Social assistance programmes and individuals’ wellbeing in Egypt

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Social assistance programmes and individuals' wellbeing in Egypt

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Authors: Vladimir Hlasny.

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The background paper has been presented and discussed in the Social Expenditure Monitor Regional Expert Group Meeting (EGM), held in Amman, on 1-2 December 2021. The author(s) acknowledge the comments and suggestions from colleagues at UNESCWA, UNDP Regional Hub in Amman, UNICEF MENARO and other participants of the EGM.

Contents

I. Motivation

General financial assistance such as indirect subsidies have been the dominant form of social assistance in the Arab region. Such subsidies are often regressive, meaning that the less poor benefit more from them than the extreme poor. General subsidies also tend to represent a greater burden on countries' GDP than more narrowly targeted interventions. Many Arab countries have thus started to transition away from general subsidies, scaling them down or replacing them by more targeted forms of social assistance including in-kind transfers and labour-market support. Labour market policies represent an important dimension of public assistance programmes and social safety nets (SSN), and are becoming an integral pillar of countries' strategy toward an equitable and sustainable development. For this reason labour market interventions and their outcomes are tracked in the Social Expenditure Monitor (SEM).[1]

In response to the economic instability and contractions of the past decade, including the COVID-19 crisis, Arab states have increased the magnitude of public support and expanded its coverage to a greater share of the population. Arab countries have also implemented more sophisticated targeting methods for identifying beneficiaries, such as proxy means tests (PMT) and social registries of present as well as prospective beneficiaries.[2]

In lights of these regional tendencies and the worldwide emphasis on ramping up social assistance amid crises, this study aims to evaluate the impact of several forms of social assistance programmes on the socio-economic outcomes of beneficiaries. Beside conditional and unconditional financial assistance, we assess workers' benefit from participating in labour-market support schemes including publicly-funded vocational training and health insurance.

The evidence in the SEM combined with the information in labour market surveys offers an opportunity to carefully assess workers' exposure to alternative public programmes, and the impacts on workers' living conditions and labour market outcomes. The role of workers' preexisting conditions and status, their eligibility for treatment and self-reported interest in being selected, their actual participation, and the degree of exposure may oftentimes be evaluated too. Survey microdata enable policymakers to assess the relative role of public versus non-public

[1] ESCWA (2019).
[2] Hlasny (2021).

labour-market support, as experienced by various demographic groups, and in relation to workers' various outcomes. At the level of individual workers, the analysis can shed light on how exposure to various programmes facilitates workers' transitions from pre-existing conditions to their up-to-date labour market status, across demographic divides such as different wealth groups and genders, youth versus non-youth, urban versus rural, or skilled versus unskilled workers.

This study contributes to existing welfare-economic literature by examining the role of several complementary social assistance programmes – namely workers' participation in publicly-funded vocation training, publicly-funded health insurance, and various financial support schemes – in addressing employment status and deprivation among workers – namely their perceived job satisfaction and food security. We control for the impact of individuals' preexisting human capital and demographic circumstances. In one supplementary analysis, we specifically assess workers' transition from unsatisfactory to satisfactory jobs. We use data from two waves of nationally representative, high-quality, harmonized panel surveys for Egypt that measure individuals' circumstances, track the socio-economic outcomes of the same individuals over time, and also link outcomes of individuals to those of their parents. To our knowledge this is one of only a handful studies examining the impact of social assistance programmes on individuals' long-term welfare using Egyptian microdata.

Tracking the socio-economic status of workers over time can provide a tremendous insight into the processes by which working conditions and the prevalence and degree of deprivation get transmitted over time, and the implications this has for social mobility and long-term vulnerabilities economy-wide. Results of our analysis of the perceptions of food security and job satisfaction will suggest how difficult it is to escape vulnerability or transition to a "decent job" if you start your life in a vulnerable state. Our findings also underline the importance of initial household circumstances in determining lifetime opportunities and point to the strong persistence of intergenerational misery. Our findings will help guide policy recommendations regarding the targeting of vulnerable groups using specific policy interventions.

The remainder of this paper is organized as follows. Section two introduces the data sources, concept definitions, and the empirical approach to isolating the effects of social assistance programmes on individuals' self-reported material deprivation and job satisfaction, directly followed by the presentation of their results in section three. Section four concludes with the discussion of policy implications.

II. Methods and Data

The proliferation of household surveys across selected Arab countries over the past decade has given rise to nationally representative micro-level evidence on workers' uptake (or reasons for not taking up) of various social assistance programmes, and their up-to-date working and living conditions. Labour market panel surveys (LMPSs) also screen workers' demographics, socio-economic endowments, and choices during their career paths.

There is a chronic need across the MENA region to assess how workers' exposure to various social assistance programmes affects their socio-economic outcomes, conditioning on workers' pre-existing circumstances and characteristics. Evidence tailored to vulnerable groups such as women, youth or rural poor is particularly needed. Several issues complicate the estimation. First, the timeline between programme participation and economic outcomes is unclear theoretically. Second, the effect of programme participation may be confounded by workers' simultaneous exposure to other programmes or by their selection into treatment based on their concurrent situation and expectations. In this study, to facilitate measurement of the one-way direct impact, programme participation in a year is linked to outcomes observed with a delay of six years. Hence, social assistance received and captured in the survey in 2012 is linked to workers' outcomes reported as of 2018. Beside publicly-funded assistance, the analysis controls for workers' participation in self-funded or employer-funded schemes.

a. Multinomial regressions

To investigate the impact of several social assistance programmes and workers' various other experiences on their perceived food security and job satisfaction, we estimate multinomial logistic regressions of workers' categorical responses regarding their self-reported degree of material deprivation or job satisfaction. This method has previously been used by Assaad et al. (2014) to study occupational distribution of all workers in Jordan 2010, by Assaad and Krafft (2014) for school-to-work transitions in Egypt 2012, by AlAzzawi and Hlasny (2020, 2022) for employment vulnerability of youth and non-youth workers, and by Dibeh et al. (2019) for the modalities of irregular migration. The contribution of this study is to link workers' self-perceived material wellbeing in a year to their past exposure to publicly-funded vocation training and health insurance, and a handful of financial assistance programmes.

