ERF Working Papers Series

Introducing the Egypt Labor Market Panel Survey 2023

Ragui Assaad and Caroline Krafft

ECONOMIC RESEARCH FORUM

منتدى البحوث الاقتصادية

Working Paper No. 1748
November 2024

INTRODUCING THE EGYPT LABOR MARKET PANEL SURVEY 2023

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We acknowledge the financial support of the International Labour Organization through the Government of the Netherlands and the Swedish International Development Cooperation Agency, the World Bank Poverty and Equity Global Practice supported by the UK-funded Strategic Partnership for Egypt's Inclusive Growth trust fund (SPEIG TF), and World Bank MENA Chief Economist office, Agence Française de Développement (AFD), Ministry of Planning, Economic Development and International Cooperation, Egypt, and UNICEF for the Egypt Labor Market Panel Survey 2023, on which this paper is based.

Send correspondence to:
Ragui Assaad
Humphrey School of Public Affairs, University of Minnesota
assaad@umn.edu

[1] Humphrey School of Public Affairs, University of Minnesota, assaad@umn.edu
[2] Current affiliation: Humphrey School of Public Affairs, University of Minnesota, kraff004@umn.edu
Previous affiliation: Department of Economics and Political Science, St. Catherine University

First published in 2024 by
The Economic Research Forum (ERF)
21 Al-Sad Al-Aaly Street
Dokki, Giza
Egypt
www.erf.org.eg

Abstract

This paper introduces the 2023 wave of the Egypt Labor Market Panel Survey (ELMPS). This is the fifth wave of the ELMPS, following a panel of households and individuals from 1998, 2006, 2012, and 2018 into 2023. The ELMPS tracks individuals even as they form new households and includes these households in the sample. Waves since 2006 have also added refresher samples to the panel. In this paper, we describe the questionnaires, sample, fielding, and weighting of the 2023 wave. We assess and model attrition on the household and individual levels and discuss how we account for this attrition in the calculation of weights. The paper also validates the ELMPS data against other sources, such as Egypt's Labor Force Survey.

Keywords: Survey, panel data, public use data, sample weights, labor market, Egypt.
JEL Classifications: J00, C81, C83.

ملخص

تقدم هذه الورقة الموجة الجديدة لسنة 2023 من المسح التتبعي لسوق العمل في مصر (ELMPS). هذه هي الموجة الخامسة من المسح التتبعي لسوق العمل في مصر، بعد مسوحات تتبعية عن الأسر والأفراد من 1998 و 2006 و 2012 و 2018 إلى 2023. يتتبع هذا المسح الجديد، الأفراد حتى عندما يشكلون أسرًا جديدة ويضم هذه الأسر في العينة. أيضاً، تم إضافة موجات منذ عام 2006 كعينات تنشيطية إلى المسح التتبعي. في هذه الورقة، نقوم بوصف الاستبيانات والعينة والمسح الميداني والأوزان لموجة 2023. نقوم بتقييم وقياس التسرب على مستوى الأسرة والفرد ونناقش كيفية حساب هذا التسرب في حسابات الأوزان. كما تثبت الورقة صحة بيانات المسح التتبعي لسوق العمل في مصر. مقابل مصادر أخرى، مثل مسح القوى العاملة في مصر.

1. Introduction

This paper introduces the 2023 wave of the Egypt Labor Market Panel Survey (ELMPS), which is the fifth wave of this longitudinal survey. Previous waves had been carried out in 1998, 2006, 2012 and 2018. The ELMPS is part of a series of comparable surveys carried out by the Economic Research Forum (ERF) in cooperation with national statistical agencies. The series also includes two waves in Jordan (JLMPS 2010 and 2016), one wave in Tunisia (TLMPS 2014) and one wave in Sudan (SLMPS 2022).[3] The 2023 wave of the ELMPS was carried out in cooperation with the Egyptian Ministry of Planning and Economic Development (MOPED) and the Central Agency for Public Mobilization and Statistics (CAPMAS).

With data spanning a quarter century, the ELMPS has become essential research infrastructure on labor markets and human development in Egypt. For instance, the data have been downloaded 1,744 times from 2013 to mid-2024. Besides being the basis for several edited volumes that undertake a first-cut analysis of the data (Assaad 2002; 2009; Assaad and Krafft 2015; Krafft and Assaad 2021b), the ELMPS data have served as the basis of a large number of studies on a wide variety of topics. While these studies are too numerous to cite here, as of June 28th, 2024, we identified through Google Scholar 195 articles in peer-reviewed journals, 72 books and chapters in edited volumes, 35 theses and dissertations, and numerous working papers, policy briefs, and official report that have utilized the public use microdata from the various waves of the ELMPS.[4]

To inform the use of the ELMPS data by researchers, this paper follows on a series of previous papers that introduce the various waves of the LMPS surveys (Barsoum 2009; Assaad and Roushdy 2009; Assaad and Barsoum 2000; Krafft and Assaad 2021a; Assaad and Krafft 2013; Krafft, Assaad, and Rahman 2021; Assaad et al. 2016; Krafft, Assaad, and Cheung 2024). The paper begins by reviewing the changes that were made to the survey instruments to accommodate new topics of interest, such as the prevalence of gig work or green jobs, or to delete questions that did not perform well from previous waves. We then discuss the organization of the fieldwork in the 2023 wave and the pattern and magnitude of sample attrition. As in previous waves, we distinguish between two types of attrition: the attrition of households interviewed in the previous wave, which we call Type I attrition, and, among households from the previous wave that were found, the attrition of individuals that split from those households, which we call Type II attrition. We develop models to predict these two types of attrition on the basis of observable characteristics from the 2018 wave. We use these models to predict the probability of attrition for households or split individuals that did not attrit. We then use these predicted probabilities to generate weights

[3] Public use microdata from all these surveys are made available through ERF's Open Access Microdata Initiative (OAMDI) one year after data collection is completed. Data are available as a set of pooled cross-sections from various waves as well as in the form of a panel. A dataset that harmonizes and integrates selected variables across all countries and waves, the Integrated Labor Market Panel Survey (ILMPS) is also available. See http://www.erfdataportal.com/index.php/catalog/LMPS.
[4] A bibliography is available on http://carolinekrafft.com/publications/.

that correct for the attrition and that thus maintain the representativeness of the panel sample. As in previous waves, we add a refresher sample of 2,000 households to preserve the representativeness of the sample. The design of this refresher sample is presented along with the calculation of its sampling weights. The weights for the panel and refresher samples are then combined into a single set of weights that render the overall sample representative of the Egyptian population in 2023.[5] Ultimately, the ELMPS 2023 captured 70,636 individuals and 17,784 households. Of these, 50,268 individuals and 13,565 households were tracked from 2018 to 2023.

We compare the results of the ELMPS 2023 on some basic demographic and labor market variables with estimates obtained from other nationally-representative surveys, such as the official Labor Force Survey, especially the combined 2022 quarterly rounds, and the Egyptian Family Health Survey of 2021. Key demographic variables tend to be quite similar. Trends in labor force statistics are also comparable, although the exact levels show some differences across sources, potentially due to more detailed data collection in the ELMPS. These differences are particularly pertinent for women, whose economic participation is more difficult to accurately measure (Assaad and Krafft 2024; Langsten and Salem 2008).

2. Data collection and sample attrition

2.1. Questionnaires

The questionnaire for the 2024 wave of the ELMPS builds on the questionnaires used in previous waves, which were described in Assaad and Krafft (2013) and Krafft, Assaad, and Rahman (2021). The various modules included in the household and individual questionnaires are listed in Table 1. Some entirely new modules were added in 2023, and some modules were substantially augmented. Three entirely new modules were added to the individual questionnaire, including a module on skills and a module on time use, both of which we will describe further below. In the individual questionnaire, the "training" module was added with questions on specific training experiences (including internships and apprenticeships, along with online skill acquisition). These modules were also implemented in the SLMPS 2022.

The "job characteristics" module was augmented with additional questions on the skill requirements of the current job, ones that attempt to detect green jobs, assess job changes since the COVID-19 pandemic, detect interest in job changes, and measure preferences regarding remote work. Questions were also added to the "job characteristics" module on the incidence and characteristics of gig work and the provision of work through digital platforms. Additional questions on social norms around gender and work were added to the "attitudes" module. The

[5] To facilitate fieldwork, a decision was made from the very first wave of the ELMPS to exclude the frontier governorates of Matruh, New Valley, Red Sea, North and South Sinai. These are sparsely populated parts of the country that represent no more than 2% of the total population (CAPMAS 2019).

“unemployment” module was augmented with questions on intent and willingness to undertake gig work and job search through online platforms.

The “information technology” (IT) module was updated to include the use of new forms of digital payments and mobile money as well as time spent on different IT purposes in the past 24 hours. The “attitudes” module was augmented with questions about life satisfaction and future expectations for such, as well as questions about migration intentions, risk taking, patience, and feelings of safety. There were also more minor changes in the “education,” “health,” “siblings,” “return migration,” and “savings and borrowing” modules. We dropped questions on workplace injuries due to low rates of injuries reported in ELPMS 2018 as well as some questions on irregular work that did not perform well in the 2018 wave.

There were fewer changes to the household questionnaire. Changes to that questionnaire included an update to the “other sources of income” module to incorporate new social assistance initiatives, some updates the “shocks and coping” module and minor updates to the non-agricultural enterprises and farm activities modules.

Table 1. Questionnaire modules

Household	Individual
• Statistical Identification	• Statistical Identification
• Tracking Splits	• Residential Mobility
• Individual Roster	• Father’s Characteristics
• Housing Information	• Mother’s Characteristics
• Current Migrants	• Siblings
• Transfers from Individuals	• Health
• Other Sources of Income	• Education
• Shocks and Coping	• Training Experiences
• Household Non-Farm Activities	• Skills
• Agricultural Assets: Lands	• Past Seven Days Subsistence Work
• Agricultural Assets: Livestock/Poultry	• Employment
• Agriculture: Crops	• Unemployment
• Agricultural Assets: Equipment	• Characteristics of Main Job
• Other Agricultural Income	• Secondary Job
	• Labor Market History
	• Marriage
	• Fertility
	• Female Employment
	• Earnings
	• Earnings in Secondary Job
	• Return Migration
	• Information Technology
	• Savings & Borrowing
	• Attitudes
	• Time Use

Source: Authors’ construction based on ELMPS 2023 questionnaire

We now turn to a brief discussion of the new skills and time-use modules. The “skills” module elicits the individual’s self-assessment of their level of skill for a variety of skills, such as literacy, mathematics, physical fitness, technical skills, management, customer service, foreign language, bookkeeping and accounting, problem-solving, communications, teamwork, manual dexterity, and computer skills. It then delves into more details about 16 specific computer skills. Whether the individual's job requires these same set of skills is revisited in the "job characteristics" module.

