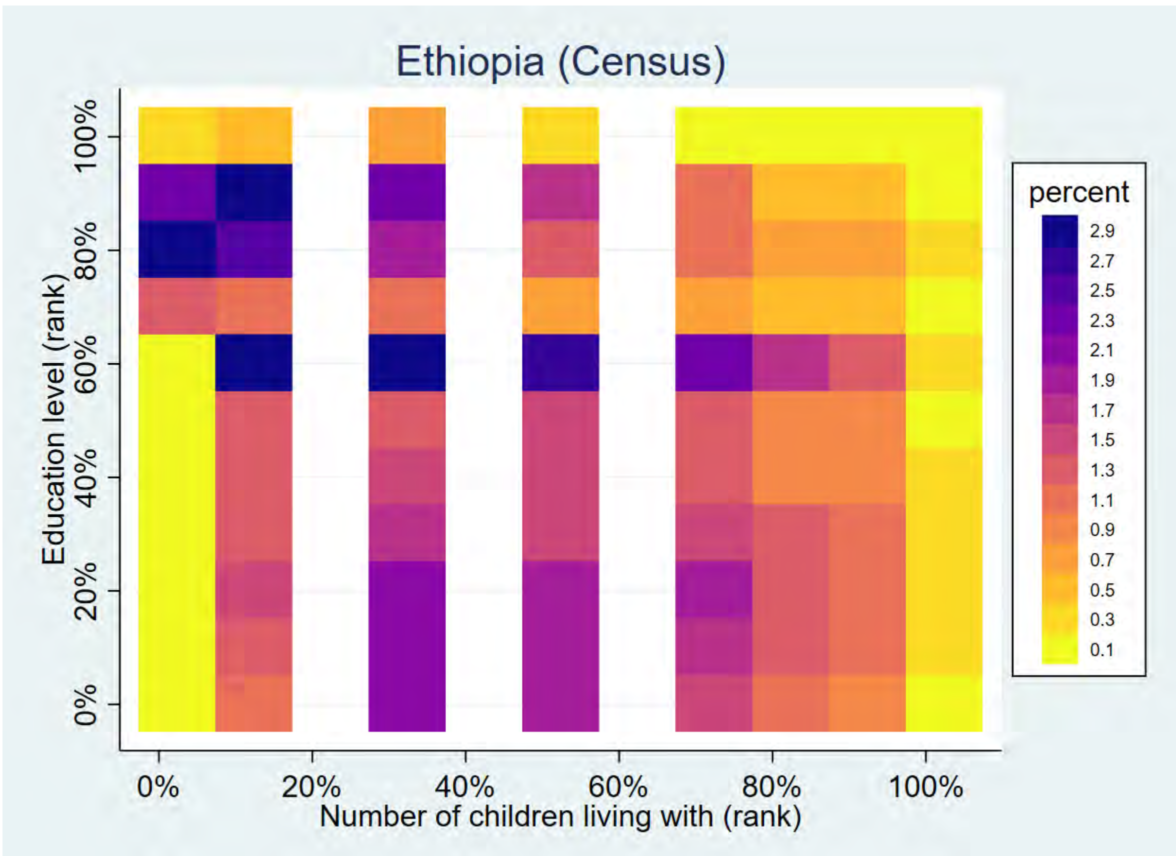
Figure I:
Theoretical Applicant Pools for Part-Time and Full-Time Jobs in the Preference for Short Working Hours-Quality Space



Notes: This figure presents the theoretical applicant pools for part-time (red triangle with the apex at the right corner) and full-time (blue triangle with the apex at the left corner) jobs from potential applicants with preferences for short working hours (x-axis) and quality (y-axis) in a unit square. It is assumed that the $[x,1] \times [x,1]$ square in the upper-right corner has the density of zero, whereas the rest of the population has the density of $l > 0$.

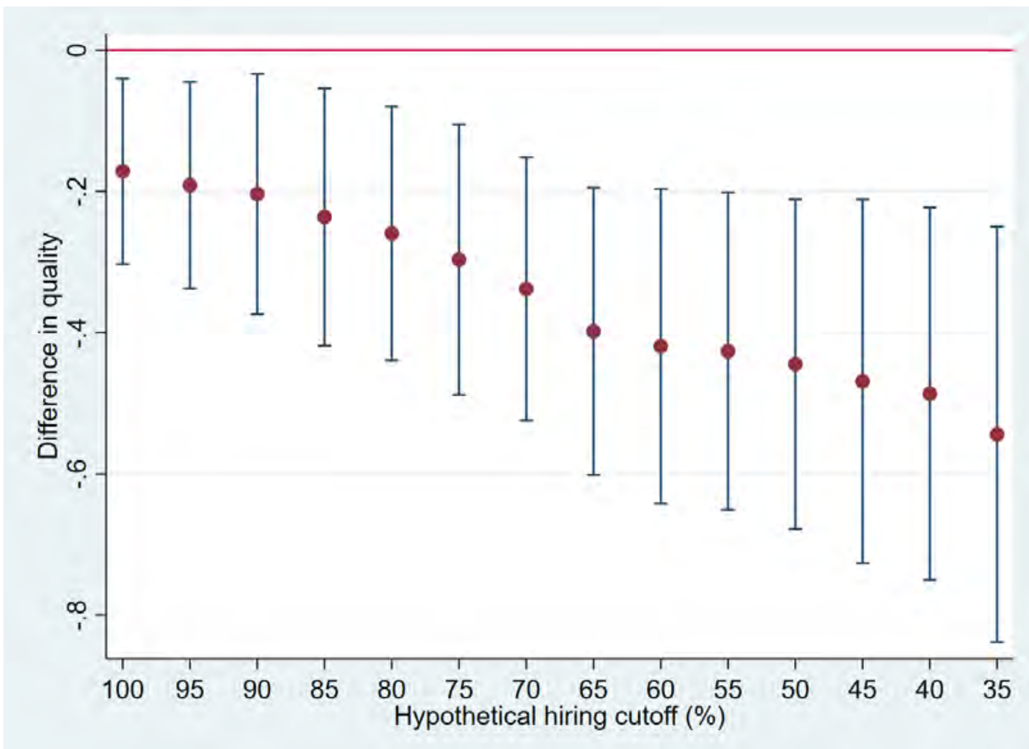
Figure II:

Distribution of Proxies for Preference for Short Working Hours and Quality, Holeta and Ejere, Ethiopia



Notes: This figure presents the distribution of the number of children living in the household (x-axis, proxy for preference for short working hours) and years of education (y-axis, proxy for quality) in rank for the population of potential applicants in Holeta and Ejere, Ethiopia, the recruitment areas. The data are collected in the census of the areas. Darker colors represent denser parts of the population.