The multinomial logistic regressions estimated using multiple linked waves of LMPSs allow us to estimate the status or changes in workers' living conditions as a function of their exposure to social assistance programmes, mitigating the potential endogeneity of workers' circumstances or other experiences by using their backgrounds from previous survey waves.

Multinomial logistic regressions estimate the probability that an individual will attain a particular value of a categorical dependent variable ($\Pr(y = j), j \in J$) – in our case the ordinal perceived degree of food deprivation or job satisfaction – relative to the probability of an *a priori* baseline condition – here, the preferred state of never experiencing severe food deprivation or (moderate) vulnerability to it, or being fully satisfied with one's job. The regression takes values of explanatory variables (x), estimates j-outcome specific coefficients on those explanatory variables (β_j) using maximum likelihood, and calculates the probabilities of all possible outcomes:

$$\Pr(y = j) = {}^{\exp(\beta_j x)}\Big/_{\sum_{k \in J} \exp(\beta_k x)} \tag{3}$$

In this expression, individual-specific subscripts are omitted for clarity of presentation. The outcome with the highest estimated probability of occurring for an individual is classified as the worker's predicted outcome. Workers' propensity to report the alternative perceptions of their food security (job satisfaction, respectively) is made a function of their 1) receiving of social assistance (publicly-funded vocational training or health insurance, or financial support from several alternative sources); 2) vulnerable group designation (fe/male and urban/rural indicators); 3) human capital (potential work experience, *age–17*; potential experience squared; education completion of level k; privately-funded vocational training); and 3) other individual and household demographics (marital status, household composition, and administrative region r). Specifically, in equation 1 we estimate:

$$\begin{aligned}\beta_j x = \beta_0 + \beta_1 public\ voc.training + \beta_2 public\ health\ ins. + \sum\nolimits_k \beta_k support_k \\ + \beta_3 private\ voc.training + \beta_4 private\ health\ ins. + \sum\nolimits_l \beta_l edu_l + \beta_5 age \\ + \beta_6 age^2 + \beta_7 male + \beta_8 wealth + \beta_9 urban + \sum\nolimits_r \beta_r region_r \\ + \beta_{10} married + \beta_{11} HH\ size\end{aligned} \tag{2}$$

where individual-level subscripts are again omitted. In this study, coefficients β_1 and β_2 are of special policy interest. In a supplementary analysis (Model 3) where data allow it – that is, in the models of job satisfaction – lagged dependent variable is added among regressors as $\sum_s \beta_s job\ satisfaction_s$ to help control for workers' pre-existing status. Coefficients β_1 and β_2 in this specification have the interpretation as the effects of policy interventions on workers' transition from their pre-existing condition.

b. Data

Data used in this study come from the Egyptian Labour Market Panel Surveys, administered by the national statistical office CAPMAS in partnership with the Economic Research Forum (ERF) and harmonized by the ERF. They are highly suitable for examining the impacts of social assistance programmes on individual-level living and working conditions.[3] These surveys track the same workers, and their experiences and outcomes over the span of 6, 12 or more years between survey waves. In each wave, the surveys screen workers' participation in social assistance programmes (conditional/unconditional cash/in-kind transfers, vocational training, access to health insurance, liability deferrals etc.). The LMPSs also include recall modules screening workers' backgrounds including parents' history, supplementing the information on workers' own status across multiple survey waves.

For the present analysis, workers' outcomes are taken from the year-2018 wave of the Egyptian LMPS, while their exposure to social assistance is taken from the year-2012 wave.[4] We restrict

[3] LMPSs are presently available for Egypt (1988, 1998, 2006, 2012, 2018), Jordan (2010, 2016) and Tunisia (2014). Refer to: https://erf.org.eg/labor-market-panel-surveys-lmps/. The second wave of the Tunisian LMPS is forthcoming in 2022.

[4] The 2012 panel is made up of 12,060 households and 49,186 individuals. The 2018 panel comprises 9,771 households from the 2012 sample, 2,221 new households that emerged from those households as a result of splits, plus a refresher sample. The total for 2018 is 15,746 households and 61,231 individuals.

the sample to individuals appearing in both waves, assuming away issues due to selective attrition or secular changes to workforce composition. This yields a sample of 9,329 individuals with a full set of non-missing variables for analysis.

Three alternative measures of perceived wellbeing are used as the dependent variables under evaluation: One, responses to the question "In the past 4 weeks, was there ever no food to eat of any kind in your HH – How often?" are used as the measure of **severe deprivation**, with ordinal categorical responses "Never" (baseline option), "Rarely (once or twice in the past four weeks)," or "Sometimes or often (more than three times)."