With regard to the time-use module, we included a full time use diary for adolescents and adults aged ten and older and a shorter summary version for children aged 6 to 9. The adult and adolescent time-use module refers to the 24-hour period ending at midnight, in the day before the interview. It first enquires about when the individual woke up and then asks about each activity the individual has engaged sequentially in intervals of at least 15 minutes. For each activity, the enumerator selects among a two-level hierarchical menu describing the various activities using the 2016 International Classification of Time-Use Statistics (ICATUS) coding, developed by the United Nations Statistics Division (UN Department of Economic and Social Affairs 2021). The two-level menu used in ELMPS classifies time-use activities at the 2-digit level of detail of ICATUS for the most part, with the exception of a few activities that are classified at the 1-digit level. The activities classified at only the 1-digit level include "employment and related activities," "unpaid volunteer, trainee, and other unpaid work," and "socializing and communication, community participation and religious practice." Once an activity has been listed, the module enquires about the amount of time spent in it in multiples of 15 minutes, whether a secondary activity took place at the same time, and if so the nature of that secondary activity. The enumerator then enquires about the next activity until the individual's bedtime is reached. If unpaid care work activities are mentioned, the individual is asked how much money they would need to spend to procure this activity from the market. The time-use module for children 6 to 9 is for a 7-day reference period and asks about participation in specific activities such as subsistence work, care work, time spent doing homework, etc., and the number of days spent during the week as well as hours per day.

We should note that to save on data collection efforts, questions whose answers did not change since the previous wave because they are pre-determined (e.g. place of birth, mother's education) or because no change in status occurred (e.g. details of schooling for those not in school since 2018), were not asked again for individuals who answered them in 2018. The raw and created variables are updated with the relevant value obtained from previous waves of the survey. Having subsequently analyzed the data resulting from these skips, in future rounds of the LMPSs we will continue to *not* re-ask mother's and father's characteristics for those aged 15+ in the preceding round; there were not problems mapping these data over time and they are truly time invariant. For individuals with completed education in the preceding round and no updates, whose experiences are thus time invariant, we will also not re-ask detailed education questions. However, we found for some of the sections that could vary over time, such as job history, had consistency problems when individuals were asked if they had any updates; individuals sometimes said no who, based on comparisons of 2018 and 2023 data, should have said yes, and thus ended up with missing data. We will therefore re-ask in full sections such as job mobility in future LMPSs.

2.2. Data collection

Data were collected on tablets using the ODK-X tools (Brunette et al. 2017), which are designed to accommodate complex data structures (e.g., nesting of individuals within households; multiple births per individual; linking and validating household roster and birth data). Training of the trainers was held from July 24-29, 2023, at CAPMAS. Enumerator training was held from August 19-30 at CAPMAS. Data collection began September 15, 2023. The vast majority of data collection finished by the end of December 2023, with a small percentage of additional households finalized through January 2024. Fieldwork was undertaken by governorate-specific teams of enumerators with 3-5 enumerators and one supervisor. All the enumerators were women.

Throughout fieldwork, quality control took place, mostly in person by separate quality control teams, with some quality control over the phone in governorates where that week's quality control sample was less than 3 households. Quality control took place on randomly selected modules, including for all individuals if random modules were from the individual questionnaire.

In an attempt to improve speed and accuracy while ensuring quality labor market data, for key variables that were coded (e.g., economic activity and occupation of the current job), while enumerators had pull-down multi-level lists for the coding in the field, they also wrote down text for the economic activity or occupation, which was then re-checked in the office, along with translation/recoding of "other, specify" responses. In ELMPS 2018, which just had text and post-coding, there were issues in post-coding (e.g. not enough text information to create an accurate code, leading to a small percentage of missings). However, we found when comparing the post-coding (done by expert CAPMAS coders in office) in ELMPS 2023 to the options selected by the enumerators in the field that the post-coding was substantially more accurate. We therefore will be returning to text only and post-coding in future LMPSs.

2.3. The 2018 sample: Attrition from 2018 to 2023

As a panel, the ELMPS data collection diligently endeavors to track all households and individuals over time. The ELMPS has households and individuals spanning 1998, 2006, 2012, 2018, 2023, and all sequential subsets of these years. So long as households and individuals remained within the sample frame (within Egypt; not in the Frontier governorates; not in collective housing), they were, inasmuch as possible, recontacted. If an entire household that was present in 2018 could not be recontacted in 2023 (not even one member), this was Type I attrition. Once 2018 households were reached in 2023, the status of all members who were present in 2018 was reviewed. It is possible that one or more 2018 members had split from the household to form a new household ("split household"). Most commonly, this would occur when youth married and formed a new household.[6] To ensure a representative sample, these splits from 2018 households are tracked. Detailed contact data on the split household was collected in an attempt to reach the split household in the field. If, however, the main 2018 household was found but there was a split household that could not be found in 2023, this would be Type II attrition of that split household.

This section describes attrition of households (Type I attrition), the disposition of 2018 individuals in 2023, and attrition of split households (Type II attrition). Models for predictors of Type I and Type II attrition, which feed into the weights (discussed in subsequent sections) are presented.

2.3.1. Attrition of entire households (Type I attrition)

Table 2 presents the disposition of 2018 households as of 2023 fielding. There were 15,746 households fielded in 2018. Of those, 13,565 (86.1%) were successfully re-contacted in 2023. These located households may have moved or had a different composition from 2018 to 2023, but the household and at least one member from 2018 was reached in 2023. Inasmuch as possible, when a household was not present in their 2018 location, information was gathered from neighbors and their 2018 phone number was used in an attempt to contact and locate them. In some cases, we know the entire household left the country or sample frame (e.g., moved to collective housing, such as a dormitory or prison, or the Frontier governorates). This occurred for 171 households in 2023 (1.1% of the 2018 sample). Likewise, for 139 households, the entire household was known to be deceased (0.9% of the 2018 sample). Leaving the sample frame and all perishing are considered "natural attrition" – these panel individuals would not have been in the sample frame in 2023 if creating a new random sample. These naturally attrited households are excluded from our calculations of the attrition rate and attrition models. Type I attrition includes households that were unreachable or unable to be completed (1,475 of the 2018 households, 9.4% of all households) or refused (396 households, 2.5% of all households). The type I attrition rate is thus 12.1%.

Table 2. Status of 2018 households in 2023

	Number	Percentage
Initial households from 2018	15,746	100.0
Households located in 2023	13,565	86.1
Natural attrition	310	2.0
Left country or frame	171	1.1
All deceased	139	0.9
Type I attrition	1,871	11.9
Unable to reach or complete household	1,475	9.4
Refused	396	2.5
Type I attrition rate		12.1

Source: Authors' calculations based on ELMPS 2018 and 2023

[6] An ongoing challenge with fieldwork for tracking splits is ensuring enumerators understand that an individual who leaves to marry should be tracked in full and collect all the needed information.

We note that this type I attrition rate is the lowest we have achieved with the LMPSs yet; the ELMPS 2018 Type I attrition rate was 15%, ELMPS 2012 was 17%, ELMPS 2006 was 24%, and JLMPS 2016 was 38% (Krafft, Assaad, and Rahman 2021; Assaad and Krafft 2013; Assaad and Roushdy 2009; Krafft and Assaad 2021a). A combination of dedicated fieldwork and a shorter gap of five years between waves may explain this reduction in the attrition rate. Additionally, the LMPSs no longer have a separate enumeration round (which did take place in ELMPS 2006, 2012, and JLMPS 2016, leading to the loss of additional households between enumeration and fielding (Krafft and Assaad 2021a; Assaad and Krafft 2013)).

We model the predictors of Type I attrition in Table 3 (excluding those who naturally attrited). A logit model is used, and odds ratios presented. We use covariates characterizing the household in 2018 to predict whether the household attrited in 2023. Characteristics include the sex and age composition of the household, governorate interacted with urban/rural location, housing type, head demographics (age, sex, marital status interacted with sex, education, and labor market status), along with the household's 2018 wealth quintile. New in this wave compared to past years, we also include the first year the household was observed, and for households observed first in 2018, whether they were sampled in 2018 based on the poor or non-poor strata.

Table 3. Type I attrition logit model: odds ratios for probability of attrition

Number of household members	
No. of Children 0-5 in HH	0.916*
	(0.036)
No. of Children 6-14 in HH	0.944
	(0.031)
No. of Males 15-64 in HH	0.822***
	(0.040)
No. of Females 15-64 in HH	0.865**
	(0.045)
No. of Males 65+ in HH	0.791
	(0.115)
No. of Females 65+ in HH	0.956
	(0.111)
Single sex households (mixed sex omit.)	
All male	2.296***
	(0.482)
All female	1.510**
	(0.191)
Governorate (Cairo (urban) omit.)	
Alex. # Urban	0.315***
	(0.055)
Port-Said # Urban	1.061
	(0.255)
Suez # Urban	1.173
	(0.237)
Damietta # Urban	0.236***
	(0.085)
Damietta # Rural	0.280***
	(0.068)
Dakahlia # Urban	0.860
	(0.135)

Table 3. Type I attrition logit model: odds ratios for probability of attrition (continued)

Dakahlia # Rural	0.387***
	(0.061)
Sharkia # Urban	0.798
	(0.139)
Sharkia # Rural	0.201***
	(0.040)
Kalyoubia # Urban	1.266
	(0.229)
Kalyoubia # Rural	0.767
	(0.122)
Kafr-Elsheikh # Urban	0.195***
	(0.063)
Kafr-Elsheikh # Rural	0.086***
	(0.028)
Gharbia # Urban	0.594**
	(0.120)
Gharbia # Rural	0.326***
	(0.060)
Menoufia # Urban	0.307***
	(0.086)
Menoufia # Rural	0.156***
	(0.047)
Behera # Urban	0.726
	(0.139)
Behera # Rural	0.514***
	(0.084)
Ismailia # Urban	1.345
	(0.243)
Ismailia # Rural	0.503***
	(0.094)
Giza # Urban	0.697*
	(0.115)
Giza # Rural	0.282***
	(0.062)
Beni-Suef # Urban	0.211***
	(0.062)
Beni-Suef # Rural	0.301***
	(0.063)
Fayoum # Urban	0.862
	(0.173)
Fayoum # Rural	0.321***
	(0.070)
Menia # Urban	0.759
	(0.147)
Menia # Rural	0.475***
	(0.075)
Asyout # Urban	0.778
	(0.130)
Asyout # Rural	0.331***
	(0.057)
Suhag # Urban	0.290***
	(0.069)
Suhag # Rural	0.386***
	(0.058)
Qena # Urban	0.285***
	(0.078)
Qena # Rural	0.233***
	(0.044)

Table 3. Type I attrition logit model: odds ratios for probability of attrition (continued)

Aswan # Urban	0.646*
	(0.126)
Aswan # Rural	0.579**
	(0.114)
Luxur # Urban	0.202**
	(0.123)
Luxur # Rural	0.045**
	(0.046)
Housing type (own or benefit omit.)	
Old rent	0.917
	(0.100)
New rent	1.593***
	(0.153)
Head age (<25 omit.)	
25-34	0.876
	(0.125)
35-44	0.874
	(0.133)
45-54	0.701*
	(0.115)
55+	0.673*
	(0.112)
Head sex (male omit.)	
Female	1.082
	(0.162)
Head marital stat. (married omit.)	
Single	1.136
	(0.269)
Divorced	1.080
	(0.341)
Widow(er)	1.105
	(0.246)
Head marital stat. and sex int.	
Female # Single	0.504
	(0.195)
Female # Divorced	1.008
	(0.394)
Female # Widow(er)	0.863
	(0.234)
Head education (illit. omit.)	
Reads & Writes	0.883
	(0.102)
Less than Intermediate	0.907
	(0.088)
Intermediate	0.931
	(0.077)
Above Intermediate	1.107
	(0.182)
University	1.291*
	(0.130)
Missing	1.074
	(0.561)
Head labor mkt. status (Government wage omit.)	
Out of manpower	1.417*
	(0.208)
Out of labor force	1.164
	(0.133)
Unemployed.	1.066
	(0.201)

Table 3. Type I attrition logit model: odds ratios for probability of attrition (continued)

Public ent. wage	0.892
	(0.184)
Priv. formal wage	1.166
	(0.139)
Priv. inf. reg. wage	1.318**
	(0.134)
Priv. irreg. wage	0.968
	(0.117)
Employer	0.966
	(0.129)
Self-emp./UFW ag.	0.536*
	(0.145)
Self-emp./UFW non-ag.	0.998
	(0.127)
Missing	1.968
	(1.043)
Wealth quintile (poorest omit.)	
Second	0.839*
	(0.074)
Third	0.938
	(0.086)
Fourth	1.095
	(0.101)
Richest	1.276*
	(0.130)
Year first obs. (1998 omit.)	
2006	0.997
	(0.066)
2012	1.015
	(0.079)
2018 non-poor strat.	1.276*
	(0.133)
2018 poor strat.	1.231
	(0.166)
Constant	0.444***
	(0.105)
Pseudo R-sq.	0.099
N (households)	15430

Source: Authors' calculations based on ELMPS 2018 and 2023

*Notes: *p < 0.05; **p < 0.01; ***p <0.001. Excludes households that naturally attrited. Standard errors in parentheses. Missing characteristics for the head occurred when he or she did not complete the 2018 individual questionnaire. Six other observations were missing characteristics for the model and given the mean predicted attrition probability.*

Although there are a number of individual covariates that are predictive of attrition, the model's overall explanatory power is modest (9.9%), and a decline from 2018 (12.2%) (Krafft, Assaad, and Rahman 2021). This result suggests that either attrition is increasingly random, or attrition is increasingly based on characteristics we are unable to observe or did not include in the model.