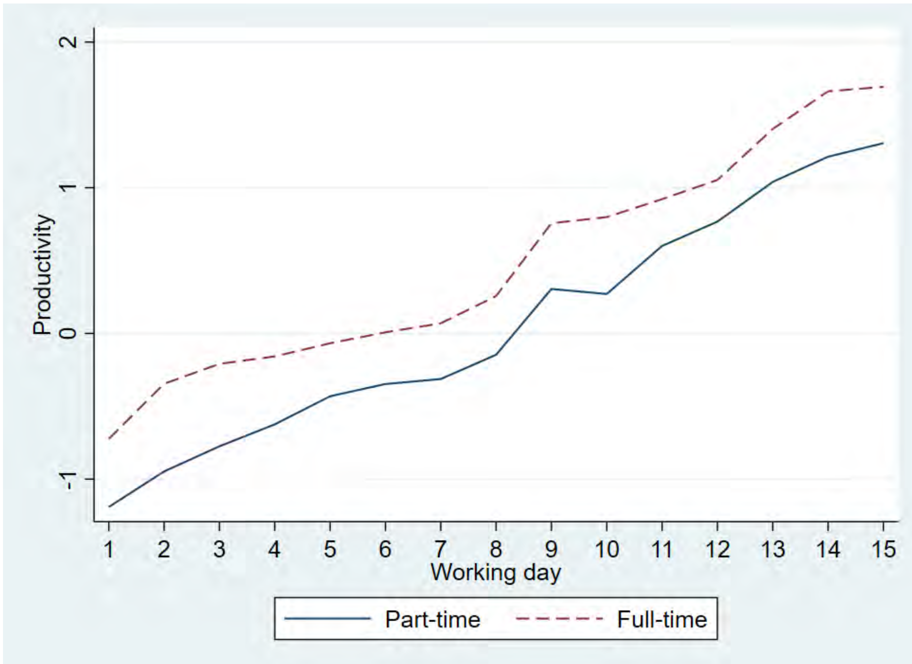
Figure III:
Quality Difference between Part-Time and Full-Time Recruited Interns Conditional on Hypothetical Hiring Cutoffs



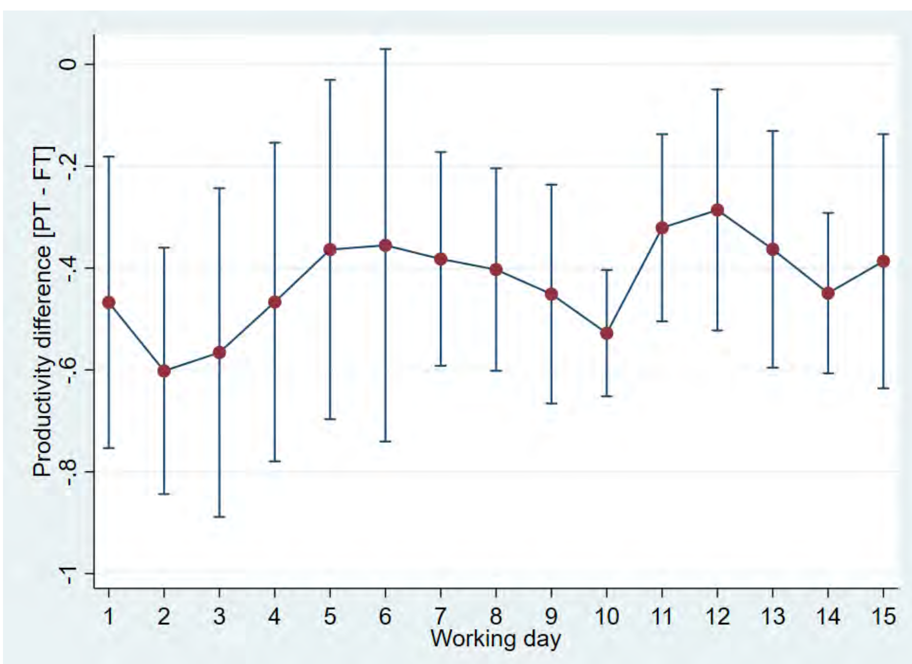
Notes: This figure presents the average difference in overall standardized quality between part-time and full-time recruited interns (red dots) and the 95 percent confidence intervals (blue bars), conditional on hypothetical hiring cutoffs from 100 percent (i.e., hiring all interns) to the top 35 percent in the distribution of average internship performance. Confidence intervals are calculated based on standard errors clustered at the village group level.