Two, responses to the question "In the past 4 weeks, did you worry that your HH would not have any food – How often?" are used as the measure of **vulnerability to severe deprivation**, or **moderate deprivation** itself, with ordinal categorical responses "Never" (baseline option), "Rarely (once or twice in the past four weeks)," or "Sometimes or often (more than three times)."

Three, we use responses to the question "How satisfied are you with your current job?" with responses "Fully satisfied" (baseline option), "Rather satisfied", and the rest of responses including "Rather dissatisfied," "Dissatisfied," and no response. Table 5 reports descriptive statistics of some socio-economic outcomes distinguishing workers' with different reported perceptions. This table confirms that the perception of deprivation or job-dissatisfaction is associated with lower economic (wealth and wage earnings) status.

For the first policy variable of interest, we use workers' responses to "Did you participate in any training programme other than regular education – Who covered most of the cost of the training?" Responses "Public agency," "NGO," "Government," "Charity," and "Ministry of Social Affairs" are classified as **publicly-funded** (while "Myself," "My family," and "Employer" are classified as **privately-funded**). These questions are asked only to wage workers employed in formal establishments. This affects the sample delineation for our analysis, and the choice of dependent variables: The sample is limited to formal wage workers, and dependent variables are limited to those varying among these workers.

For the second policy variable of interest, we use workers' responses to "What type of health insurance do you have?" Responses "Through the General Agency for Health Insurance," "Through military," and "Through state" are classified as **publicly-provided** as long as the worker reports having no medical insurance in his/her primary job. (Responses "Myself," "My family," "Employer," or "Medical insurance in primary job" are classified as **privately-provided**.)

Among the types of financial support, we distinguish **Pension** (of any kind including normal, sadat's/mubarak's, and other), **Ministry of Social Solidarity (MOSS) assistance**, and **non-profit/NGO assistance**, all in logarithmic terms of the respective monetary amounts, and **lagged by 6 years (to survey wave 2012)**. The time lags help the models to capture the one-way effects of public assistance on individual's outcomes, without any feedback or simultaneity effects. In any case, the assistance received by individuals in 2012 is associated highly positively with that received in 2018.

In additional to this main specification (Model 1), for completeness, Model 2 also accounts for individuals' receiving of Takaful, Karama, Food Smart Card or other assistance in 2018 that was not surveyed in 2012, all in logarithmic scale of the respective monetary sums. These additional variables aim to account for other, and more recent, public assistance that may impact individuals' non-transient welfare. Finally, in a supplementary analysis of job satisfaction (Model 3), lagged dependent variable in a distributed form – as "Non-satisfied" and "Rather satisfied" – is added among regressors. Descriptive statistics of all variables used are reported in Table 1.

The coefficients in Tables 2–3, upon exponentiation and subtraction of 1, give the estimated changes in the probability of an outcome relative to the probability of being out of labour force (a.k.a. odds, or relative risk ratios, $\Pr(j)/\Pr(baseline) = e^{\beta}$), due to a unit increase in the corresponding explanatory variables. Positive coefficients in Tables 2–3 imply an increase in the probability of an outcome relative to the baseline while negative coefficients imply a reduction.[5] Because all three alternative dependent variables indicate negative outcomes relative to the baseline, while the explanatory variables are all positive characteristics or experiences, we expect all regression coefficients to be negative. This facilitates the formulation of hypotheses to be evaluated in the following section.

[5] Average marginal effect of x on the probability of an outcome j for an individual i, relative to the probability of the baseline outcome, can be computed as: $\partial\pi_{ij}/\partial x_i = \pi_{ij}\left(\beta_j - \sum_{r\neq j}\pi_{ir}\beta_r\right)$.

III. Results

Tables 2–3 report the result of the main regressions of individuals' perceived welfare as a function of their prior exposure to various forms of social assistance, and their other characteristics and experiences. In the following discussion, we will omit mentioning that the probabilities are relative to the most preferred option (baseline).

Perceived food insecurity

Table 2 shows that the individuals' perceived experience of severe food insecurity (the first four columns), and vulnerability to food insecurity (the last four columns) is systematically related to individuals' prior participation in publicly-funded vocational training and health insurance, and receiving of financial assistance (especially pensions), and individuals' demographics (especially sex, education, household size, and wealth). Prior participation in publicly-funded vocational training lowers the propensity for food insecurity by all measures – in all columns – especially so for the case of frequent experience of food insecurity – columns 2, 4, 6 and 8. Reassuringly, this effect is in the same direction as, and even stronger than, in the case of private-funded vocational training. Publicly-provided health insurance also has a mitigating effect on food insecurity by all measures, significantly for the case of frequent vulnerability to food insecurity – columns 6 and 8. (The effect of publicly-funded vocational training gains in significance when health insurance is omitted, and vice versa, indicating some positive association between the two.) In general, we conclude that **the social assistance programmes targeting workers' health and skills have long-term effects alleviating the most frequent forms of food insecurity from occurring 'sometimes/often' (in even columns).**

Financial assistance also appears to mitigate food insecurity overall, significant in the case of pensions, and consistently also in the case of NGO assistance. **The results are mixed and insignificant in the case of the MOSS assistance, and the participation in the Takaful, Karama, and Food Smart Card programmes.**

