Measuring Labor Market Discrimination: Egypt's First Audit Study

Pre-analysis plan

October 16, 2022

Principal investigator: Caroline Krafft

J-PAL MENA team: Mona Amer and Salma Rizk

1. Motivation

Egypt's labor market is highly segmented, with women concentrated in specific occupations (Assaad, Krafft, Rahman, & Selwaness, 2019; El-Hamidi & Said, 2014). In the private sector, women typically earn less than men, even after accounting for differences in their characteristics (El-Hamidi & Said, 2014; Said, Galal, & Sami, 2022). This wage differential is often interpreted as a sign of discrimination against women but could also be driven by unobserved characteristics of women or selection into specific jobs. Norms that prioritize jobs for men over women, when jobs are scarce (Keo, Krafft, & Fedi, 2022), may also lead to employer discrimination in challenging economic times.

Egyptian women frequently work in the private sector in advance of marriage and leave private sector work at marriage (Assaad, Krafft, & Selwaness, 2022; Krafft, Assaad, & Keo, 2022; Selwaness & Krafft, 2021). The degree to which exits are driven by women choosing to leave work versus employer discrimination against married women are unknown but have very different implications for interventions to improve women's employment. Generally, understanding the role of employer discrimination and the labor demand side of the market in Egyptian women's low and declining employment rates is a critical but under-researched area.

There has been little research on employer discrimination and its impact on hiring in Egypt.[1] This research will undertake Egypt's first audit study, randomizing the gender on applications and resumes in order to assess the degree of employer discrimination against women in Egypt.

2. Methods

Audit studies are a form of random field experiments that allow researchers to test for discriminatory behavior (Gaddis, 2018). The random experimental design allows for estimation of causal impacts. For example, in the case of gender discrimination in employment, audit studies randomize the gender of job applications to job postings. The results allow for an

[1] Osman, Speer, and Weaver (2021) use a list experiment to assess discrimination among employers in retail, information technology, hotels, and restaurant sectors, and show 51% of establishments prefer hiring men over women.

assessment of how much employer discrimination reduces callback or interview rates for women relative to men. To date, there is only one audit study on gender discrimination in the labor market in the Middle East and North Africa, which focused on a selection of educated occupations in Tunisia (Alaref, Towfighian, Paez, & Audah, 2020). The study did not find discrimination on average but did find substantial occupation-specific discrimination.

This audit study would randomize the following characteristics of applicants:

· Gender (male/female)

· Marital status (unmarried/married)

As these are the key dimensions potentially contributing to employer discrimination and low female labor force participation.

3. Data

3.1. Sample of job postings

The audit study would necessarily focus on the segment of jobs that are publicly posted on online job platforms and that accept resumes online. These jobs are likely to be aimed at more educated hires, from larger firms, concentrated in certain locations, and may be disproportionately for certain occupations. We will collect data on the occupations, industries, and educational requirements of jobs and compare these characteristics to nationally representative data (from the Egypt Labor Market Panel Survey [ELMPS] 2018) to assess how publicly posted, online job ads compare to wage employment in Egypt overall.

For positions on websites that require a login and profile, first, we will try to locate the job elsewhere (e.g. on another job search website that does not require a profile, on the employer's website or elsewhere). Second, we will try to find an email for HR to send the resume. If we cannot find the job anywhere that does not require a profile and cannot find an email for HR, we will record the job characteristics, this outcome, and move to the next position.

We only included job websites that include submitting a resume and excluded those that only apply via profile (no resume allowed), in order to be able to consistently vary sex and marital status on resumes and thus applications.

Preliminary research will determine the volume of job postings per day and their nature, contributing to decisions about what percentage of postings per day to apply to. Assuming there are too many postings to apply to in a day, we will select postings randomly.

We will exclude the following job postings from our analyses:

- Position is in the public sector or a state-owned enterprise
- Position is a job working outside of Egypt
- Position is for non-Egyptians only

- Position is a volunteering position (unpaid) (paid internships are still included)
- Position requires a minimum of more than five years of experience
- Position is senior/executive level
- Position has extremely specific technical requirements that are beyond our understanding to be able to create a fake resume
- Position age range does not include 18-29 (includes part, e.g. 25-40 is okay, do not exclude)
- Position or application requires a license or certification be provided (e.g. a medical license)
- Application requires upload of documents other than a resume and/or cover letter (e.g. a writing sample)
- Position is at an organization requiring a profile and is NOT posted elsewhere and no HR email.
- Position is at an organization with no name or "confidential"

These exclusion criteria reflect both the focus of the study (paid jobs in Egypt and the private sector) and practical considerations (preparing additional materials or for a position with very specific requirements; a limited age range to make photos and variation in marital status plausible). We will record these exclusion outcomes to be able to describe the percentage of jobs within our universe and why jobs were excluded.