Figure IV:
Labor Productivity of Part-Time and Full-Time Recruited Interns

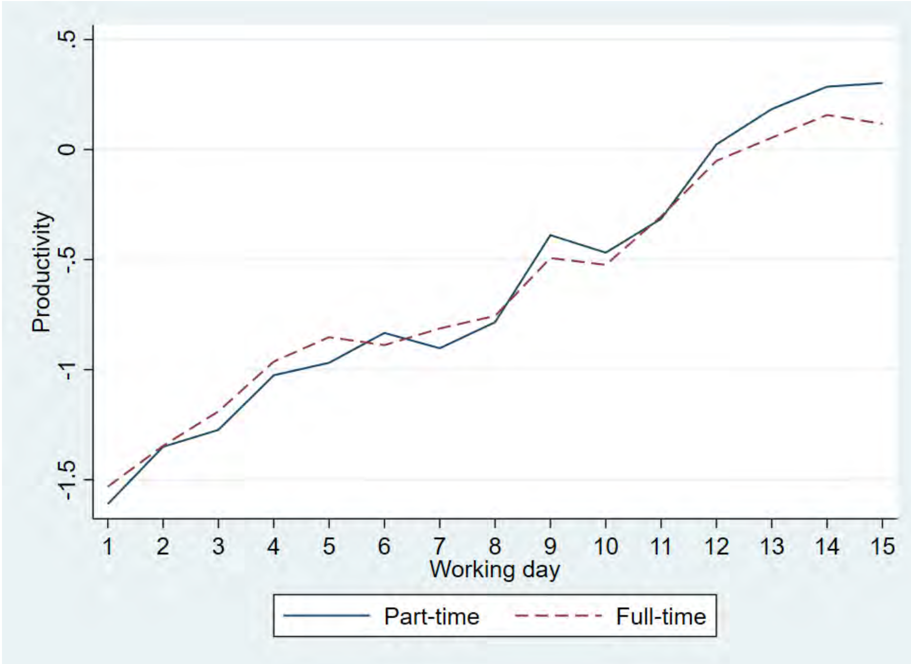
Panel A.
Above-the-Median Interns



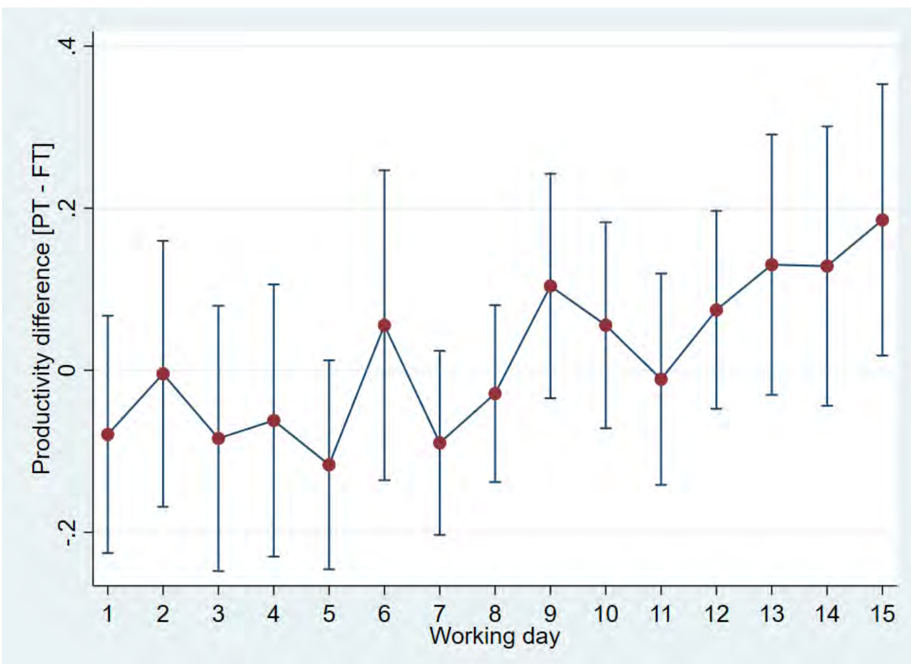
Panel B.
Above-the-Median Interns – Differences Between Part- and Full-Time Recruited Interns, with Confidence Intervals



Panel C.
Below-the-Median Interns

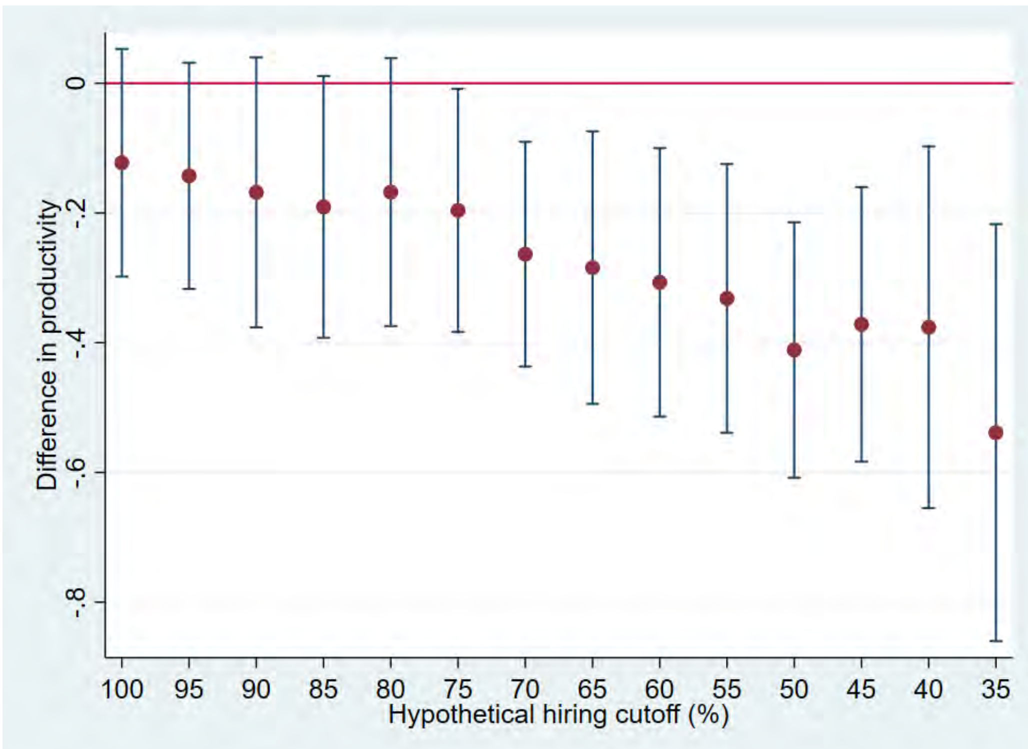


Panel D.
Below-the-Median Interns – Differences Between Part- and Full-Time Recruited Interns, with Confidence Intervals



Notes: This figure presents coefficient estimates from a variant of equation (2) that replaces the *Part* indicator with the indicators for part-time and full-time recruited interns, interacted with indicators for working days (from 1 through 15). Panels A and C (B and D) show standardized labor productivity trends separately for part- and full-time recruited interns (average differences between the part- and full-time recruited interns and the 95 percent confidence intervals) over working days. Confidence intervals are calculated based on standard errors clustered at the village group level. Panels A and B (C and D) use interns with above- (below-) the-median performance.

Figure V:
Labor Productivity Difference between Part-Time and Full-Time Recruited Interns Conditional on Hypothetical Hiring Cutoffs



Notes: This figure presents the average difference in standardized labor productivity between part-time and full-time recruited interns (red dots) and the 95 percent confidence intervals (blue bars), conditional on hypothetical hiring cutoffs from 100 percent (i.e., hiring all interns) to top 35 percent in the distribution of average internship performance. Confidence intervals are calculated based on standard errors clustered at the village group level.

Table I: Experimental Stages

			Number and percentage of job-eligible women					(4) - (6)
Approximate timing	Experimental stage	Participants	Part-time		Full-time		Total	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
May to July 2016	Census taken (job ads distributed)	job-eligible women	3,202	100.0%	3,093	100.0%	6,295	-
July to August 2016	Submitted job application materials	preliminary job applicants	230	7.2%	226	7.3%	456	0.92
December 2016	Participated in job survey and aptitude tests	job applicants	162	5.1%	171	5.5%	333	0.68
August to December 2017	Participated in internship (in 2nd or 3rd week)	interns	61	1.9%	61	2.0%	122	0.90

Notes: This table presents the stages in the experiment and the number of participants by stage. Columns 4 and 6 show the fraction of job-eligible women continuing over experiment stages in village groups where the part-time and full-time jobs were posted, respectively. Column 8 shows p-values for differences in the fraction continuing between the village groups with part-time and full-time job postings.