Figures 1 and 2 illustrate these results in regard to propensity for food insecurity (as severe deprivation; Fig.1), and vulnerability to it (as moderate deprivation; Fig.2). They show the probability of holding specific perceptions ("Sometimes/oft no food," "Rarely no food," versus baseline “Never”) by individuals with different household wealth, distinguishing publicly-assistance recipients from non-recipients. Panel (i) shows this for beneficiaries of publicly-funded vocation training, versus non-beneficiaries, while panel (ii) shows this for recipients of financial assistance, versus non-recipients. **The key finding from Figures 1 and 2 is that the propensity for deprivation of all measures falls significantly across wealth deciles**. The recipients of publicly-funded vocation training (panel (i)) have a clearly lower propensity to experience food insecurity than non-recipients, with the effect being the largest for individuals' between the 2nd and 6th wealth decile. The effect is much smaller or unclear among individuals in the bottom decile or in the top 4 deciles. **In distinguishing recipients and non-recipients of financial assistance, the assistance appears to have little effect on food insecurity, with the probabilities for insecurity being at most marginally lower among recipients.** Figure 4 shows similar patterns distinguishing publicly-funded vocational trainees versus non-trainees across different ages, and suggests that the advantage of beneficiaries over non-beneficiaries is same across all age groups.

The rest of rows in Table 2 show that individuals' demographics have for the most part the expected effects on food deprivation. **Higher education and household wealth are strongly and consistently associated with lower food insecurity.** Household size – here apparently proxying for the number of mouths to feed, rather than a number of earners in the household – has a positive effect on food deprivation and vulnerability to it. Individuals' propensity for job insecurity varies across governorates significantly (individual coefficients are reported in Table 4). **Unexpectedly, men are consistently more likely to report perceiving food insecurity than women**. This presumably stems from sample selection issues, an issue discussed more in the following section. Finally, individuals' potential work experience (age-17), marital status, and urban residence (after controlling for the 21 governorates of residence) have little or unclear effect on food insecurity. These covariates are retained in the models for consistency with the job-satisfaction models in Table 3.

a. Dissatisfaction with current job

Table 3 reports similar trends for individuals' (dis)satisfaction with current job. Having had publicly-funded vocational training is associated with holding more satisfactory jobs six years later, even more so than with private-funded training. Having benefited from publicly-provided health insurance has the same beneficial effect on holding more satisfactory jobs in the future. In this case, however, privately-provided insurance appears to render stronger benefits for workers' future career outcomes. Likewise, higher education and potential work experience (age-17) are associated with higher job satisfaction. This evidence jointly suggests that investments in workers' human capital have a strong return in terms of allowing workers to be matched to suitable jobs with decent working conditions.

Financial assistance (in the past or present) has little effect on workers' current job satisfaction, or is even associated with lower satisfaction. Workers' receiving pensions (in 2012) or Takaful (in 2018) are significantly more likely to report lower job satisfaction, perhaps reflecting a selection problem due to the work-related eligibility criteria for receiving these forms of assistance.

Importantly, these results remain unchanged when we control for workers' prior job satisfaction in the year 2012 (columns 5–6 in Table 3). Adding lagged dependent variable to a model is a very intrusive procedure that changes the interpretation of the model. The coefficients can be interpreted as contributions of the covariates to the transition of workers from their prior working conditions (non-satisfactory or rather-satisfactory) to their new working conditions, regardless of the level of the starting conditions. The advantage of this procedure is that it alleviates unobserved heterogeneity across workers with different historic or time-invariant profiles, and reduces potential selection biases. On the downside, this method typically reduces the explanatory power of contemporaneous covariates, because the level of the dependent variable is essentially controlled out.[6] Coefficients in columns 5–6, however, appear robust to the transformation, even though the two additional coefficients for the lagged job-satisfaction indicators (near bottom of Table 3) are highly significant. We conclude that our coefficients of interest are robust to the selection and unobserved-heterogeneity issues because of our inclusion of a high number of covariates, and our narrow delineation of the sample frame.

Figures 3 and 5 illustrate the effects of social assistance on workers' reported current job satisfaction. The propensity for job satisfaction increases with one's wealth, and with age.

[6] It could be controlled out perfectly in the case of first-differencing of the dependent variable.

Beneficiaries of publicly-funded vocational training (Figure 3 panel (i), and Figure 5) are significantly more likely to be fully satisfied with their current job than non-beneficiaries, and significantly less likely to be rather satisfied or not satisfied. The gap between beneficiaries and non-beneficiaries diminishes only gradually across wealth deciles, and is constant across ages. By contrast, recipients of financial assistance (Figure 3 panel (ii)) are less likely to be fully satisfied, as likely to be "rather satisfied," and more likely to be non-satisfied, equally across all wealth deciles.

The rest of rows in Table 3 show the role of workers' demographics with regard to their job satisfaction. Household wealth is associated with higher job satisfaction among workers, apparently by giving workers an outside option or an opportunity to search for better-fitting jobs. Urban residence (after controlling for governorate), marital status and household size have unclear effects on one's job satisfaction.

In what appears to be as puzzling as in the food-insecurity regressions, women hold better perceptions of their job satisfaction than men. An explanation for this lies in the women's (endogenous) self-selection into the labour force: most women remain in the labour force only if they hold formal public/private sector employment, and very few women retain informal/irregular positions, instead opting to remain out of the labour force. Because our sample is restricted to formally employed workers – for whom all covariates are surveyed – our models cannot comment on the working conditions in the labor force at large. To the extent that the two genders are represented differently in the irregular economy, and outside of the formal labor markets, the gap in working conditions may be greater, smaller or may even be upturned in the population at large. Moreover, men and women in our sample may not be entirely comparable to one another in their labor market position, despite all the covariates that we control for, so it would not be appropriate to extrapolate to average male and female workers.