There are modest differences in attrition based on household composition with households being significantly less likely to attrite the more children aged 0-5 they had in 2018, along with the more working age (15-64) men and women. Single-sex households (both all-male and all-female) were significantly more likely to attrite than mixed-sex households. Compared to urban Cairo, a number of other locations were significantly less likely to attrite, often particularly so in rural locations.

Households with new rent (market-rate) contracts were significantly more likely to attrite than those who owned (or had as a benefit, less commonly) their residence, but there were not significant differences for old (rent-controlled) housing.

In terms of head characteristics, compared to heads who were younger (<25 in 2018), those with older heads were less likely to attrite, often significantly so. There were not significant differences by head sex, head marital status, or interactions between the two. Compared to illiterate heads, only university-educated heads were significantly more likely to attrite. There were a few, modest differences by head’s labor market status. Compared to government wage workers, those households whose heads were out of the manpower basis, or private informal regular wage workers were significantly more likely to attrite, while self-employed and unpaid family worker (UFW) agricultural heads were significantly less likely to attrite.

Compared to the poorest wealth quintile of households, households from the second wealth quintile in 2018 less likely to attrite, while households in the richest quintile in 2018 were significantly more likely to attrite. Furthermore, compared to households with a member first observed in 1998, there were not significant differences for those first observed in 2006 and 2012. For households first observed in 2018 in the non-poor strata, they were significantly more likely to attrite, but the 2018 poor strata had a similar odds ratio (albeit insignificant).

2.3.2. Attrition of split households (Type II attrition)

When a 2018 household was found in 2023, we learned whether the 2018 members were still there, and if not, followed up on their disposition. Table 4 explores these individual-level results. Of the 61,231 individuals in 2018, 54,252 of them were, in 2018, members of households that were then found in 2023. The vast majority (47,782, 88.1%) of these individuals were still in their original households. Among the 6,470 individuals no longer in their households, 2,277 (4.2% of the original sample) were lost due to natural attrition. Among those, 1,523 (2.8%) died, 706 (1.3%) emigrated or left the sample frame geographically, and 48 (0.1%) moved to collective housing.

Table 4. Status of individuals and split households in 2023, conditional on 2018 household being found

	Number	Percentage
Individuals present in 2018 in original households found in 2023	54,252	100.0
Individuals still in original households in 2023	47,782	88.1
Individuals no longer in original households in 2023	6,470	11.9
Natural attrition	2,277	4.2
Died	1,523	2.8
Emigrated or left sample frame	706	1.3
Moved to group housing	48	0.1
Individual splits to form households within the sample frame	4,193	7.7
Potential split households (households accounting for individuals who split together)	3,682	
Split households found	2,181	59.2
Split households not found (attrited)	1,501	40.8
Type II attrition rate		**40.8**
Individuals from 2023 in split households found	2,486	59.3
Individuals from 2023 in split households not found	1,707	40.7
Total individuals from 2023 who were found	50,268	

Source: Authors' calculations based on ELMPS 2018 and 2023

Among the 4,193 individuals (7.7% of the individuals whose households were found) who formed or moved to new households within the sample frame, 3,682 households were formed. A split household thus had an average of 1.14 individuals from 2018 (plus any new members). Because our sampling frame is based on households, we track these split households and attempt to contact them in their new locations, based on the information provided by their 2018 household members still in their original household during 2023 fielding. Of the 3,682 split households, we reached 2,171, but 1,501 attrited. This pattern yields an attrition rate of 40.8%. This Type II attrition rate is unfortunately higher than 2018 when it was 18.4 as well as the 30.3% of ELMPS 2012 but lower than the 50.5% of JLMPS 2016 (Krafft, Assaad, and Rahman 2021; Assaad and Krafft 2013; Krafft and Assaad 2021a).

Table 5 presents the Type II attrition logit model for split households. The overall model has a pseudo R-squared of 16.3%, lower than 2018's 22.3% (Krafft, Assaad, and Rahman 2021). This pseudo-R-squared is appreciably higher than for Type I attrition. However, there are relatively few demographic differences. Most of the significant differences related to geographical location, with a number of areas (of origin, for the 2018 household) having significantly lower attrition than the omitted category of urban Cairo. There are not significant differences by any of the number of household members variables or housing type.

In terms of head characteristics, we identify the "split head" as the most senior 2018 member of the household per the 2018 roster. There are not significant differences by split head age, nor by sex for the main effect of female. The single main effect shows lower attrition for single individuals, and the female and single interaction indicates a significantly lower probability of attrition particularly for single women. Older women are particularly likely to attrite per the interactions, significantly so for those aged 45+ in 2018. There are not significant differences by split head education or labor status, aside from missing education. Compared to the poorest households, other quintiles are significantly less likely to attrite, although only the second quintile significantly so. Split households who moved to another building and especially another area, as compared to the same building, are significantly more likely to attrite, highlighting an important area for future fieldwork improvements. Although data were transferred across teams in different areas and detailed addresses and contact information collected in all cases, locating an individual who moved across teams' areas proved challenging. Overall, Type II attrition is primarily geographic in nature, which is promising for the representativeness of our sample, as geographic covariates and population estimates are accounted for in the weighting.

Table 5. Type II split household attrition logit model: odds ratios for probability of attrition

Number of household members	
No. of Children 0-5 in HH	0.786
	(0.130)
No. of Children 6-14 in HH	0.775
	(0.127)
No. of Males 15-64 in HH	1.086
	(0.343)
No. of Females 15-64 in HH	0.693
	(0.224)
No. of Males 65+ in HH	2.589
	(2.621)
No. of Females 65+ in HH	0.362
	(0.270)
Governorate (Cairo (urban) omit.)	
Alex. # Urban	0.114***
	(0.035)
Suez # Urban	2.003
	(1.543)
Damietta # Urban	2.156
	(1.138)
Damietta # Rural	0.437*
	(0.152)
Dakahlia # Urban	0.338**
	(0.131)
Dakahlia # Rural	0.304***
	(0.093)
Sharkia # Urban	0.438*
	(0.182)
Sharkia # Rural	1.089
	(0.308)
Kalyoubia # Urban	1.411
	(0.683)
Kalyoubia # Rural	0.974
	(0.314)
Kafr-Elsheikh # Urban	0.106***
	(0.044)
Kafr-Elsheikh # Rural	0.086***
	(0.029)
Gharbia # Urban	0.401*
	(0.160)
Gharbia # Rural	0.553*
	(0.162)
Menoufia # Urban	0.305**
	(0.138)
Menoufia # Rural	0.227***
	(0.076)

Table 5. Type II split household attrition logit model: odds ratios for probability of attrition (continued)

Behera # Urban	0.138***
	(0.054)
Behera # Rural	0.180***
	(0.055)
Ismailia # Urban	0.181***
	(0.087)
Ismailia # Rural	0.360**
	(0.118)
Giza # Urban	0.336**
	(0.132)
Giza # Rural	0.625
	(0.195)
Beni-Suef # Urban	0.146***
	(0.052)
Beni-Suef # Rural	0.188***
	(0.054)
Fayoum # Urban	0.142***
	(0.058)
Fayoum # Rural	0.206***
	(0.064)
Menia # Urban	0.436*
	(0.165)
Menia # Rural	0.360***
	(0.099)
Asyout # Urban	0.257***
	(0.085)
Asyout # Rural	0.293***
	(0.079)
Suhag # Urban	0.016***
	(0.010)
Suhag # Rural	0.107***
	(0.031)
Qena # Urban	0.238***
	(0.098)
Qena # Rural	0.187***
	(0.052)
Aswan # Urban	0.204***
	(0.074)
Aswan # Rural	0.155***
	(0.052)
Luxur # Urban	0.580
	(0.479)
Luxur # Rural	0.711
	(0.357)
Housing type (own or benefit omit.)	
Old rent	0.863
	(0.184)
New rent	1.044
	(0.280)
Head sex (male omit.)	
Female	0.869
	(0.461)

Table 5. Type II split household attrition logit model: odds ratios for probability of attrition (continued)

Head age (<15 omit.)	
15-24	0.475
	(0.264)
25-34	0.445
	(0.250)
35-44	0.919
	(0.577)
45+	0.286
	(0.219)
Head age and sex int.	
Female # 15-24	2.219
	(1.432)
Female # 25-34	3.026
	(2.000)
Female # 35-44	1.202
	(0.903)
Female # 45+	6.705*
	(6.086)
Head marital stat. (married omit.)	
Single	0.544*
	(0.157)
Divorced/Widow(er)	0.519
	(0.334)
Head marital stat. and sex int.	
Female # Single	0.484*
	(0.163)
Female # Divorced/Widow(er)	0.898
	(0.632)
Head education (illit. omit.)	
Reads & Writes	0.973
	(0.217)
Less than Intermediate	1.110
	(0.181)
Intermediate	1.111
	(0.179)
Above Intermediate	0.913
	(0.287)
University	1.264
	(0.249)
Missing	3.901**
	(1.651)
Head labor mkt. status (Government wage omit.)	
Out of manpower	1.230
	(0.592)
Out of labor force	1.034
	(0.259)
Unemployed.	1.135
	(0.321)
Public ent. wage	0.569
	(0.335)
Priv. formal wage	0.878
	(0.288)
Priv. inf. reg. wage	1.060
	(0.277)
Priv. irreg. wage	0.916
	(0.255)
Employer	1.369
	(0.572)

Table 5. Type II split household attrition logit model: odds ratios for probability of attrition (continued)

Self-emp./UFW ag.	0.755
	(0.246)
Self-emp./UFW non-ag.	1.245
	(0.403)
Missing	0.439
	(0.243)
Wealth quintile (poorest omit.)	
Second	0.776*
	(0.084)
Third	0.825
	(0.098)
Fourth	0.980
	(0.130)
Richest	0.852
	(0.131)
Location of move (same building omit.)	
Moved to another building in the same area	1.477**
	(0.175)
Moved to another area	3.748***
	(0.466)
Constant	5.258*
	(3.411)
Pseudo R-sq.	0.164
N (households)	3657

Source: Authors' calculations based on ELMPS 2018 and 2023

*Notes: *p < 0.05; **p < 0.01; ***p <0.001. Standard errors in parentheses. Missing characteristics for the head occurred when he or she did not complete the 2018 individual questionnaire. Mean values of predicted attrition used if other characteristics were missing. Urban Port-Said was a perfect predictor of being found (N=5).*

2.4. Panel sample

The ELMPS panel follows individuals over time; with multiple waves, there are a wide variety of potential sequences of individuals within the panel. Because refreshers are added each wave, the sample sizes are generally increasing with later waves. Across all five waves, 106,637 individuals have been observed – potentially multiple times, as shown in Table 6. There are 67,469 individuals observed in more than one wave, such that they can be used in panel analyses. We focus our remaining discussion on combinations including 2023. There are 7,913 individuals who were in all five waves, 10,452 who were in only the 2006-2023 waves, 13,600 only in the 2012-2023 waves, and 18,304 individuals in only the 2018-2023 waves, along with 20,367 in the 2023 wave only. Individuals who were in multiple waves can be assessed in any combination of waves; for instance, there are therefore 50,268 individuals in both 2018 and 2023 whose changes in outcomes can be assessed in the panel.