Table II: Effects of Part-Time Work on the Applicant Pool through Selection

Sample	All applicants			Above-the-median interns			Below-the-median interns		
Variable	N	FT applicants	Mean diff. (PT-FT)	N	FT applicants	Mean diff. (PT-FT)	N	FT applicants	Mean diff. (PT-FT)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. Measures of Quality (Standardized)									
Data-entry test score	333	0.103	-0.221**	61	0.744	-0.598**	61	0.149	-0.206
Clerical ability	333	0.015	-0.030	61	0.534	-0.502**	61	-0.131	-0.109
Computation ability	330	-0.008	0.016	60	0.237	-0.111	60	-0.109	0.068
Computer literacy	329	0.034	-0.069	61	0.508	-0.632***	60	-0.174	0.054
Manual dexterity	332	0.114	-0.223*	61	0.460	-0.567**	60	0.000	0.073
Years of education	311	1.322	0.097	58	1.649	-0.331*	54	1.061	0.366*
Working in official sector	322	-0.170	-0.048	59	-0.006	-0.409***	59	-0.176	0.058
Overall quality (pooled)	2,290	0.193	-0.069	421	0.581	-0.445***	415	0.072	0.047
Panel B. Measures of Preference for Short Work Hours (Standardized)									
Preference for family to work	331	-0.077	0.157	61	-0.159	0.122	59	0.072	0.154
Preference for non-work, working part- to full-time	325	-0.060	0.123	60	-0.146	0.121	60	-0.042	0.118
Preference for part-time to full-time work	330	-0.048	0.099	61	-0.182	0.273	61	-0.066	0.081
(Reverse) Supportive spouse for work	280	-0.498	0.350***	49	-0.614	0.721**	52	-0.490	0.332
Number of children in household	304	-1.259	0.129	57	-1.423	0.271	57	-1.276	0.065
Overall preference for short working hours (pooled)	1,570	-0.371	0.167***	288	-0.494	0.293***	289	-0.353	0.160
Panel C. Individual Characteristics									
Age	286	22.721	-0.146	53	21.167	1.075	51	22.036	0.747
Married	323	0.313	-0.044	60	0.231	0.063	60	0.303	-0.155
Subjective health status [1-5]	330	4.429	0.077	61	4.296	0.233	61	4.559	-0.225
Asset score [1-10]	330	6.875	0.088	61	7.360	0.568	60	5.909	0.572
Panel D. Importance in Choosing Jobs [1-4]									
Intrinsic motivation	333	3.225	0.023	61	3.166	0.110	61	3.252	0.013
Extrinsic motivation	333	2.952	-0.006	61	2.951	-0.031	61	2.987	0.036
Accomplishment	333	3.528	0.007	61	3.590	-0.024	61	3.516	-0.024
Status	333	3.282	0.033	61	3.370	-0.080	61	3.340	0.087
Career progress	332	2.865	-0.087	61	3.012	-0.316	61	2.804	0.122
Compensation and benefits	332	3.196	0.015	61	3.267	-0.203**	61	3.176	0.098

Notes: Columns 2 and 3 (columns 5 and 6) [columns 8 and 9] show means for full-time applicants and mean differences between the part-time and full-time applicant pools for all applicants (above-the-median performing interns) [below-the-median performing interns]. All variables in Panels A and B are standardized by subtracting the respective mean and scaling by the standard deviation. *Data-entry test score* is the number of fields that the applicant enters correctly from census forms in 15 minutes. *Computer literacy* is based on 12 questions about basic knowledge of computer hardware and software, such as Microsoft Windows and Office. *Years of education* is the total number of years the applicant has been in school. *Working in official sector* = 1 if the applicant is employed in an official sector. *Number of children in household* is the number of children who live in the same household. *Age* is in years. *Married* = 1 if the applicant is married. *Subjective health status* ranges from 1 ("very bad") to 5 ("very good"). *Asset score* is the number of the following items that a household owns: 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. See the Data Appendix for definitions of other variables. ***, **, and * denote the significance level at 1%, 5%, and 10%, respectively, based on standard errors clustered at the village group level.

Table III: Effects of Part-Time Work on Labor Productivity through Selection

	All interns	**Above the median**	**Below the median**
	(1)	(2)	(3)
Dep. Var.:		Productivity	
Panel A: Without time trend			
Part	-0.123	-0.411***	0.036
	(0.089)	(0.100)	(0.054)
Constant	0.072	0.682***	-0.477***
	(0.066)	(0.093)	(0.031)
Productivity measure fixed effects	Y	Y	Y
Wave fixed effects	Y	Y	Y
Work day fixed effects	Y	Y	Y
Trial fixed effects	Y	Y	Y
R^2	0.500	0.513	0.543
N	4,821	2,511	2,310
Panel B: With time trend			
Part	-0.341***	-0.509**	-0.126
	(0.112)	(0.209)	(0.089)
Day	0.141***	0.172***	0.119***
	(0.004)	(0.011)	(0.006)
Part × Day	0.024**	0.011	0.017*
	(0.009)	(0.016)	(0.009)
Constant	-1.238***	-0.916***	-1.579***
	(0.069)	(0.177)	(0.042)
Productivity measure fixed effects	Y	Y	Y
Wave fixed effects	Y	Y	Y
Trial fixed effects	Y	Y	Y
R^2	0.494	0.503	0.529
N	4,821	2,511	2,310

Notes: Panel A of this table presents estimates from equation (2) on samples of all interns (column 1), above-the-median performing interns (column 2), and below-the-median performing interns (column 3). Panel B presents estimates from a variant of equation (2) that includes the *Part* indicator, the variable *Day* that represents the number of working days, and their interaction term. The dependent variable is standardized error-adjusted typing speed or data-entry speed. $Part = 1$ (0) if the intern is recruited in a village where the part-time (full-time) job was posted. 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 (For Online Publication)

Figure A1. Job Ads

Panel A. Part-Time Job

Panel B. Full-Time Job

Figure A2. Internship Program and 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)				

Notes: This figure presents the detailed internship program and schedule for participants in the morning session (from 9 a.m.–12 p.m.). Participants in the afternoon session (from 2 p.m.–5 p.m.) had an identical program.

Figure A3. Distribution of Proxies for Preference for Short Working Hours and Quality, 24 African Countries