Finally worth noting, the models presented in Tables 2 and 3 are highly significant according to multiple diagnostic tests including the joint coefficient significance F-tests on groups of variables, and the Wald chi-squared model tests. McFadden's pseudo R squared of 0.15–0.17 can be interpreted as 15–17% proportions of explained variation in the respective dependent variables, which is a decent measure of explained variation in logistic models on unit-record data.

IV. Conclusions

This study was motivated by the traditional dominance of financial transfers in Arab countries' social assistance policy, and the recent focus on transitioning away from general transfers toward social protection and labour market support, and their expansion and proper targeting. While financial handouts have been instrumental to reducing acute deprivation, there is a broad-based recognition that governments should adopt a graduation strategy that allows households to permanently transition out of deprivation, and that makes social assistance sustainable in the long term. Investing in workers' human capital should be integral to that strategy.

In light of these considerations, this study aimed to evaluate the performance of various support schemes on workers' long-term welfare. Since the questions regarding individuals' recipience of social assistance were asked only to wage workers in formal establishments, our choice of dependent and explanatory variables was limited to those varying among this group, in the formal wage worker subsample. We have chosen to assess individuals' perception of their food security and of job satisfaction as proxies for individuals' wellbeing and their labour market outcomes.

We have found that the ex-beneficiaries of publicly-funded vocation training and health insurance achieve a less precarious status in terms of food security and a higher job satisfaction than non-beneficiaries (training and insurance jointly significant). This result extended to other channels of advancement of workers' human capital including private-funded vocational training and health insurance, formal education, and work experience such as apprenticeships (El-Hamidi, 2006; Krafft, 2013). By contrast, recipients of financial assistance – either in the past or presently – are not necessarily better off than non-recipients. We interpret these findings as confirming that investments in human capital have a lasting positive impact on workers and their families. At the same time, financial transfers appear to have at most fleeting effects on welfare, perhaps because they may crowd out private investment in the commodities of interest, or because they pose a moral hazard of inducing some counteracting behavioral changes (particularly in the case of conditional transfers).

The policy advice is thus to support workers and residents – especially the socially vulnerable ones – by assisting them with increasing their human capital and other forms of intransient capabilities. These can empower workers and their families to improve their own condition across various socio-economic spheres, such as the job quality and nutrition evaluated in this study.

A further implication of these findings is that access to vocational training, health and social insurance, and other labour market assistance should be further developed and expanded in coverage to non-formally employed workers, to reduce the burden of economic informality and address the problem of the "missing middle" of the population that is excluded from narrowly targeted transfer programmes. This is important particularly today, as many informal workers and their families have lost their steady stream of earnings amid the COVID-19 pandemic[7]. Expansion of benefits should be synchronized with the eligibility criteria for social assistance to avoid the perpetuation of "missingness" and to avoid the moral hazard of individuals choosing their preferred type of misery in order to maximize their long-term welfare status. Broadly speaking, mutual compatibility of contributory and non-contributory social protection systems should be ensured.

[7] Krafft et al. (2021)

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Annex I

Table 1. Descriptive statistics of model variables

	N	Mean	St.Dev.	Min	Max
Dependent variables					
Food insecurity (Severe)	9,279	0.12*	0.43*	0	2
Food insecurity (Vulnerability/moderate)	9,329	0.25*	0.61*	0	2
Job satisfaction	9,329	1.24*	0.72*	0	2
Lagged dependent variables					
Job satisfaction ‘12: Non-satisfied	9,329	0.28	0.45	0	1
Job satisfaction ‘12: Rather satisfied	9,329	0.28	0.45	0	1
Lagged programme participation					
Vocational training (Publicly-funded) ‘12	9,329	0.05	0.21	0	1
Vocational training (Privately-funded) ‘12	9,329	0.05	0.23	0	1
Health insurance (Publicly-provided) ‘12	9,329	0.02	0.15	0	1
Health insurance (Privately-provided) ‘12	9,329	0.37	0.48	0	1
log(Pension) 2012	9,329	1.05	2.33	0	9.62
log(MOSS assistance) 2012	9,329	0.22	1.05	0	7.44
log(Nonprofit) 2012	9,329	0.03	0.41	0	7.09
Contemporaneous programme participation					
log(Takaful) 2018	9,329	0.29	1.29	0	7.08
log(Karama) 2018	9,329	0.10	0.79	0	8.52
log(Food Smart Card) 2018	9,309	4.21	1.96	0	7.82
log(Other assistance) 2018	9,323	0.16	0.97	0	7.60
Demographics					
Reads & writes	9,329	0.07	0.26	0	1
Less than intermediate edu.	9,329	0.13	0.33	0	1
Intermediate edu.	9,329	0.36	0.48	0	1
Above intermediate edu.	9,329	0.24	0.43	0	1
Age-17	9,329	24.30	9.02	2	42
Age-17 squared	9,329	671.71	459.73	4	1,764
Male	9,329	0.80	0.40	0	1
Wealth decile 2012	9,329	5.62	2.78	1	10
Married	9,329	0.86	0.35	0	1
Household size	9,329	4.43	1.31	1	6
Urban	9,329	0.42	0.49	0	1
Governorate	9,329	15.64*	8.03*	1	29

Source: Authors’ calculations based on ELMPS 2012 & 2018 (OAMDI, 2019), using individual-level weights.
* Ordinal categorical variables where the specific values are not used in models.