Table 6. Individuals present in various combinations of waves, 1998-2023

	Number	Percentage
In 1998 & 2006 & 2012 & 2018 & 2023	7,913	7.4
In 1998 & 2006 & 2012 & 2018	2,232	2.1
In 1998 & 2006 & 2012	3,073	2.9
In 1998 & 2006	4,143	3.9
In 1998 only	6,636	6.2
In 2006 & 2012 & 2018 & 2023	10,452	9.8
In 2006 & 2012 & 2018	2,304	2.2
In 2006 & 2012	2,796	2.6
In 2006 only	4,227	4.0
In 2012 & 2018 & 2023	13,600	12.8
In 2012 & 2018	2,652	2.5
In 2012 only	4,164	3.9
In 2018 & 2023	18,304	17.2
In 2018 only	3,774	3.5
In 2023 only	20,367	19.1
Total	106,637	100.0

Source: Authors' calculations based on ELMPS 1998-2023

2.5. The 2023 refresher sample

The ELMPS 2023 added a nationally representative refresher sample, as with all previous waves. The refresher sample is a stratified cluster sample, as described in Table 7. The refresher sample was executed as planned over 200 primary sampling units (PSUs) stratified by governorate and urban/rural. Note that Cairo, Alexandria, Port Said, and Suez are entirely urban. Although Egypt is majority rural, ELMPS 2023 over-sampled urban areas to ensure an adequate sample size in these more economically diverse labor markets. Thus, 120 urban PSUs and 80 rural PSUs were sampled. Within each location/governorate strata after assigning the number of PSUs, PSUs were selected randomly probability proportional to size.

Table 7. Refresher cluster samples by governorate and urban/rural location

Governorate	Urban	Rural	Total
Cairo	21		21
Alexandria	11		11
Port Said	5		5
Suez	5		5
Damietta	3	2	5
Dakhalia	6	7	13
Sharkia	6	8	14
Kalyoubia	6	5	11
Kafr-Elsheikh	3	4	7
Gharbia	4	6	10
Menoufia	3	5	8
Behera	5	7	12
Ismailia	3	2	5
Giza	13	4	17
Beni-Suef	3	3	6
Fayoum	3	4	7
Menia	4	6	10
Asyout	3	5	8
Suhag	4	5	9
Qena	3	4	7
Aswan	3	2	5
Luxor	3	1	4
Total	120	80	200

Source: Authors' calculations based on ELMPS 2023

Each cluster (PSU) was supposed to sample 10 households, for an intended refresher household sample of 2,000. Up to two backup households were provided in the sample. The realized refresher sample was 2,036 households. In one cluster, only one household was sampled (response rate of 10%), in another cluster only three households (30%), in two clusters only four households (40%), and likewise for five households (50%). In six clusters only six households were sampled (60%), while in four clusters only seven households were sampled (70%). More common were realized samples of 8 households (80%, 16 clusters), 9 households (90%, 20 clusters), 10 households (100%, 42 clusters), 11 households (110%, 50 clusters), and 12 households (120%, 56 clusters). The response rate in the cluster is an input into the weights, discussed below. In urban areas the response rate was slightly lower (98.2%) than rural areas (107.3%).

3. Sample weights

This section describes how the refresher and panel data, accounting for non-response and attrition, were used to create weights for the sample. In brief, we start with the 2018 weights for panel households, and then account for Type I attrition. For split households, we use weights based on their 2018 households and then account for Type II attrition. For split households, we also account for whether the new household was formed out of one or more previous households (commonly referred to as a share adjustment for component households). The refresher sample weights are based on the stratified cluster sample and non-response at the cluster level. The final weights incorporate both the panel and refresher samples. After applying population projections from CAPMAS, these inputs into the weights ensure the sample remains nationally representative, a point we validate against other data in the following section. In what follows, we discuss the technical details of weighting.[7]

3.1. Weights for panel and split households

The intuition of our weighting for the panel and split households is that by identifying the households that are more likely to attrite, we can apply a higher weight to similar households that remain in the sample, ensuring it is representative. To implement this, we predict $\Pr(A_h)$, the probability of Type I attrition (attrition of the entire household) for 2018 household h, based on the Type I attrition model (model shown in Table 3). Denote a split household as s. For split households, we use the Type I and Type II (model shown in Table 5) to calculate the following predicted probability of attrition:

$$\Pr(A_{hs}) = 1 - \Pr(h \text{ found}) * \Pr(s \text{ found} \mid h \text{ found}) \tag{1}$$

We use the inverse of these probabilities of attrition to create response adjustment factors, first r_h, for original households:

$$r_h = \frac{1}{1 - \Pr(A_h)} \tag{2}$$

For split households, we calculate r_{hs} incorporating c_s, the number of component households:

$$r_{hs} = \frac{1}{[1 - \Pr(A_{hs})] * c_s} \tag{3}$$

Component households are the number of originating households in the population (not the 2018 sample) that contributed individuals to the (newly formed, from the sample's perspective) split household. For example, perhaps two friends (Friend 1, Friend 2) were living with their families in Assuit while they went to university, and one of their families was in the 2018 sample, so Friend 1 was captured as a 2018 sample member, but Friend 2 was not. In 2023, the two friends have moved to Cairo and are sharing a flat and meals; they are thus a household. Friend 1's parents were found in 2023, but Friend 1 had formed a split household, one that is composed of two component households (because Friend 2 would have been in a different household in the population if sampled in 2018). Because it was formed of two component households, this new household has, theoretically, double the probability of selection. This double probability is accounted for when weighting by dividing by the number of component households (referred to as a share correction) (Himelein 2014). In cases where the split household has only members from a 2018 household or individuals born since 2018, there is only one component household. For example, if Friend 1 had moved to a flat by herself.[8]

[7] Notation as in Assaad and Krafft (2013) and Krafft, Assaad, and Rahman (2021).
[8] Unlike for the wave-specific cross-sectional weights, for panel weights, which follow the individuals seen in previous rounds over time, the share correction is omitted.

3.2. Weights for the refresher sample

As shown in Table 7, the refresher sample over-sampled urban areas relative to rural ones and had a varying sampling rate across governorates. In what follows, we describe the refresher sample weights. These weights are subsequently combined with the 2018 households' sample weights, as described in the next section. The refresher sample and its weights can also be used to validate the results of the 2023 sample overall, since they do not suffer from the attrition of the panel.

Household weights for the refresher sample are calculated based on the strata of governorate, g, and urban/rural location, l. Each of these strata includes a number of clusters (per Table 7), which we denote $P_{g,l}$. If each cluster p from the refresher sample had sampled the planned 10 households per cluster, the planned total number of households per stratum would have been:

$$h_{g,l} = \sum_{p=1}^{P_{g,l}} 10 \tag{4}$$

As discussed above, there were deviations from the planned number of households in many clusters, with some having fewer than 10 and others more than 10 to make up for the shortfalls. Accounting for the cluster non-response rate, we generate an initial refresher household weight, w_p, based on the successfully completed number of households in the cluster, namely m_p, as follows:

$$w_p = \frac{10}{m_p} \tag{5}$$

Population projections from CAPMAS for October 1, 2023 (during ELMPS fielding) detailed the population number of individuals in each of our strata. We used the 2022 wave of the LFS to estimate the mean household size in each stratum and calculate the number of households from the number of individuals via division. The resulting count of the household population for a stratum can be noted $c_{g,l}$. The household weight for the refresher sample is thus:

$$w_{p,g,l} = w_p \ \frac{c_{g,l}}{h_{g,l}} \tag{6}$$

By construction, this weight yields expansion weights with the same number of households in each stratum and nationally as in the population. The number of individuals estimated using these weights may, however, be different. One reason is that individuals can refuse to respond to the individual questionnaire, as part of the consent process. In the refresher sample 87 individuals did not consent, and 403 in the sample of households derived from the 2018 sample. Because the questionnaire starts with a household roster, we do know these individuals exist and have some basic demographic information. We use sex (x) and age-group (e) non-response rates, $r_{x,e}$. We then adjusted the household weight by this non-response to get an individual weight, as:

$$w_{p,g,l,x,e} = \frac{w_{p,g,l}}{1 - r_{x,e}} \tag{7}$$

After this correction, with the refresher sample, rather than the expected 103.7 million, the expansion weights yielded closer to 106.1 million individuals. We therefore implemented a new, additional correction for the individual level weights, expanding the population to the projected individual population nationally, by sex (53.3 million men and 50.4 million women).

3.3. Combined sample weights

The final weights combine the panel and refresher samples. We weight observations equally when combining these two sources of data by dividing the weights in each group (from 2018 and refresher) by their means to have a mean of one. Denote this normalized weight for a household in a particular governorate and urban/rural location (stratum) as $\widetilde{w}_{g,l}$. The household combined sample weight then is based on the population projection counts and this weight, as:

$$w_{g,l} = \widetilde{w}_{g,l} \frac{c_{g,l}}{\sum \widetilde{w}_{g,l}} \tag{8}$$

As with the refresher sample, we account for sex and age-group non-response rates ($r_{x,e}$) and initially adjusted to create individual weights as:

$$w_{g,l,x,e} = \frac{w_{g,l}}{1 - r_{x,e}} \tag{9}$$

In the combined sample, rather than 103.7 million (true population projection), in this case the result was an estimated 103.3 million individuals. Furthermore, the estimated male population was 51.2 million (per projection, should be 53.3 million) and the female population 52.1 million (per projection, should be 50.4 million). Especially since labor market outcomes in Egypt are highly gendered (Krafft, Assaad, and Keo 2022), as with the refresher sample, we implemented an additional correction, adjusting (nationally) the individual weights for the population to be 53.3 million men and 50.4 million women. These individual weights should be used in all individual-level analyses.