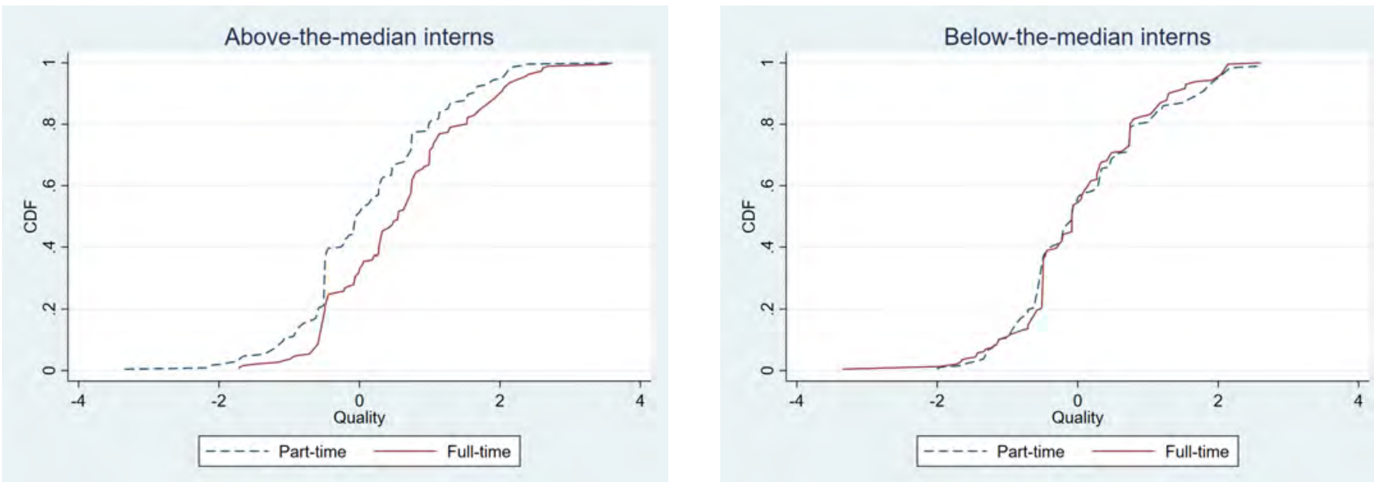
Panel A. All Residents

Panel B. Urban Residents

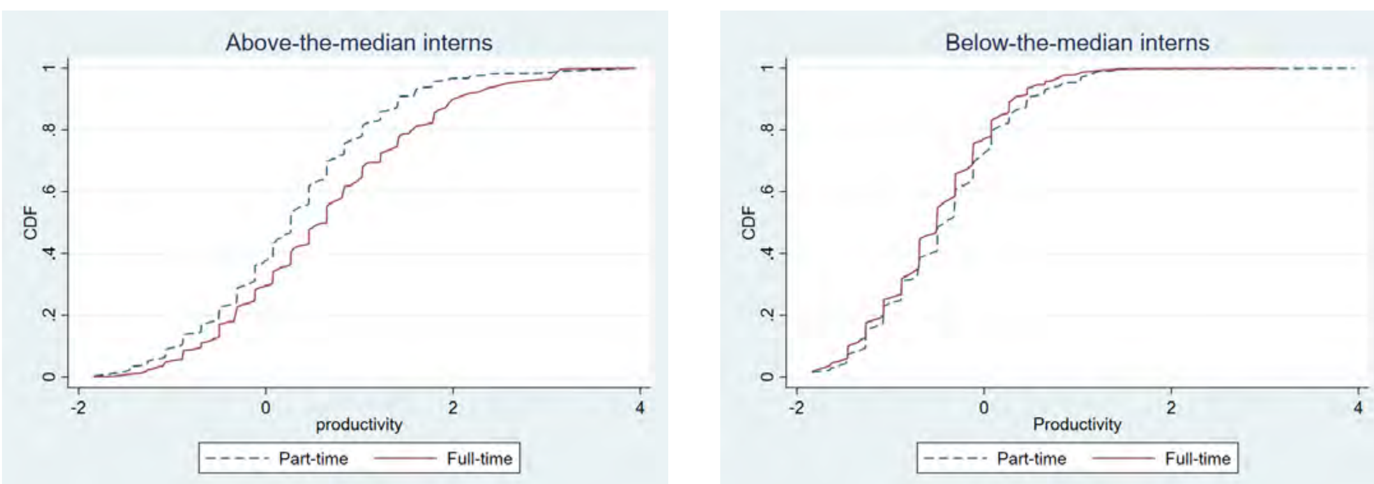
Notes: This figure presents the distribution of the number of children living in the household (x-axis, proxy for preference for short working hours) and years of education (y-axis, proxy for quality) in rank for women aged 20 and over for 24 African countries. Panels A and B are for all residents and urban residents, respectively. The data are from the Demographic and Health Surveys (DHS).

Figure A4. Cumulative Distributions of Quality and Labor Productivity for Part-Time and Full-Time Recruited Interns