Table 2. Multinomial logit regressions of workers' food security, Egypt 2018

	Was there ever no food to eat of any kind in your HH?				Did you worry that your HH would not have food?			
	Model 1 (lagged assistance)		Model 2 (lagged+current)		Model 1 (lagged assist.)		Model 2 (lagged+current)	
	Rarely (1-2/mo)	Sometimes/ often (3+)	Rarely (1-2/mo)	Sometimes/ Often (3+)	Rarely (1-2/mo)	Sometimes/ Often (3+)	Rarely (1-2/mo)	Sometimes/ Often (3+)
Vocational Training	-0.215	-0.474	-0.230	-0.473	-0.061	-0.562	-0.063	-0.533
(Public) 2012	(0.360)	(0.490)	(0.365)	(0.497)	(0.345)	(0.355)	(0.328)	(0.346)
Health Insurance	-0.115	-0.717	-0.194	-0.723	0.038	-0.468*	0.017	-0.548*
(Public) 2012	(0.350)	(0.552)	(0.366)	(0.556)	(0.278)	(0.273)	(0.290)	(0.284)
log(Pension) 2012	-0.027	-0.060*	-0.029	-0.064**	-0.063***	-0.007	-0.064***	-0.013
	(0.029)	(0.032)	(0.028)	(0.032)	(0.022)	(0.020)	(0.023)	(0.020)
log(MOSS	0.084*	-0.015	0.083*	-0.016	0.055	0.057	0.050	0.034
Assistance) 2012	(0.045)	(0.049)	(0.045)	(0.051)	(0.045)	(0.035)	(0.045)	(0.038)
log(NGO	-0.102	-0.087	-0.112	-0.102	-0.040	0.066	-0.043	0.064
Asisstance) 2012	(0.165)	(0.137)	(0.167)	(0.140)	(0.132)	(0.087)	(0.131)	(0.086)
log(Takaful) 2018			0.015	0.050			0.104***	0.043
			(0.046)	(0.042)			(0.037)	(0.029)
log(Karama) 2018			-0.086	-0.143**			0.188***	0.093**
			(0.052)	(0.066)			(0.046)	(0.038)
log(Food Smart			-0.073*	-0.039			0.112***	0.085***
Card) 2018			(0.038)	(0.039)			(0.035)	(0.029)
log(Other			0.034	0.053			-0.001	0.168***
Assistance) 2018			(0.045)	(0.055)			(0.045)	(0.032)
Vocational Training	-0.062	0.191	-0.046	0.185	-0.191	-0.145	-0.266	-0.153
(Private) 2012	(0.349)	(0.420)	(0.350)	(0.420)	(0.271)	(0.241)	(0.281)	(0.240)
Health Insurance	-0.082	-0.138	-0.081	-0.120	-0.390***	-0.303**	-0.340**	-0.271*
(Private) 2012	(0.195)	(0.223)	(0.195)	(0.223)	(0.139)	(0.141)	(0.141)	(0.142)
Reads & Writes	-0.251	-0.639**	-0.246	-0.664**	-0.013	-0.243	0.012	-0.204
	(0.257)	(0.281)	(0.259)	(0.285)	(0.202)	(0.180)	(0.203)	(0.184)
Less than Intermed.	-0.063	-0.345	-0.067	-0.345	-0.165	-0.329**	-0.108	-0.298*
	(0.226)	(0.214)	(0.231)	(0.217)	(0.170)	(0.155)	(0.170)	(0.156)
Intermed. Edu.	-0.383**	-1.116***	-0.388**	-1.113***	-0.384***	-0.700***	-0.319**	-0.642***
	(0.177)	(0.181)	(0.181)	(0.182)	(0.141)	(0.134)	(0.140)	(0.135)
Above Interm. Edu.	-1.049***	-1.299***	-1.054***	-1.301***	-0.676***	-1.434***	-0.577***	-1.371***
	(0.246)	(0.274)	(0.251)	(0.276)	(0.205)	(0.212)	(0.205)	(0.215)
Age-17	0.015	-0.013	0.017	-0.015	-0.027	0.011	-0.041	0.004
	(0.041)	(0.042)	(0.041)	(0.043)	(0.031)	(0.029)	(0.031)	(0.030)
Age-17 squared	-0.000	-0.000	-0.000	0.000	0.001	-0.000	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Urban	0.214	-0.345**	0.212	-0.341*	-0.034	-0.081	0.009	-0.056
	(0.167)	(0.174)	(0.167)	(0.175)	(0.119)	(0.116)	(0.119)	(0.117)
Male	0.085	0.179	0.073	0.169	0.028	0.236*	0.061	0.257*
	(0.178)	(0.197)	(0.178)	(0.197)	(0.138)	(0.141)	(0.140)	(0.142)
Wealth decile (1	-0.129***	-0.147***	-0.132***	-0.146***	-0.085***	-0.119***	-0.082***	-0.113***
Lowest, 5 Top) '12	(0.033)	(0.031)	(0.033)	(0.031)	(0.023)	(0.024)	(0.023)	(0.024)
Married	0.059	-0.077	0.025	-0.083	0.048	-0.106	0.084	0.031
	(0.208)	(0.229)	(0.212)	(0.229)	(0.160)	(0.148)	(0.165)	(0.147)
Household size	0.125**	0.102*	0.156***	0.122**	0.121***	0.186***	0.062	0.145***
	(0.051)	(0.054)	(0.053)	(0.057)	(0.042)	(0.037)	(0.044)	(0.039)
Governorate Indictrs	Y***	Y***	Y***	Y***	Y***	Y***	Y***	Y***
Constant	-4.584***	-3.245***	-4.442***	-3.177***	-2.096***	-2.356***	-2.315***	-2.658***
	(0.743)	(0.832)	(0.748)	(0.827)	(0.484)	(0.446)	(0.509)	(0.459)
Observations	9,279	9,279	9,242	9,242	9,329	9,329	9,292	9,292