3.2. Data on each job posting

For each job posting identified, its characteristics will be recorded in terms of the following:

- Number of workers required
- Gender requirements (male required, female required, male preferred, female preferred, or none specified)
    - If only male or only female are required, only that gender will have fake resumes submitted, with variation in marital status, but data on the position will be entered and used for assessing discrimination
- Marital status requirements (single required, married required, single preferred, married preferred, none specified)
    - If only single or married are required, only that marital status will be submitted, with variation in gender, but data on the position will be used for assessing discrimination
    - If only one gender-marital status combination is required, only that resume will be sent (to get callback outcomes).
- Age requirements (minimum, maximum ages)
- Education requirements
    - Degree level
    - Specialization (using same coding as ELMPS 2018)
- Industry (ISIC 4.1 coding, down to the four-digit level, same as ELMPS)

- Occupation (ISCO-08 coding, down to the six-digit level, same as ELMPS)
- Location
    - Governorate
    - Kism/markaz
- Specific skills (a pre-populated list including technical, literacy, mathematics/statistics, physical fitness, computer (and specific software), management, customer service, foreign language skills and also open-ended fields to record each additional skill)
- Requirement for driver's license
- Military status requirement
- Work experience (in years) (minimum, maximum of range given)

3.3. Generation of resumes

Four resumes (one single male; one single female; one married male; one married female) will be randomly generated that match the position requirements, but with the specifics randomly different (e.g. name, university attended, etc.).

In order to have a manageable number of phones to answer by name, we will use only sixteen first names (four for each identity combination). We will select eight common male and eight common female first names (no names that are common for both men and women). Common last names will also be selected. Names will be Muslim, reflecting the majority religion in Egypt, and to avoid confounding religious with other discrimination. Names will be selected to be free of socioeconomic status identifiers. First names will be randomized across marital statuses and last names across sex and marital status before beginning the generation of resumes.

Resumes will include photos. We will use artificially generated (composite) photos. Women will be shown wearing the hijab (photoshopped onto the generated pictures), since 95% of women aged 15-29 in Egypt wear the hijab (Population Council, 2011). Within gender, photos will be randomized in creating resumes, which will allow us to test for any photo fixed effects. We will carefully match the photos across gender in terms of similar apparent age, skin tone, etc., to avoid any confounders. Photos will have neutral backgrounds and avoid any markers of socioeconomic status as much as possible (e.g. in hairstyle or dress).

Photos will be selected to plausibly cover ages 18-29.

For each position, we will generate resumes with the following data:

- Gender and marital status (one each of female single, male single, female married, male married)
- Randomly, one of the four names for the identity
    - The corresponding phone number
    - The corresponding email address

- Randomly, one of the eight photos for the gender identity
- Random age (within position and education plausible range)
- Nationality (all Egyptian)
- Military status (for men, and only if mentioned in the job ad to match)
- Governorate (per position ad)
- Kism/Markaz (per position ad)
- Degree (per position ad)
- Specialization (per position ad)
- School/university (in governorate of position ad, randomized from ELMPS distribution for schools and randomly matching specialization (prioritized) and governorate (secondarily, by job ad) for universities)
- Score/grade/GPA: Five levels (randomized across excellent, very good, and good per ELMPS distribution)
- Skills as per ad, plus a few random/general skills
- Driver's license (only if mentioned in the job ad to match)
- Past experience:
  - Four sets of fake experiences will be developed to match the position descriptions. These will be randomized across the identities. These can enter an "experience bank" to re-use (and re-randomize) for common positions
  - For jobs that require no previous experience, we will randomize 50% of the time for workers to have previous experience and 50% not.
  - Workshops and trainings will be developed together with experience into profiles for the "experience bank"

The resumes will be designed to be well-qualified for the positions in order to maximize the power of the experiment and the chances of callback (and thus be better able to assess discrimination). The resumes will be sent from corresponding email addresses and with specific phone numbers for the randomly generated identity.

The sample size of jobs and resumes will ultimately depend on the time intensity and productivity within a fixed budget, but we will target 1,500-2,500 postings (6,000-10,000 resumes).