Panel A. Quality



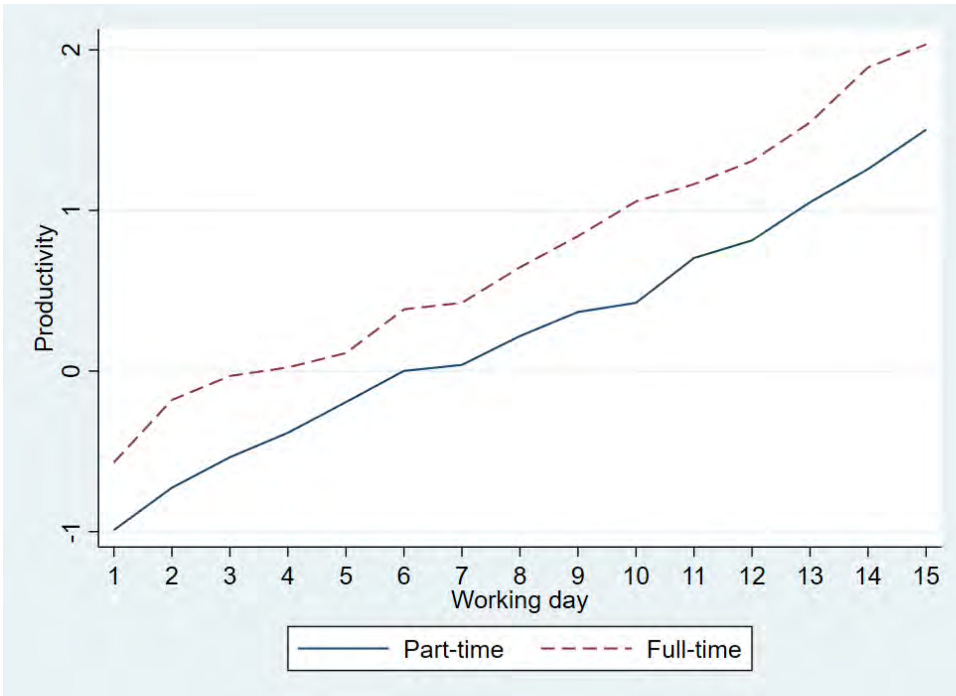
Panel B. Labor Productivity



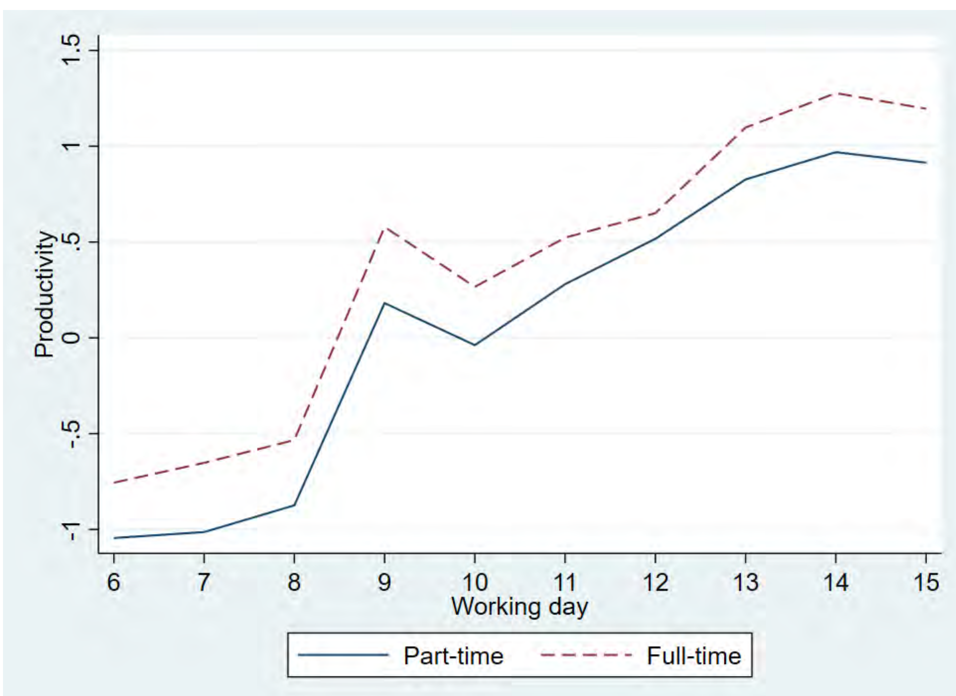
Notes: This figure presents the cumulative distribution functions of overall standardized quality (Panel A) and standardized labor productivity (Panel B) for interns performing above-the-median (left) and below-the-median (right), separately for those recruited through part-time and full-time job postings.

Figure A5. Labor Productivity of Part-Time and Full-Time Recruited Interns by Productivity Measure

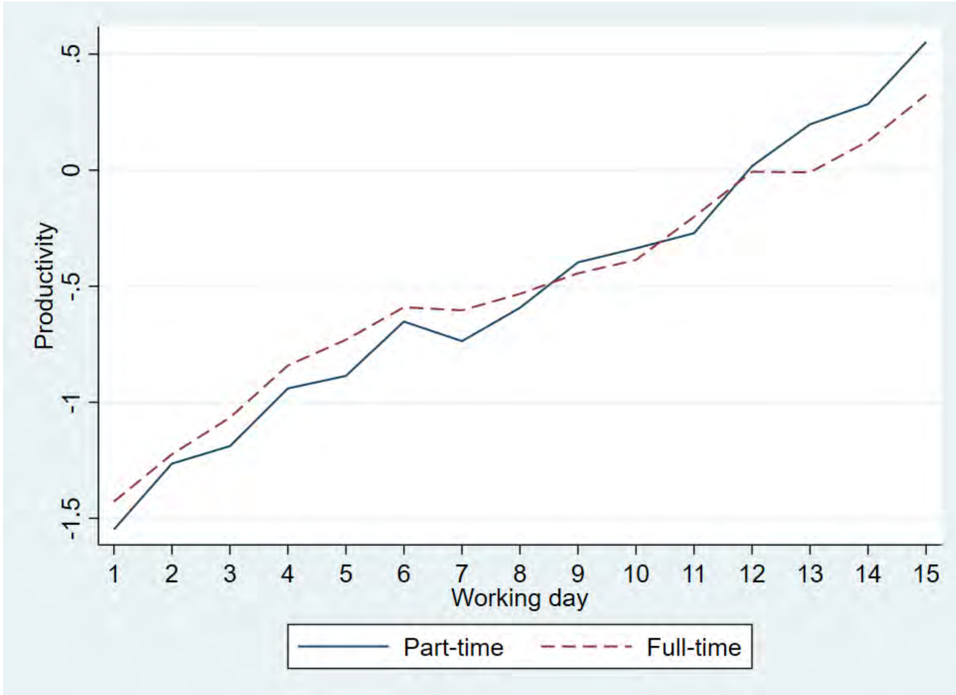
Panel A. Above-the-Median Interns – Typing Speed



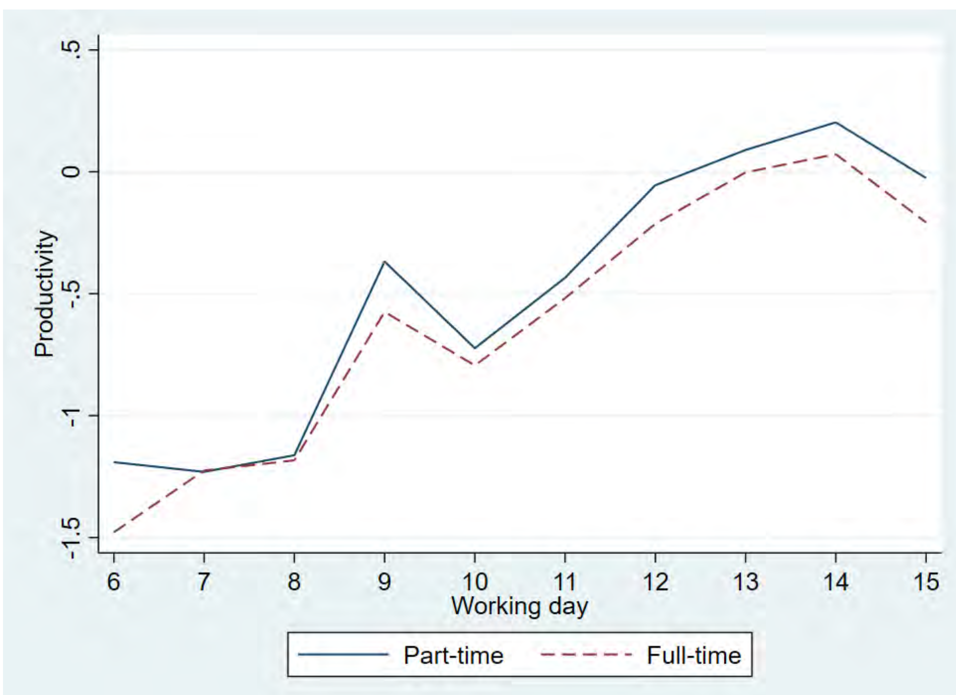
Panel B. Above-the-Median Interns – Data-Entry Speed



Panel C. Below-the-Median Interns – Typing Speed



Panel D. Below-the-Median Interns – Data-Entry Speed



Notes: This figure presents coefficient estimates from a variant of equation (2) that replaces the *Part* indicator with the indicators for part-time and full-time recruited interns, interacted with indicators for working days (from 1 through 15) by productivity measure. Panels A and C (B and D) use standardized error-adjusted typing speed (data-entry speed) as a productivity measure. Panels A and B (C and D) use interns with above- (below-) the-median performance.