Chi-squared	45,306***	45,306***	42,363***	42,363***	23,049***	23,049***	23,443***	23,443***
Pseudo R-squared	0.162	0.162	0.165	0.165	0.154	0.154	0.165	0.165

Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019). Samples weighted using individual-level weights. Standard errors robust to heteroskedasticity in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Baseline category "Never experienced."

Table 3. Multinomial logit regressions of workers' job satisfaction, Egypt 2018

	Model 1 (lagged assistance)		Model 2 (lagged+current assist.)		Model 3 (lagged+current assist. and lagged dep.var.)	
	Not rather satisf. or fully satisf.	Rather satisfied	Not rather satisf. or fully satisf.	Rather satisfied	Not rather satisf. or fully satisf.	Rather satisfied
Vocational Training	-0.258	-0.294*	-0.263	-0.301*	-0.266	-0.299*
(Public) 2012	(0.285)	(0.162)	(0.284)	(0.162)	(0.284)	(0.162)
Health Insurance	-0.416*	-0.505**	-0.383	-0.498**	-0.357	-0.475**
(Public) 2012	(0.247)	(0.239)	(0.247)	(0.239)	(0.247)	(0.238)
log(Pension) 2012	0.036*	0.060***	0.038**	0.060***	0.033*	0.057***
	(0.019)	(0.016)	(0.019)	(0.015)	(0.019)	(0.015)
log(MOSS	0.034	0.030	0.031	0.028	0.039	0.034
Assistance) 2012	(0.033)	(0.030)	(0.033)	(0.030)	(0.033)	(0.030)
log(NGO	-0.001	-0.038	-0.003	-0.040	-0.003	-0.041
Asisstance) 2012	(0.082)	(0.083)	(0.083)	(0.082)	(0.082)	(0.083)
log(Takaful) 2018			0.052*	0.042	0.054*	0.044
			(0.031)	(0.027)	(0.031)	(0.027)
log(Karama) 2018			0.033	0.009	0.029	0.006
			(0.039)	(0.038)	(0.039)	(0.038)
log(Food Smart			-0.064***	0.002	-0.064***	0.001
Card) 2018			(0.023)	(0.021)	(0.023)	(0.021)
log(Other			0.015	-0.010	0.010	-0.012
Assistance) 2018			(0.037)	(0.036)	(0.038)	(0.036)
Vocational Training	-0.126	-0.029	-0.130	-0.032	-0.124	-0.024
(Private) 2012	(0.236)	(0.149)	(0.236)	(0.150)	(0.235)	(0.151)
Health Insurance	-1.807***	-0.768***	-1.795***	-0.754***	-1.690***	-0.684***
(Private) 2012	(0.118)	(0.081)	(0.118)	(0.082)	(0.121)	(0.084)
Reads & Writes	-0.630***	-0.356**	-0.619***	-0.353**	-0.645***	-0.373**
	(0.175)	(0.155)	(0.175)	(0.156)	(0.175)	(0.154)
Less than Intermed.	-0.433***	-0.346**	-0.429***	-0.339**	-0.451***	-0.354**
	(0.149)	(0.138)	(0.149)	(0.139)	(0.151)	(0.139)
Intermed. Edu.	-0.547***	-0.420***	-0.525***	-0.412***	-0.560***	-0.434***
	(0.124)	(0.109)	(0.125)	(0.110)	(0.126)	(0.111)
Above Interm. Edu.	-1.388***	-0.896***	-1.375***	-0.883***	-1.411***	-0.903***
	(0.163)	(0.129)	(0.164)	(0.130)	(0.165)	(0.131)
Age-17	-0.147***	-0.106***	-0.144***	-0.108***	-0.144***	-0.108***
	(0.025)	(0.023)	(0.025)	(0.023)	(0.025)	(0.023)
Age-17 squared	0.002***	0.001***	0.002***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Urban	-0.008	0.059	-0.014	0.067	-0.009	0.069
	(0.098)	(0.081)	(0.099)	(0.082)	(0.099)	(0.082)
Male	-1.200***	0.446***	-1.211***	0.447***	-1.262***	0.420***
	(0.103)	(0.096)	(0.104)	(0.096)	(0.104)	(0.096)
Wealth decile (1	-0.056***	-0.029*	-0.052***	-0.028*	-0.041**	-0.021
Lowest, 5 Top) '12	(0.019)	(0.016)	(0.019)	(0.016)	(0.019)	(0.016)
Married	-0.182	0.197*	-0.217*	0.199*	-0.219*	0.194
	(0.129)	(0.118)	(0.130)	(0.121)	(0.131)	(0.121)
Household size	0.019	0.027	0.036	0.025	0.037	0.026
	(0.033)	(0.029)	(0.034)	(0.030)	(0.034)	(0.029)
Non-satisfied with					0.505***	0.325***
job '12					(0.104)	(0.089)

Rather satisfied with job ‘12					0.283***	0.193**
					(0.103)	(0.085)
Governorate Indictrs	Y***	Y***	Y***	Y***	Y***	Y***
Constant	2.440***	1.950***	2.528***	1.941***	2.176***	1.723***
	(0.366)	(0.310)	(0.369)	(0.312)	(0.378)	(0.318)
Observations	9,333	9,333	9,296	9,296	9,296	9,296
Chi-squared	1,486***	1,486***	1,506***	1,506***	1,528***	1,528***
Pseudo R-squared	0.150	0.150	0.151	0.151	0.153	0.153

Notes: Authors’ calculations based on ELMPS 2012 & 2018 (OAMDI, 2019). Samples weighted using individual-level weights. Standard errors robust to heteroskedasticity in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Baseline category “Fully satisfied.”