4. Comparisons with other data sources for Egypt

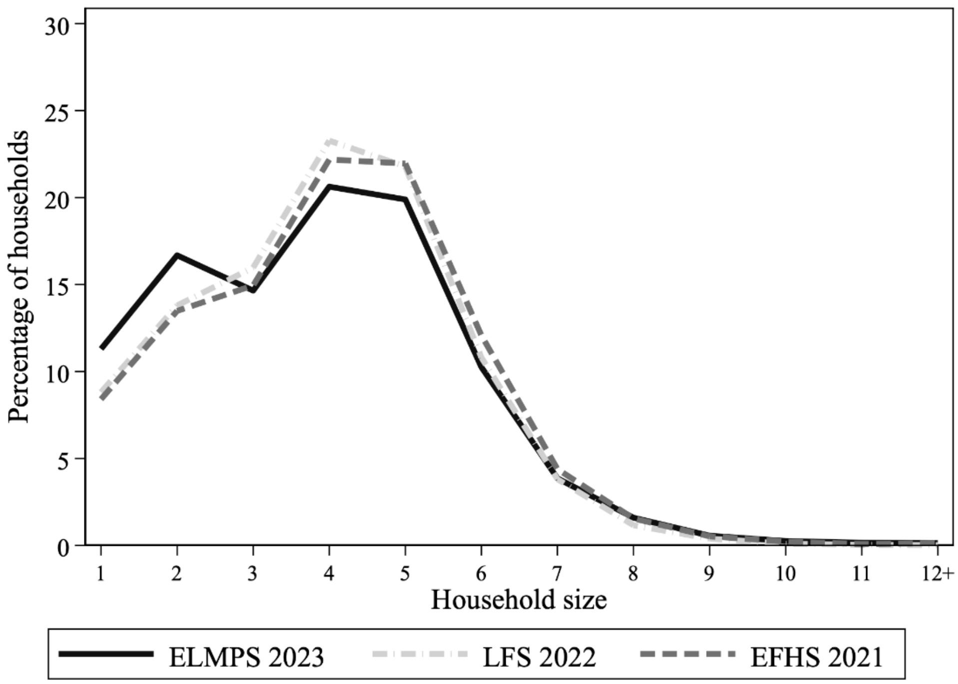
In this section, we validate the ELMPS 2023 against other data sources. Egypt's labor force survey (LFS) is a nationally representative survey undertaken quarterly. We use the microdata of the LFS from 2007-2022 (OAMDI 2023).[9] As the microdata for 2023 are not yet available, we use the official quarterly bulletins from the LFS for the four quarters of 2023 (CAPMAS 2023a; 2023b; 2023c; 2024). Analyses also incorporate the 2021 Egypt Family Health Survey (EFHS) microdata (Central Agency for Public Mobilization and Statistics (CAPMAS) 2022a; 2022b). We compare demographics (household size, age distribution, marital status, educational attainment, and enrollment) across the ELMPS, LFS, and EFHS. We compare labor market outcomes (labor force participation, employment, unemployment, types of employment, and wages) across the ELMPS and LFS, since labor market characteristics are not available for all household members in the EFHS.

4.1. Demographic comparisons

For our demographic comparisons we focus on the ELMPS 2023 in comparison to the LFS 2022 and EFHS microdata. Household sizes are generally similar across the data sources (Figure 1). The ELMPS 2023 finds slightly more one person households (11%) than the LFS 2022 (9%) or EFHS 2021 (8%). Likewise, it finds slightly more two person households (17%) than the other data sources (13-14%). The ELMPS then finds slightly fewer larger households, for instance 20% five person households compared to 22% in the EFHS and LFS. For six person households, the EFHS finds 12%, the LFS 11%, and the ELMPS 10%. The distribution of larger households (7+ individuals) is quite similar across data sources. The pattern of finding slightly more small households in the ELMPS than LFS also occurred in 2018 (Krafft, Assaad, and Rahman 2021) and may be due to different implementations of the definition of a household across data sources.

[9] See Krafft, Assaad, and Rahman (2021) for comparisons with earlier years based on ILOSTAT data.

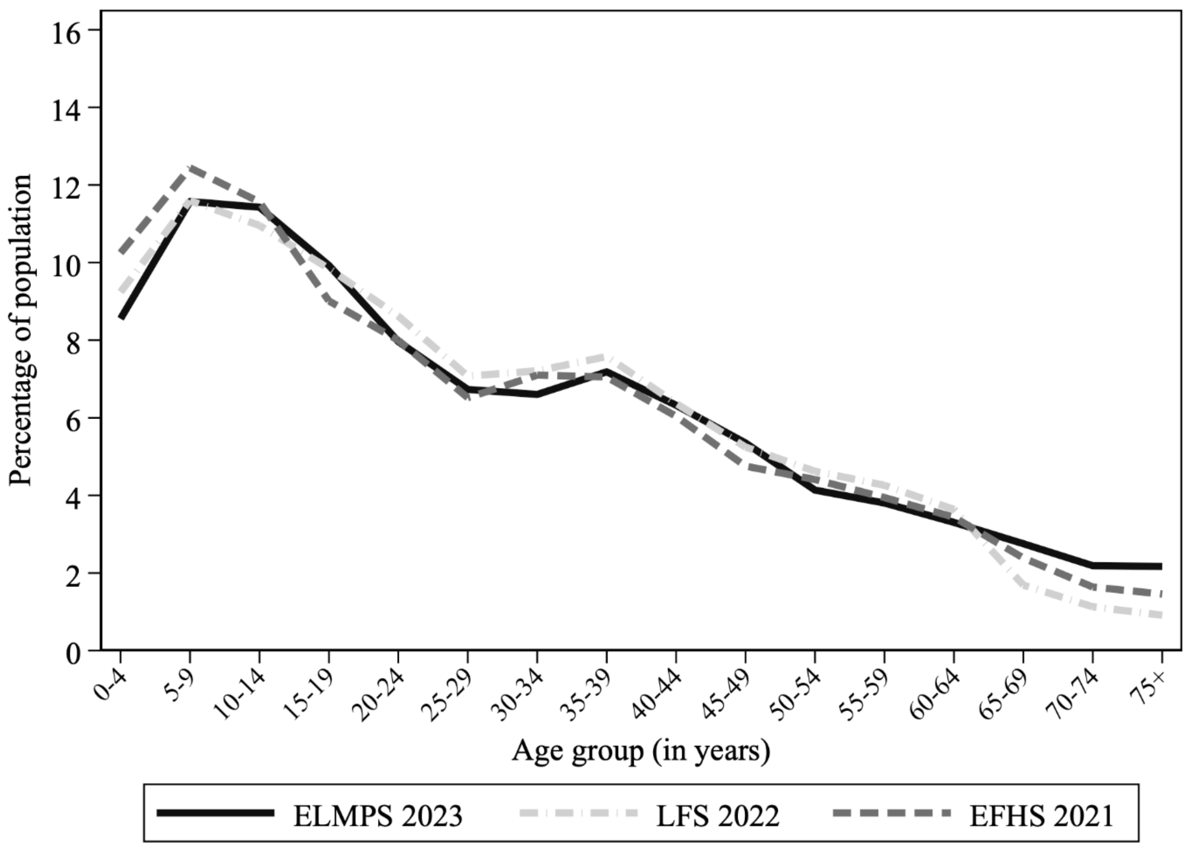
Figure 1. Household size (percentage of households), by data source, 2021-2023



Source: Authors' calculations based on ELMPS 2023, LFS 2022, and EFHS 2021

The "echo" of Egypt's youth bulge is abating, as shown in Figure 2. Egypt had a sizeable youth bulge in the early 2000s, that as of the 2020s was aged 35-39. When this group of young people reached peak childbearing age in the 2010s, an "echo" of the youth bulge formed, compounded by a stall and increase in fertility rates (Krafft and Assaad 2014; Assaad 2022; Krafft 2020; Krafft, Assaad, and Keo 2022). The age 5-9 group is now the largest age group in Egypt (12% of the population across data sources). While still placing appreciable pressure on services such as the primary education system, the aging of the youth bulge past peak childbearing ages, compounded by a drop in fertility rates (see Krafft, Assaad, and McKillip 2024 for a discussion of fertility trends), has led to a smaller age group aged 0-4 than 5-9. Only 10% of the EFHS 2021, and 9% of the LFS 2022 and ELMPS 2023 population was aged 0-4, a clear decline compared both to the 5-9 group as well as somewhat across the different survey years. The surveys show some small differences at other ages, but differences are not systematic and are small (less than a percentage point across data sources through age 64). The ELMPS 2023 does capture slightly more elderly individuals, for instance 2% of the population as aged 75+ compared to 1% in the other data sources.

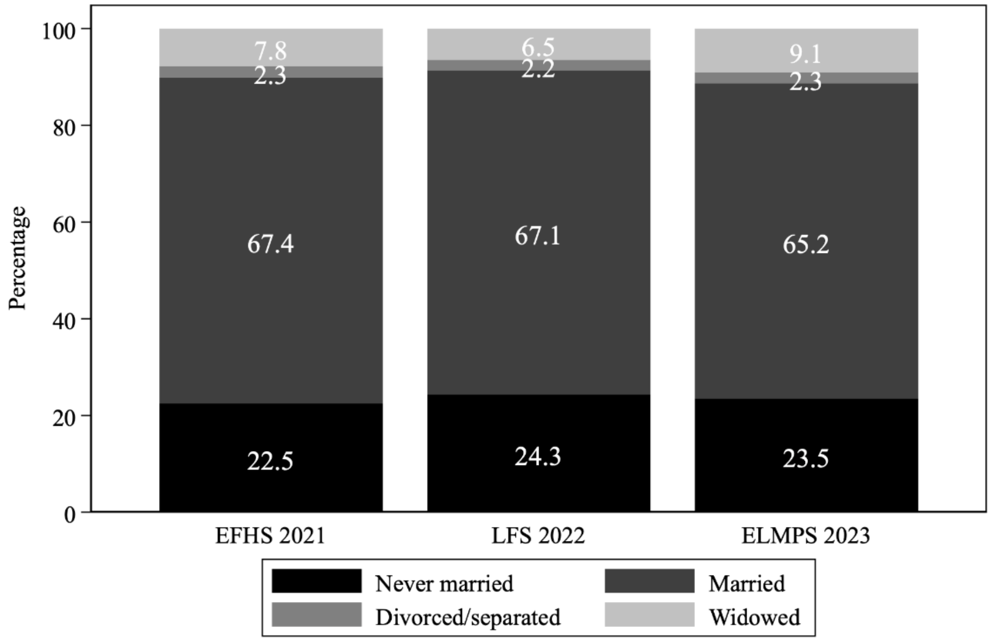
Figure 2. Age distribution (percentage in age group), by data source, 2021-2023



Source: Authors' calculations based on ELMPS 2023, LFS 2022, and EFHS 2021

Figure 3 explores marital status for individuals aged 18 and above across data sources. The EFHS found a slightly lower share of never married adults, 22.5%, than the ELMPS, 23.5%, or LFS, 24.3%. All three sources find a similar share, 2.2-2.3%, of separated or divorced adults. There are some small differences across data sources in currently married (67.1-67.4% in other sources and 65.2% in the ELMPS). Correspondingly, the ELMPS has more widowed individuals (9.1%) than the EFHS (7.8%) or LFS (6.5%), which may be related to the slightly larger elderly population captured in the sample.