3.4. Outcome

Whether and what phone or email follow-up occurred from the employer will be the key outcome. Callbacks and their details will be collected for each fictitious applicant (at their phone or email address). The key outcome will be a callback that signals the possibility of hiring (asking for an interview, interview on the spot, asking for additional information, offering the position). We will look primarily at the outcome of receiving a callback, but also analyze the distribution of employers' responses in callbacks by gender and marital status. When a position was specifically designated as for one gender or marital status only, the other excluded identities will be considered not to have callbacks (although we will be able to distinguish between applied, no call back and excluded, no call back in the data).

A secondary outcome will be the expected monthly wage (calculated as the average of the minimum and maximum if a range is given). We will model this outcome as log wages, since coefficients can then be interpreted in approximately percentage terms. This outcome will only be available for a sub-sample of job postings with wage data posted and will be calculated only for positions that receive a callback.

4. Methods

Our first model will estimate the degree of discrimination against women in the labor market for outcome *y* (callback or wages). Using data on each job posting, *j*, and identity, *i* we will estimate the following:

$y_{i,j}=\alpha+\beta Female_i+\varepsilon_{i,j}$

The coefficient β on the female dummy will test our hypothesis (H1) that there is discrimination against women in the labor market.

Our second model will include a covariate for being married, along with an interaction between being married and being female. We will thus estimate:

$y_{i,j}=\alpha+\beta_1 Female_i+\beta_2 Married_i+\beta_3 Female_i * Married_i+\varepsilon_{i,j}$

β_1 will then be the test for discrimination for single women versus single men. We hypothesize (H2) there is discrimination against single women.

β_2 will then be the test for discrimination for married men versus single men. We hypothesize (H3) there will be a preference for married over single men.

$\beta_1=\beta_2+\beta_3$ will then be the test for whether there is differential discrimination for single women versus married women. We hypothesize (H4) that there will be additional discrimination against married women.

$\beta_2=\beta_1+\beta_3$ will then be the test for whether there is discrimination for married women versus married men. We hypothesize (H5) that there will be additional discrimination against married women.

We will use ordinary least squares regressions for all our models. Standard errors will be clustered at the level of the job (position). We will adopt a critical level of 5% for our tests. All estimates will be weighted by the number of workers required for the posting and the sampling rate for the posting website.

4.1. Heterogeneity

Analyses will also estimate heterogeneity in the callback outcome by a number of key characteristics. We will not estimate heterogeneity for wages given that it will be a limited sub-sample. We will specifically re-estimate our two main models for subgroups based on:

·Occupation (white-collar versus blue collar)

·Industry (agriculture; construction and utilities; mining and manufacturing; wholesale and retail; transportation and storage; accommodation and food service; professional activities (including ICT, finance, and real estate); administrative and support service; Education and health; other services) (Note: if the sample size for any industry is too small (N<50 postings), it will be combined with the most-similar other industry).

·Skills required (whether the position requires physical fitness; whether the position requires socio-emotional skills; whether the position requires computer skills; whether the position requires literacy skills; whether the position requires mathematics skills) (for each of these skills will test discrimination for not required and required separately).

· Education required (Less than secondary; secondary; higher education)

4.2. Planned Figures and Tables

Figure 1. Gender and marital status requirements in job postings

- Distribution of positions by sex, marital status requirements (combinations and sub-totals), total

Table 1. Outcomes: Callback rates and average wages if called back, by gender and marital status

- % of applications receiving a callback, by gender and marital status (and number of observations)
- Mean monthly wages for position if called back, by gender and marital status

Table 2. Callback outcomes by gender and marital status, individuals receiving a callback

- % of applications receiving an interview invite, interview on the spot, request for further information, job offer, or other, by gender and marital status

Table 3. Main model of callbacks for gender (spec. 1) and gender and marital status (spec. 2)

- Table with coefficients of models, observations, clusters, R-squared
- Hypothesis tests (H1-H5)

Table 4. Heterogeneity of callbacks by occupation, industry, skills, and education required for gender (spec. 1) and gender and marital status (spec. 2)

- Table with coefficients of models, observations, clusters, R-squared, H1-H5 as rows
- Panels for categories of heterogeneity (occupation; industry; requires a certain skill [not mutually exclusive]; education required)

Table 5. Main model of wages by gender (spec. 1) and gender and marital status (spec. 2)

- Table with coefficients of models, observations, clusters, R-squared

Appendix Table A1. Occupations, economic activities, educational and skill requirements of jobs: job advertisement sample versus ELMPS 2018 (proportions and t-tests)

- Limiting ELMPS 2018 to an equivalent sample in terms of workers aged 18-29, etc.
- Nine one-digit occupations
- ~11 economic activities
- Education requirements: None listed, Basic education, Secondary education, Post-secondary Institute, University, Post-graduate degree
- Skills: Technical, literacy, mathematics/statistics, physical fitness, computer, management, customer service, foreign language
- Average salary per month
- Governorates