Table A1. Characteristics of Study Population and Balance of Randomization

Variable	(1) N	(2) All	(3) Part-Time	(4) Full-Time	(5) Diff. (PT-FT)	(6) p-value
Panel A. Characteristics of Potential Applicants						
Age	6,160	26.032	25.740	26.329	-0.588	0.339
Married	6,167	0.419	0.441	0.397	0.044	0.160
Ethnicity						
Amhara	6,234	0.202	0.177	0.227	-0.050	0.201
Oromo	6,234	0.735	0.754	0.716	0.038	0.430
Language						
Amharic	6,236	0.415	0.372	0.460	-0.088	0.235
Oromigna	6,236	0.581	0.623	0.538	0.085	0.256
Religion						
Orthodox	6,225	0.694	0.660	0.729	-0.068	0.205
Protestant	6,225	0.251	0.275	0.226	0.049	0.312
Muslim	6,225	0.021	0.026	0.016	0.010	0.176
Post-secondary education	6,265	0.389	0.376	0.402	-0.026	0.516
Working						
within household	6,115	0.132	0.090	0.175	-0.085*	0.074
in official sector	6,078	0.195	0.193	0.196	-0.003	0.952
Panel B. Household Characteristics						
Number of household members	20,255	4.216	4.166	4.267	-0.101	0.499
Asset score [1-10]	20,383	4.582	4.474	4.693	-0.219	0.679
Number of children living in household	16,159	2.501	2.496	2.505	-0.009	0.695
Having savings account	20,382	0.278	0.266	0.292	-0.026	0.695
Receiving government subsidy	20,371	0.016	0.018	0.013	0.004	0.307
Panel C. Village Characteristics						
Holeta (=1) vs. Ejere (=0)	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

Notes: This table presents descriptive statistics on individual, household, and village characteristics for the population of potential applicants in the recruitment areas. Columns 2, 3, 4, and 5 show means for all villages, villages with part-time and full-time job postings, and the mean differences between the part-time and full-time villages. Column 6 shows the p-value for the mean differences. Variables under *Ethnicity*, *Language*, and *Religion* = 1 if the applicant belongs to the ethnic group, is able to use the language, and has the religion. *Post-secondary education* = 1 if the applicant has education at a post-secondary level. *Working within household (in official sector)* = 1 if the applicant is employed within the household (in an official sector). *Number of household members* is the number of individuals in the household. *Having savings account* = 1 if anyone in the household has a savings account. *Receiving government subsidy* = 1 if anyone in the household receives a government subsidy. *Holeta* = 1 if the viliage is in Holeta (= 0 if in Ejere). *Population* is the number of individuals enumerated in the census in the village. *Gender ratio (F/M)* is the ratio between females and males in the village. See notes to Table 2 for the definitions of other variables. The variables are collected in the census of the recruitment areas. * denotes the significance level at 10%.

Table A2. Comparison of Non-Applicants and Applicants

Variable / Sample	(1) Non-applicants N	(2) Non-applicants Mean	(3) Applicants N	(4) Applicants Mean	(5) Difference (4)-(2)
Age	5,844	26.2	316	23.1	-3.1***
Married	5,844	0.426	323	0.291	-0.135***
Ever given birth	4,601	0.494	276	0.330	-0.165***
Number of children living in household	5,340	1.367	304	0.819	-0.548***
Working	5,848	0.299	324	0.182	-0.117***
Working in official sector	5,756	0.199	322	0.118	-0.081***
Post-secondary education	5,950	0.380	315	0.556	0.175***
Asset score [1-10]	5,934	7.013	330	6.918	-0.095
Supportive spouse for work	5,227	3.958	280	4.259	0.301***

Notes: This table compares the mean characteristics of the non-applicants (columns 1 and 2) and applicants (columns 3 and 4) among potential applicants in the recruitment areas. Column 5 shows the mean differences between the applicants and non-applicants. *Ever given birth* = 1 if the worker has ever given birth to child(ren). *Post-secondary education* = 1 if the worker has education at a post-secondary level. *Working* = 1 if the worker is employed within the household or in an official sector. See notes to Table 2 for the definitions of the other variables. The variables are collected in the census of the recruitment areas. *** denotes the significance level at 1%.

Table A3. Quantile Regression of Labor Productivity on Part-Time Recruitment Status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dep. Var.:	Productivity							
Estimates:	OLS	Quantile regression						
Quantile:		0.05	0.1	0.25	0.5	0.75	0.9	0.95
Part	-0.123	0.010	-0.014	-0.046	-0.042	-0.064	-0.333	-0.575***
	(0.089)	(0.070)	(0.072)	(0.060)	(0.058)	(0.130)	(0.210)	(0.180)
Productivity measure fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Wave fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Work Day fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Trial fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.500	0.469	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

Notes: Column 1 reproduces the OLS estimates in column 1 of Table 3, Panel A. Columns 2 through 8 present quantile regression estimates of equation (2) from quantiles 0.05 to 0.95 of the labor productivity distribution among the interns. The dependent variable is standardized error-adjusted typing speed or data-entry speed. $Part = 1$ (0) if the intern is recruited in a village where the part-time (full-time) job was posted. Standard errors clustered at the village group level are reported in parentheses. *** denotes the significance level at 1%.

Table A4. Internship Attendance by Part-Time Recruitment Status

	All interns		**Above-the-median interns**		**Below-the-median interns**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.:	1(Attend)					
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)
Wave fixed effects	N	Y	N	Y	N	Y
Work day 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	3,538	3,538	1,769	1,769	1,769	1,769

Notes: This table shows estimates of linear probability models that explain the intern's attendance by the part-time recruitment status. The dependent variable is an indicator = 1 if the intern attends in a given work day-trial in the second or third week of the internship. $Part = 1$ (0) if the applicant is recruited in a village where the part-time (full-time) job was posted. Standard errors clustered at the village group level are reported in parentheses. *** and ** denote the significance level at 1% and 5%, respectively.

Table A5. Estimates of Part-Time Productivity Gaps with Controls for Quality and Work Hour Preference

	All interns				**Above-the-median interns**				**Below-the-median interns**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep. Var.:	Productivity											
Part	-0.123	0.056	-0.068	0.054	-0.411***	-0.081	-0.332***	-0.066	0.036	0.053	0.061	0.049
	(0.089)	(0.055)	(0.088)	(0.054)	(0.100)	(0.094)	(0.118)	(0.091)	(0.054)	(0.048)	(0.053)	(0.050)
Controls for quality		Y		Y		Y		Y		Y		Y
Controls for work hour preference			Y	Y			Y	Y			Y	Y
Productivity measure fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Wave fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Work day 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	4,890	4,890	4,890	4,890	2,511	2,511	2,511	2,511	2,310	2,310	2,310	2,310

Notes: Columns 1, 5, and 9 reproduce OLS estimates from Panel A of Table 3. Columns 2, 6, and 10 include measures of applicants' quality shown in Panel A of Table 2 as controls, including *data-entry test score*, *clerical ability*, *computation ability*, *computer literacy*, *manual dexterity*, *years of education*, and *official sector working status*. Columns 3, 7, and 11 include variables that capture preference for short work hours shown in Panel B of Table 2 as controls, including *preference for family to work*, *preference for non-work*, *working part- to full-time*, *preference for part-time to full-time work*, *(reverse) supportive spouse for work*, and *number of children in household*. Columns 4, 8, and 12 include both the quality and work hour preference measures as controls. The dependent variable is standardized error-adjusted typing speed or data-entry speed. $Part = 1$ (0) if the intern is recruited in a village where the part-time (full-time) job was posted. Standard errors clustered at the village group level are reported in parentheses. *** denotes the significance level at 1%.