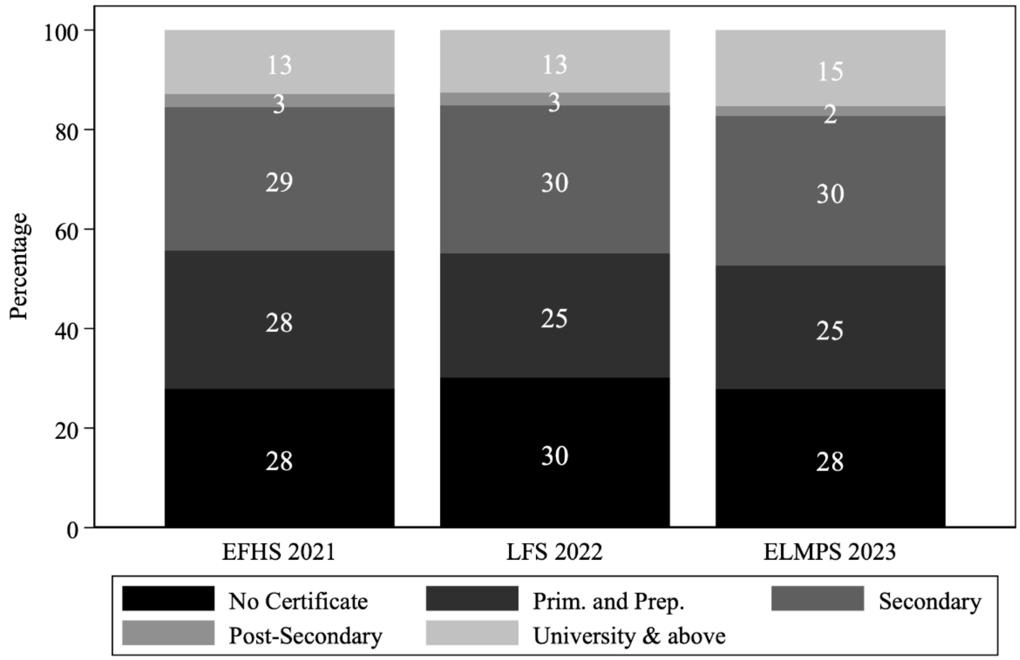
Figure 3. Marital status (percentage), individuals aged 18+, by data source, 2021-2023



Source: Authors' calculations based on ELMPS 2023, LFS 2022, and EFHS 2021

There are only small differences in the educational attainment of those aged 10 and older across data sources (Figure 4). The EFHS and ELMPS find 28% of the population has no certificate, and 30% in the LFS. Both the LFS and ELMPS find 25% of the population has completed primary or preparatory, and 28% in the EFHS. Across data sources 29-30% have attained secondary degrees. A small share, 2-3% across sources, have post-secondary degrees. The ELMPS 2023 finds slightly more university and above graduates, 15%, than the EFHS and LFS (13%). Overall, educational attainment is quite consistent across sources.

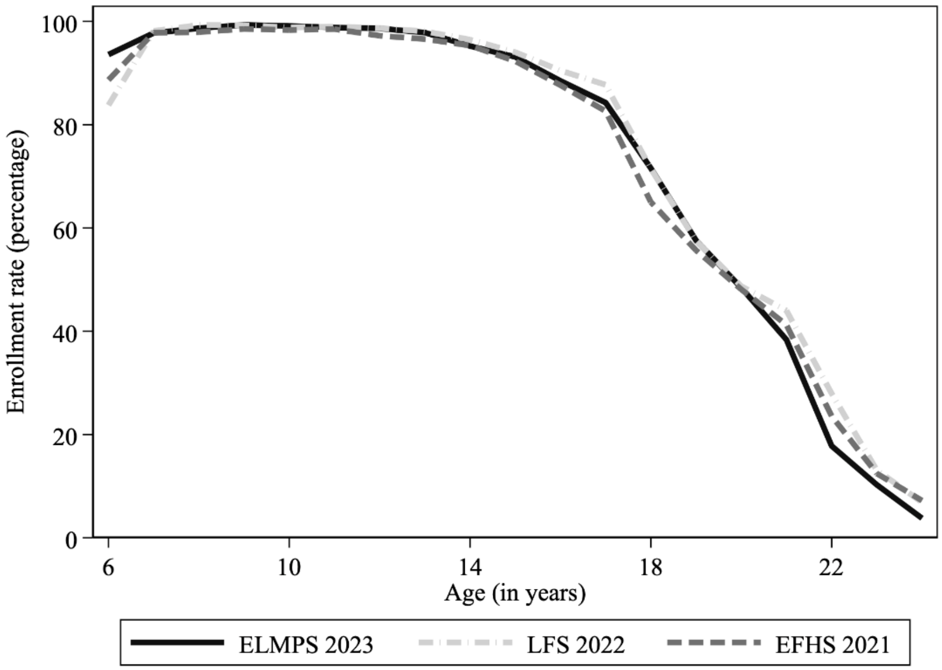
Figure 4. Educational attainment (percentage), individuals aged 10+, by data source, 2021-2023



Source: Authors' calculations based on ELMPS 2023, LFS 2022, and EFHS 2021

School enrollment patterns are, as with educational attainment, very similar across data sources. Figure 5 shows enrollment by age (at the time of fielding). Because ELMPS 2023 was fielded in fall, the LFS throughout the year (all four quarters), and the EFHS in the fall and winter (Central Agency for Public Mobilization and Statistics (CAPMAS) 2022a), children age six at the time of fielding would not necessarily have been eligible to enroll in school based on being age six September 30 (the cutoff for primary eligibility), particularly in the LFS. It is therefore unsurprising to see slightly different age six enrollment rates across data sources, with the lowest for the LFS, and then near universal enrollment starting at age seven and continuing for a number of years. For the teenage years, as enrollments begin to dip, the ELMPS rate falls in between that of the LFS, which is slightly higher, and EFHS. All three have similar rates around age 17, and then the EFHS is slightly lower through age 20 while the LFS and ELMPS are very similar. The ELMPS has slightly lower enrollment rates past age 20, but overall patterns of enrollment by age are very similar.

Figure 5. School enrollment rate (percentage), individuals aged 6-24, by age at time of survey and data source, 2021-2023



Source: Authors' calculations based on ELMPS 2023, LFS 2022, and EFHS 2021

4.2. Labor market comparisons

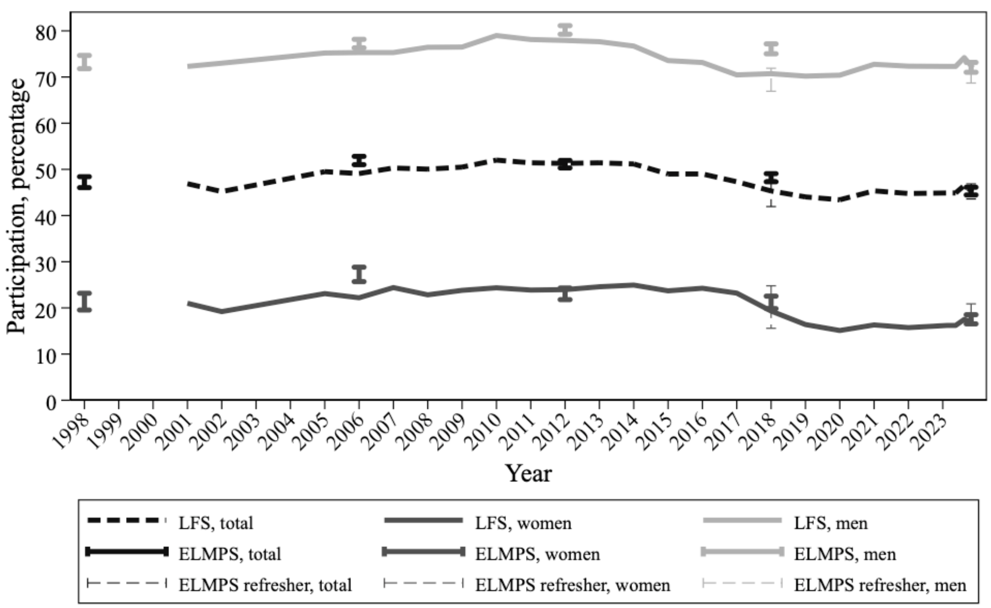
The initial labor force comparisons we present relate to key labor market indicators: the labor force participation rate, the employment rate, and the unemployment rate. Individuals are employed if they worked (even just one hour) within the past seven days for pay or profit (as per the International Conference of Labour Statisticians definition of employment (ILO 2013)). Individuals are unemployed if they were not employed in the past seven days, wanted to work, and were searching for work within the past three months. Individuals are in the labor force if they are either unemployed or employed. The employment rate and labor force participation rate are relative to the population; the unemployment rate is as a share of the labor force.

We compare the ELMPS labor force participation rate, over time, with the LFS data in Figure 6. The figure presents both the total ELMPS sample estimates and 95% confidence intervals for all years, and for the refresher samples in 2018 and 2023 (when distinct refresher weights were generated). We located the ELMPS 2023 estimates in Q4 of 2023, reflecting the time of the majority of fielding relative to LFS quarterly reports, but note that fieldwork started in September so did include part of Q3. Estimates of labor force participation rates are generally similar, and in fact are closer than in past years.

For 2023, the overall labor force participation rate for the third quarter of the LFS was 46.5% and for the fourth quarter was 45.1%. The ELMPS overall estimate was 45.3% and refresher estimate was 45.2%. We note, first, the very close alignment between the refresher and overall estimates, suggesting that (after weighting) panel attrition has not affected our ability to accurately estimate key labor market indicators. The confidence interval for ELMPS 2023 included the fourth quarter but not the third quarter estimates for the overall sample; the refresher sample confidence interval, which is larger, includes the estimates for both the third and fourth quarters.

The male estimate for the labor force participation rate was 74.2% for LFS Q3 and 72.0% for LFS Q4. The male rate in the ELMPS was very similar to LFS Q4 at 72.1% in the ELMPS full sample and 71.1% in the ELMPS refresher. LFS estimates were within both ELMPS full sample and refresher confidence intervals for Q4, but not Q3. The female estimate of labor force participation was 17.5% for LFS Q3 and 16.9% for LFS Q4. This statistic was 17.5% in the ELMPS full sample and 18.8% in the refresher sample, and the confidence intervals for both ELMPS 2023 full and refresher samples overlapped both Q3 and Q4 LFS estimates. Overall, the differences in labor force participation across sources were small, similar to quarterly fluctuations, and often within the estimated confidence intervals. Differences in 2023 are also smaller than occurred in previous waves.

Figure 6. Labor force participation rate (percentage of the population), by data source and sex, ages 15-64, 1998-2023



Source: Authors' calculations based on ELMPS 1998-2023 and LFS 2008-2022; LFS 2023 data are from quarterly bulletins (CAPMAS 2023a; 2023b; 2023c; 2024); LFS 2001-2007 data are from ILOSTAT (ILO 2019).

Notes: ELMPS 2023 shown in quarter corresponding to fieldwork. Bars show 95% confidence intervals.