Appendix Table A2. Details of position requirements

- Has an age requirement (%)
    - Average minimum age
    - Average maximum age
- Work experience
    - % include: 0, 1, 2, 3, 4, 5, more than 5 years
- Require driver's license (%)
- Requires military service (men only) (%)
- Percentage requiring: 10 most common skills

Appendix Table A3. Sample of positions and exclusion criteria

- N all positions, included and each of exclusion criteria
- Percentages of all positions, included and each of exclusion criteria

Appendix Table A4. Ten most common occupations (4-digit)

- N and % of occupations for each of top 10
- % requiring female, male, none specified in each occupation

Appendix Table A5. Ten most common industries (4-digit)

- N and % of industries for each of top 10
- % requiring female, male, none specified in each industry

References

Alaref, J., Towfighian, S. N., Paez, G. N., & Audah, M. (2020). *Tunisia Labor Market Field Experiment Paper*. World Bank.

Assaad, R., Krafft, C., Rahman, K. W., & Selwaness, I. (2019). *Job Creation in Egypt: A Sectoral and Geographical Analysis Focusing on Private Establishments, 1996-2017*. *ERF Policy Research Report*. Cairo, Egypt.

Assaad, R., Krafft, C., & Selwaness, I. (2022). The Impact of Marriage on Women's Employment in The Middle East and North Africa. *Feminist Economics*.

El-Hamidi, F., & Said, M. (2014). Gender-Based Wage and Occupational Inequality in the New Millenium in Egypt. *The Journal of Developing Areas*, *48*(1), 21–41.

Gaddis, S. M. (Ed.). (2018). *An Introduction to Audit Studies in the Social Sciences*. *Audit Studies: Behind the Scenes with Theory, Method, and Nuance* (Methodos S.). Springer.

Keo, C., Krafft, C., & Fedi, L. (2022). Rural Women in Egypt: Opportunities and Vulnerabilities. In C. Krafft & R. Assaad (Eds.), *The Egyptian Labor Market: A Focus on Gender and Vulnerability No. 1359* (pp. 225–256). Oxford, UK: Oxford University Press.

Krafft, C., Assaad, R., & Keo, C. (2022). The Evolution of Labor Supply in Egypt, 1988-2018. In C. Krafft & R. Assaad (Eds.), *The Egyptian Labor Market: A Focus on Gender and Vulnerability* (pp. 13–48). Oxford: Oxford University Press.

Osman, A., Speer, J. D., & Weaver, A. (2021). *Discrimination against Women in Hiring*. *Working Paper*.

Population Council. (2011). *Survey of Young People in Egypt: Final Report*. Cairo, Egypt: Population Council.

Said, M., Galal, R., & Sami, M. (2022). Evolution of Wages, Inequality, and Social Mobility in Egypt. In C. Krafft & R. Assaad (Eds.), *The Egyptian Labor Market: A Focus on Gender and Vulnerability* (pp. 89–114). Oxford, UK.

Selwaness, I., & Krafft, C. (2021). The Dynamics of Family Formation and Women's Work: What Facilitates and Hinders Female Employment in the Middle East and North Africa? *Population Research and Policy Review*, *40*(3), 533–587.

Change Log

Changes during training (before piloting)

1. Updated names to be Muslim (since Egypt is majority Muslim and since the women wearing the hijab in photos would denote Muslim; hence, for men need Muslim names as well to avoid confounding gender and religion).

Changes during initial posting phase

2. Dropped one of the websites used to generate postings – they don't post the name of the employer and direct applicants to Whatsapp numbers
3. Added "good" to the grade options to better reflect real world distribution
4. Updated to reflect specialization (first) and governorate (secondary/if possible) for universities, no longer ELMPS distribution for universities
5. Given substantial variation in number of jobs per day per site in preliminary research, we undertook variable sampling rates and will incorporate the site-specific weights in our analyses.
6. We collected data on job postings but excluded from sending resumes when the posting did not list the employer or listed the employer as "confidential" since we could not match these positions with callbacks without the employer being identifiable.
7. Due to logistical delays, we started collecting position data before mobile phones were available. Due to further delays, some positions' deadlines passed before we could submit resumes and we therefore include these positions in our analysis of positions but not callbacks.

Changes during early application phase

8. Included military service status as done or exempted for all male applicants, as HRs are very attuned to this topic, even if posting did not mention status.
9. Included both BA and MA education information on resumes for job postings that required both (had only highest for first batch of applications)