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 work.

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

Practice Questions

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

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

15. Multiply

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

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

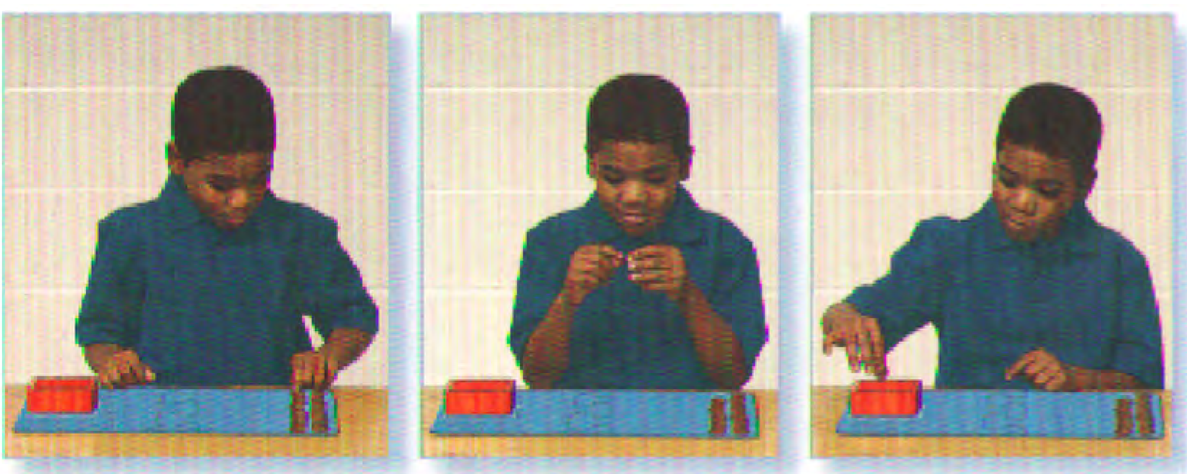
16. Divide

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

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 use the manual dexterity test, which is most relevant for the data-entry work. We asked survey participants to transfer 20 small coins from a table to a small box in 15 seconds. Study participants could try twice, and the higher number is the final score. The following image depicts the manual dexterity test.



B.2 Measures of preference for short working hours

We measure the applicants' preference for short working hours using three sets of survey questions. The first measures the importance of family over work using ten survey questions. We calculate a composite score of preference for family over work by subtracting the average score for work from that for family. Scores range from ten to 50, and a higher score implies stronger preferences for family (i.e., shorter hours).

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.						

Second, we measure preference for full-time, part-time, and no-work arrangements in five life stages. To calculate a composite score, we assign one, two, and three for full-time, part-time work, and no-work arrangements, respectively, and add scores for the five questions. A higher score implies stronger preferences for working short hours.

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, relative to those for compensation and work that they like. We assign one when individuals choose the arrangement with a part-time option (B in Q509-1 and Q509-2), and zero otherwise. We calculate a composite score by adding scores for the two questions. A higher score implies stronger preferences 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. Expectations toward work

Intrinsic motivation

Intrinsic motivation is an individual 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). We calculate an average score after accounting for (any) reverse coding.

Q502. Below is a list of statements concerning intrinsic motivation. Please indicate how strongly you agree or disagree with each statement.		**1 = Strongly disagree 2 = Disagree 3 = Agree 4 = Strongly agree**			
1	I enjoy trying to solve difficult problems.	1	2	3	4
2	I enjoy simple, straightforward tasks.	1	2	3	4
3	I enjoy tackling problems that are completely new to me.	1	2	3	4
4	What matters most to me is enjoying what I do.	1	2	3	4
5	It is important for me to be able to do What I most enjoy.	1	2	3	4
6	The more difficult the problem, the more I enjoy trying to solve it.	1	2	3	4
7	I want my work to provide me with opportunities for increasing my knowledge and skills.	1	2	3	4
8	I like to figure things out for myself.	1	2	3	4
9	No matter what the outcome of a project, I am satisfied if I feel I gained a new experience.	1	2	3	4
10	Wanting to know more is the driving force behind much of what I do.	1	2	3	4
11	I prefer work I know I can do well over work that goes beyond what I can manage.	1	2	3	4
12	I am more comfortable when I can set my own goals.	1	2	3	4
13	I enjoy doing work that is so involving that I forget about everything else.	1	2	3	4
14	It is important for me to have space to express myself.	1	2	3	4
15	I want to find out how good I really can be at my work.	1	2	3	4

Extrinsic motivation

Extrinsic motivation is an individual 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). We calculate an average score after accounting for (any) reverse coding.

Q503. Below is a list of statements concerning extrinsic motivation. Please indicate how strongly you agree or disagree with each statement.		**1 = Strongly disagree** **2 = Disagree** **3 = Agree** **4 = Strongly agree**			
1	I am not that concerned about what other people think of my work.	1	2	3	4
2	I prefer having someone set clear goals for me in my work.	1	2	3	4
3	I am very much aware of the income goals I have for myself.	1	2	3	4
4	To me, success means doing better than other people.	1	2	3	4
5	I am very much aware of the career promotion goals I have for myself.	1	2	3	4
6	I am less concerned with what work I do than what I get for it.	1	2	3	4
7	I am concerned about how other people are going to react to my ideas.	1	2	3	4
8	I rarely think about salary and promotions.	1	2	3	4
9	I believe that there is no point in doing a good job if nobody else knows about it.	1	2	3	4
10	I am strongly motivated by the money I can earn.	1	2	3	4
11	I prefer working on projects with clearly specified procedures.	1	2	3	4
12	As long as I can do what I enjoy, I am not that concerned about exactly what I am paid.	1	2	3	4
13	I am strongly motivated by the recognition I can earn from other people.	1	2	3	4
14	I have to feel that I am earning something for what I do.	1	2	3	4
15	I want other people to find out how good I really can be at my work.	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). We calculate an average score after accounting for (any) reverse coding.

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 much one cares about his/her career in the future. All items were answered using a 4-point Likert scale format ranging from *strongly disagree* (1) to *strongly agree* (4). We calculate an average score after accounting for (any) reverse coding.

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

Concerns for compensation and benefits

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). We calculate an average score after accounting for (any) reverse coding.

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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