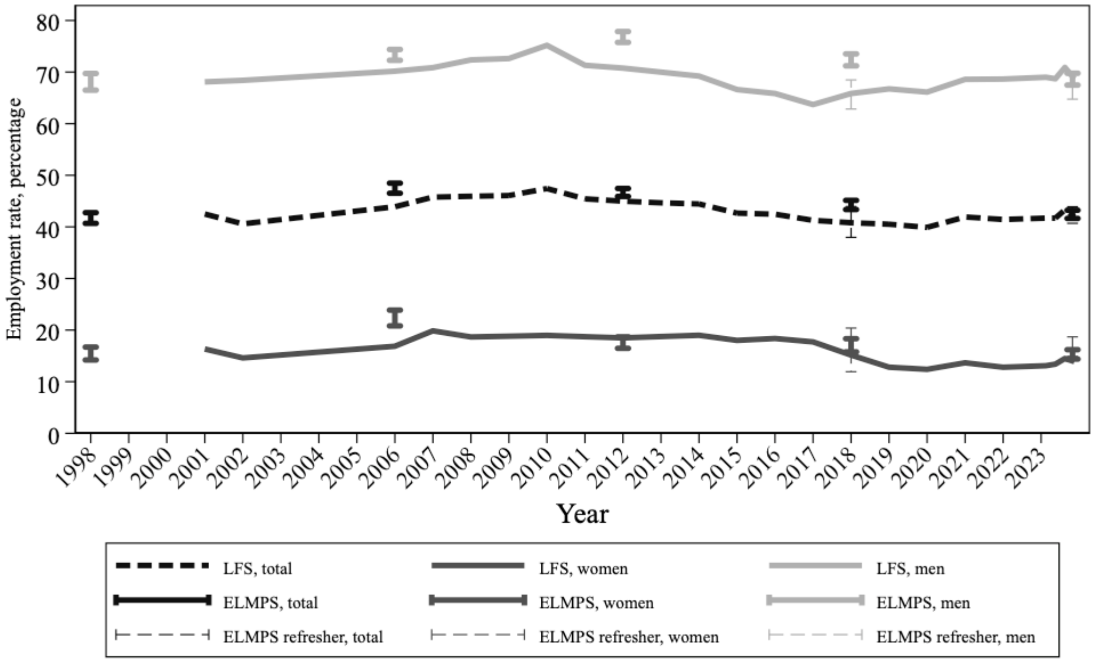
While the 2023 labor force participation rates are very similar across the ELMPS and LFS, there are some differences in the trends they capture over time. The LFS data suggests that overall labor force participation rates for those aged 15 to 64 have been declining in Egypt since the early 2010s. According to the LFS, overall participation went from 51% in 2012, to 45% in 2018, declined further during 2019 and 2020 and then recovered to the 2018 level (45%) by quarter four of 2023 (when the ELMPS was fielded). The trend over 2018 to 2023 was thus flat in the LFS but there was a decline in the ELMPS, which showed overall participation declining from 48 to 45%. This disparity was driven by higher participation in the ELMPS 2018 than LFS 2018.

There are also some differences across the two sources regarding the trend in participation by gender. Men's participation rate as ascertained by the ELMPS fell from 80% in 2012 to 76% in 2018, which is a less steep fall than in the LFS (which saw a fall from 78 to 71%), but it continued to fall steeply according to the ELMPS to 71% in 2023, when the LFS shows a relatively stable 72% in quarter four of 2023.[10] Per the LFS, female participation rates went from 24% in 2012 to 19% in 2018 and further down to 17% in quarter four of 2023. According to the ELMPS, women's participation rates fell from 23% in 2012, to 21% in 2018, more slowly than in the LFS. Then in the ELMPS, women's participation rate fell by a further 3 percentage points (p.p.) from 2018 (21%) to 2023 (18%), similar to the decline reported by the LFS. Overall, while the ELMPS and LFS show some divergence in the timing of labor force participation declines for men, they show declining participation overall, for men, and for women when comparing 2012 to 2023.

Figure 7 explores specifically employment rates (as a percentage of the population) over time and across data sources. The overall employment rate in 2023 Q3 per the LFS was 43.3%, and 41.9% in Q4. The ELMPS had an overall employment rate of 42.4%, between the two quarters, and a very similar 42.3% using the refresher sample. The ELMPS confidence intervals encompass the 2023 Q4 estimate but not the Q3 estimate for the full sample, and both quarters for the refresher sample. For men, estimates are 70.9% LFS Q3, 68.7% LFS Q4, 68.6% ELMPS full sample, 67.3% ELMPS refresher sample. Confidence intervals encompass Q4 but not Q3 LFS estimates for both ELMPS estimates for men. For women, there are slightly higher employment estimates in the ELMPS (14.5% LFS Q3; 13.9% LFS Q4; 15.3% ELMPS 2023 full sample; 16.8% ELMPS refresher) and confidence intervals overlap with LFS Q3 but not Q4 estimates for the full sample, and neither quarter for the refresher sample.

[10] The sharp recovery in male participation in the LFS actually occurred between 2020 and 2021, after which male participation remained flat.

Figure 7. Employment rate (percentage), by data source and sex, ages 15-64, 1998-2023



Source: Authors' calculations based on ELMPS 1998-2023 and LFS 2008-2022; LFS 2023 data are from quarterly bulletins (CAPMAS 2023a; 2023b; 2023c; 2024); LFS 2001-2007 data are from ILOSTAT (ILO 2019).

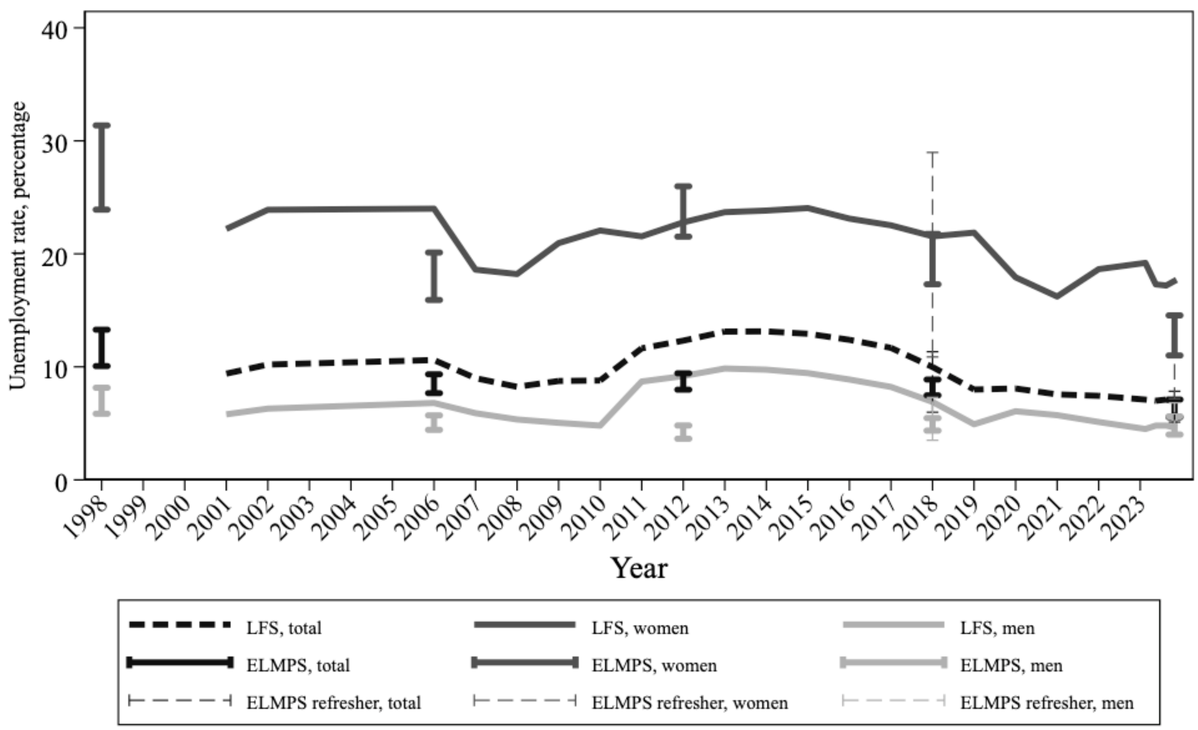
Notes: ELMPS 2023 shown in quarter corresponding to fieldwork. Bars show 95% confidence intervals.

In terms of the longer-term trends captured by the ELMPS and LFS, as with labor force participation, there is an overall decline in employment rates visible in both sources, although the levels and timing differ a bit across the two sources. The LFS reports an employment rate of 44% in 2006 (ELMPS 2006 had 48%), which rose to 47% in 2010 and then declined to 45% in 2012 (the ELMPS had 47%), 41% in 2018 (44% in the ELMPS), and then recovered somewhat to 42% in quarter four of 2023 (the ELMPS also has 42%). Therefore, while the ELMPS shows a slowing in the rate of decline of the overall employment rate since 2018, the LFS shows a modest reversal of the decline. The LFS shows a similar decline in male employment rates from 2012 to 2018 from 71% to 66% (ELMPS had from 77% to 72%), but a recovery from 2018 to quarter four of 2023 back to 69% (the ELMPS 2023 had the same 69%), thus a much smaller relative decline of 2 percentage points over the entire period (Assaad and Krafft 2024). LFS and ELMPS data show a similar decline in female employment rates, with rates going from 18% in 2012 (same in ELMPS) to 14% in quarter four of 2023, when the ELMPS 2023 found a 15% employment rate (Assaad and Krafft 2024).

In Figure 8 we turn to comparisons of the unemployment rate as a share of the labor force. The overall ELMPS unemployment rate was 6.3% (6.5% in the refresher sample), compared to 7.1% in Q3 with the LFS and 6.9% in Q4 with the LFS. Both confidence intervals for the ELMPS include both quarters of the LFS estimates. Unemployment rates for men are quite similar; 4.8% Q3 of the

LFS and 4.6% Q4, similar to the 4.8% with the ELMPS full sample and 5.4% with the refresher. Confidence intervals for male unemployment include both quarters of the LFS estimates for both the full and the refresher samples. Female unemployment is high in the LFS, 17.2% in Q3 and 17.7% in Q4, but relatively lower in the ELMPS, 12.8% with the full sample and 10.8% with the refresher sample. Confidence intervals do not overlap with LFS estimates. The lower unemployment rate for women may be driven in part by the higher employment rate; the additional women who are employed are in the denominator but not the numerator of unemployment.

Figure 8. Unemployment rate (percentage of the labor force), by data source and sex, ages 15-64, 1998-2023



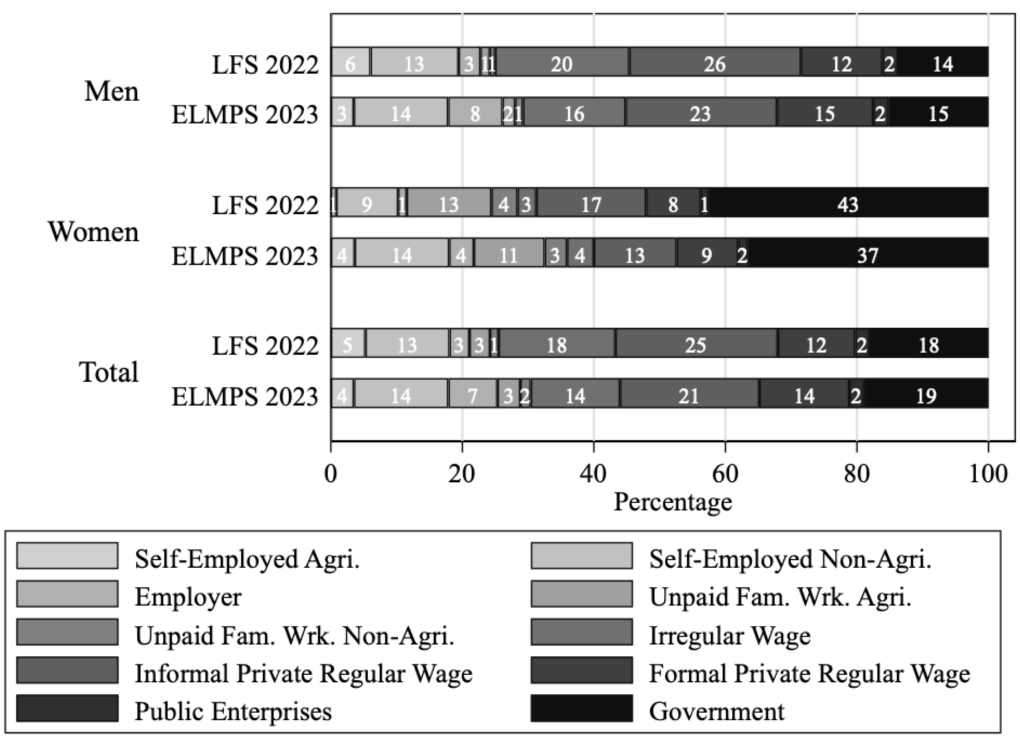
Source: Authors' calculations based on ELMPS 1998-2023 and LFS 2008-2022; LFS 2023 data are from quarterly bulletins (CAPMAS 2023a; 2023b; 2023c; 2024); LFS 2001-2007 data are from ILOSTAT (ILO 2019).

Notes: ELMPS 2023 shown in quarter corresponding to fieldwork. Bars show 95% confidence intervals.

Lower unemployment rates in the ELMPS have also been observed often in other rounds; these may be the result of asking the respondent him or herself about search behaviors and thus generating a more accurate estimate of the unemployed in the ELMPS. According to LFS data, the overall unemployment rate declined from a peak of 13.1 percent in 2014 to 6.9 percent in quarter four of 2023. The decline was slow at first and then accelerated in the 2017 to 2019 period, reversed briefly in 2020 at the peak of the pandemic, and then resumed through 2023. Although the ELMPS and LFS often diverge in the levels of unemployment they capture, they do show broadly the same overall unemployment trends, with unemployment rates fairly stable from 2006 to 2012, some decline by 2018, and further decline by 2023. The trends by gender are more disparate for men across the ELMPS and LFS, although they do agree on some decline in women's unemployment rates from 2012 to 2023, but not on the magnitude.

Figure 9 explores types of employment, among the employed aged 15-64, and by sex, comparing LFS 2022 and ELMPS 2023. Results overall are relatively similar for the percentage that are self-employed (18%), with some differences in agriculture versus non-agriculture across data sources. The ELMPS 2023 detects far more employers (7% vs. 3% in the LFS), and also slightly more unpaid family workers (5% vs. 4% in the LFS). The ELMPS then detects fewer irregular wage workers (14% vs. 18% in the LFS) and fewer informal[11] regular private wage workers (21% vs. 25% in the LFS). Higher shares of private formal regular wage workers are in the ELMPS (14%) than LFS (12%). However, similar shares of public enterprise (2%), and government (18-19%) workers are detected. While results for men follow the overall pattern, the ELMPS seems to be detecting more non-wage work particularly for women, which may help explain their slightly higher employment rates in the ELMPS, if such work goes undetected in the LFS.

Figure 9. Type of employment (percentage), employed individuals aged 15-64, by sex and data source, 2022 and 2023

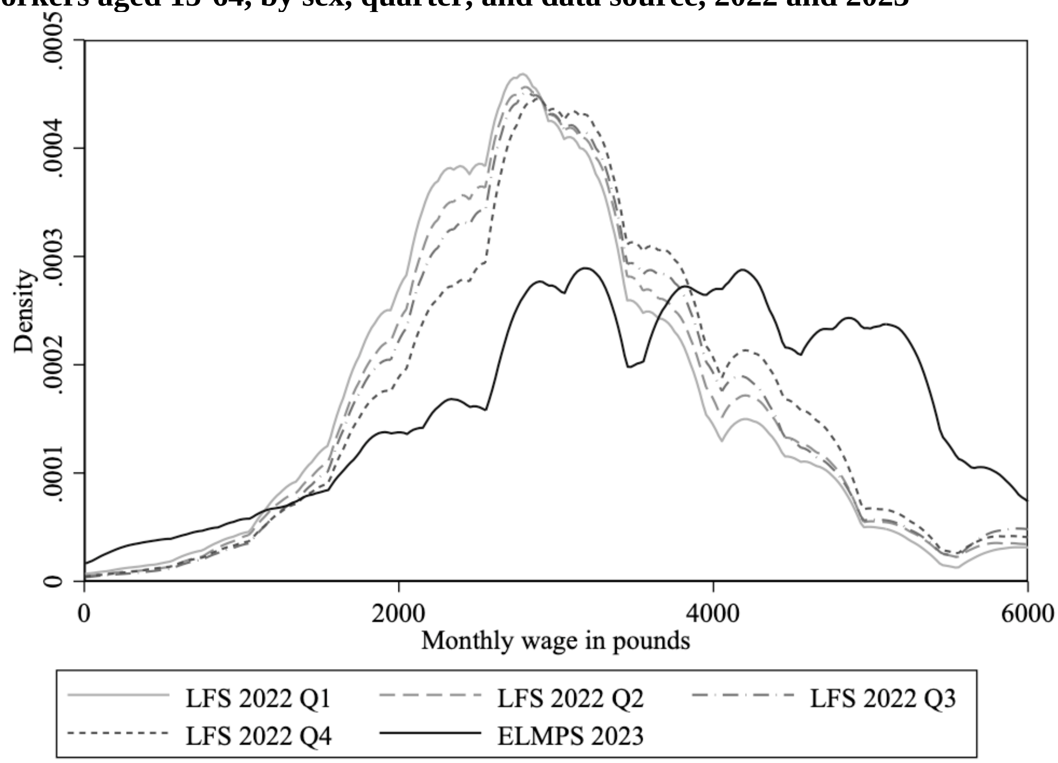


Source: Authors' calculations based on ELMPS 2023, LFS 2022, and EFHS 2021

[11] Informal workers lack social insurance; formal workers have social insurance coverage.

Figure 10 explores the distribution of monthly wages across data sources for regular wage workers (as this group has comparable, monthly wages in the LFS and ELMPS). Wages are presented in nominal terms, in Egyptian pounds (LE). Because there has been rapid inflation in Egypt (35.2% annual inflation as of December 2023 (Office of the Chief Economist - Middle East & North Africa - The World Bank 2024)), we would not expect wages to be the same over time, and indeed, present 2022 LFS wages by quarter to show some of this evolution. We do not, however, try to update wages into real terms, because they have not necessarily kept up with inflation. The figure shows some shift over the quarters of the LFS 2022, with higher wages in later quarters, but an overall similar distribution. The mean wage[12] in Q1 2022 from the LFS was 3,029 LE per month, rising to 3,140 in Q2, 3,208 in Q3, and 3,289 in Q4. In the ELMPS 2023, the mean wage was 3,978 LE. The ELMPS also notably has a different distribution in general, not just shifted with time, but rather capturing more of both low-wage earners (e.g., less than 1,000 pounds per month), and higher wage earners (e.g., above 4,000 pounds per month). Getting wages from the respondent him or herself may improve the accuracy and thus the range of estimates.

Figure 10. Distribution of monthly wages in Egyptian pounds (proportion), regular wage workers aged 15-64, by sex, quarter, and data source, 2022 and 2023



Source: Authors' calculations based on ELMPS 2023, LFS 2022, and EFHS 2021

Notes: Epanechnikov kernel, bandwidth 200. Wages are nominal. Presenting only wages below the 95th percentile to reduce the impact of outliers and improve visualization.

[12] Winsorized at the 95th percentile to minimize the influence of outliers.

5. Conclusions

In this paper, we introduce the fifth wave of the ELMPS, which was carried out in September-December of 2023. To assist researchers interested in using the ELMPS data, we began by discussing changes in the survey instruments with a focus on the new modules and questions that were added in 2023 to incorporate new topics of policy interest, such as skills and training, remote work and work through digital platforms (gig work), and involvement in green tasks at work. We then discussed the organization of the data collection process and the pattern and magnitude of the attrition between the 2018 and 2023 round of the survey. While household attrition was reduced to 12%, split household attrition rose to 41%. Based on models of the two possible attrition processes, we generate weights to adjust the panel sample for systematic attrition along observable characteristics. As in previous waves, the panel sample is supplemented by a nationally-representative refresher sample, which in 2023 was designed to have 2,000 households distributed over 200 PSUs of 10 households each. The calculation of the sampling weights for this sample is discussed as well as the weights for the combined panel and refresher sample.

As in previous waves, we compared the results of the 2023 wave for basic demographic and labor market indicators to those of other nationally representative sources in Egypt. The distribution of the ELMPS 2023 sample by household size was fairly similar to distributions obtained from the 2022 rounds of the LFS and the EFHS 2021 except for a slight over-representation of very small households and under-representation of 4-5 member households. The age distribution of the population in ELMPS 2023 is very similar to that of the other two sources, with the exception of a slight under-representation of young adults 30-34 and an over-representation of elderly individuals 65 and older. School enrollment rates of children and youth are almost identical across the three sources with the exception of some small differences for post-secondary enrollment ages.

With regard to labor market variables, labor force participation rates in 2023 are very similar overall, for men, and for women when comparing the ELMPS to LFS and ELMPS full sample to refresher sample. Overall and for men, employment and unemployment rates were also quite similar. There is a small difference in female employment rates in favor of ELMPS 2023, and correspondingly significantly lower female unemployment rates in ELMPS 2023 compared to LFS 2023. This pattern was also the case in ELMPS 2006 and ELMPS 2018. These differences may be due in part to women whose families consider them unemployed, but upon detailed questioning of the individual herself in the ELMPS 2023 are detected as undertaking some sort of part-time or intermittent work.

A comparison of the structure of employment by type of employment across the ELMPS 2023 and LFS 2022 reveals some small differences overall and among men. ELMPS 2023 found more employers, fewer private regular informal or irregular wage workers, and more formal private sector regular wage workers. Consistent with the interpretation that ELMPS is better at detecting non-standard forms of employment among women, ELMPS detects more self-employment for women and thus reports a lower proportion of both informal regular wage work and government work. The final comparison we made is for the distribution of wages across the ELMPS 2023 and data from the quarters of the LFS 2022. We find a much broader distribution of wages in the ELMPS than in the LFS. This is in part due to the fact that ELMPS is more likely to obtain the information from the individual him or herself, resulting in less under-reporting of higher wages. The higher incidence of wages at the low end of the distribution in ELMPS may be due to ELMPS's ability to detect employment among some marginally employed individuals who may not be captured at all as employed in LFS.

The ELMPS is a critical complement to other sources of labor and human development data for Egypt. While the LFS provides high-frequency quarterly data, the ELMPS provides less frequent data, but greater depth on labor market experiences and history, along with their links with key economic, demographic, and social phenomena. The panel and retrospective data of the ELMPS will be particularly valuable for updating our understanding of the labor market, including topics such as school-to-work transitions. The new modules and questions in ELMPS 2023 can be used to research topics such as gig work, green jobs, skills supply and demand, and time use. The data also are critically important for providing insight into key economic and social topics, for instance identifying a recent decline in fertility (Krafft, Assaad, and McKillip 2024) or examining the performance of social assistance programs. The ELMPS 2023 data will be made publicly available in October 2024 with the goal of facilitating research on a wide-variety of policy relevant topics.

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