Table 4. Governorate-level effects from regressions in Tables 2 and 3

	Was there ever no food to eat of any kind in your HH?				Did you worry that your HH would not have food?				Are you satisfied with your current job?			
	Model 1		Model 2		Model 1		Model 2		Model 1		Model 2	
	Rarely	Sometimes/oft	Rarely	Sometimes/oft	Rarely	Sometimes/oft	Rarely	Sometimes/oft	Not	Rather	Not	Rather
Alex.	1.609**	2.732***	1.522**	2.691***	1.147***	1.529***	1.326***	1.691***	1.737***	1.039***	1.726***	1.056***
	(0.676)	(0.760)	(0.676)	(0.754)	(0.305)	(0.319)	(0.305)	(0.328)	(0.256)	(0.206)	(0.258)	(0.207)
Port-Said	1.123	-20.687***	1.170	-20.659***	-0.974	-20.252***	-1.015	-20.602***	-0.104	-0.207	-0.121	-0.215
	(1.178)	(0.726)	(1.177)	(0.729)	(1.025)	(0.316)	(1.029)	(0.324)	(0.421)	(0.306)	(0.417)	(0.306)
Suez	-21.507***	-21.027***	-21.526***	-21.025***	0.087	2.749***	0.100	2.771***	-0.014	0.754*	-0.024	0.763*
	(0.659)	(0.789)	(0.682)	(0.796)	(0.659)	(0.430)	(0.660)	(0.431)	(0.523)	(0.436)	(0.533)	(0.437)
Damietta	2.581***	1.483*	2.585***	1.497*	1.000***	0.077	1.070***	0.123	1.295***	1.990***	1.334***	2.001***
	(0.641)	(0.818)	(0.640)	(0.820)	(0.298)	(0.414)	(0.296)	(0.421)	(0.334)	(0.231)	(0.333)	(0.231)
Dakahlia	3.123***	3.569***	3.185***	3.596***	1.285***	2.055***	1.281***	2.045***	1.281***	1.171***	1.355***	1.192***
	(0.619)	(0.727)	(0.616)	(0.732)	(0.286)	(0.304)	(0.284)	(0.312)	(0.246)	(0.172)	(0.244)	(0.174)
Sharkia	1.101	-1.135	1.158*	-1.094	-0.084	-0.450	-0.053	-0.441	0.848***	0.722***	0.939***	0.740***
	(0.688)	(1.061)	(0.684)	(1.064)	(0.329)	(0.405)	(0.326)	(0.413)	(0.250)	(0.175)	(0.247)	(0.176)
Kalyoubia	1.905***	0.287	1.841***	0.284	0.315	-0.735*	0.443	-0.574	1.401***	1.158***	1.354***	1.181***
	(0.653)	(0.880)	(0.662)	(0.874)	(0.307)	(0.429)	(0.314)	(0.438)	(0.263)	(0.194)	(0.269)	(0.195)
Kafr-	1.394**	-0.948	1.454**	-0.933	-0.372	-3.657***	-0.447	-3.761***	0.086	0.066	0.129	0.067
Elsheikh	(0.677)	(1.020)	(0.673)	(1.024)	(0.332)	(1.043)	(0.332)	(1.043)	(0.267)	(0.171)	(0.266)	(0.173)
Gharbia	2.441***	2.998***	2.521***	3.052***	0.250	0.996***	0.219	0.999***	0.156	0.641***	0.235	0.652***
	(0.630)	(0.734)	(0.626)	(0.740)	(0.311)	(0.321)	(0.308)	(0.328)	(0.264)	(0.170)	(0.262)	(0.171)
Menoufia	2.112***	1.735**	2.174***	1.772**	1.223***	1.590***	1.235***	1.629***	0.907***	0.585***	0.988***	0.607***
	(0.672)	(0.782)	(0.671)	(0.787)	(0.304)	(0.342)	(0.302)	(0.349)	(0.267)	(0.199)	(0.265)	(0.200)
Behera	-0.822	-2.648**	-0.800	-2.644**	-4.084***	-3.654***	-4.075***	-3.658***	0.643***	0.394**	0.705***	0.405**
	(0.923)	(1.239)	(0.920)	(1.241)	(1.042)	(0.786)	(1.042)	(0.789)	(0.242)	(0.172)	(0.240)	(0.173)
Ismailia	1.403**	0.684	1.409**	0.709	0.451	1.893***	0.556*	1.996***	-0.741***	-0.351*	-0.671**	-0.311*
	(0.673)	(0.836)	(0.674)	(0.838)	(0.316)	(0.315)	(0.314)	(0.323)	(0.287)	(0.185)	(0.288)	(0.185)
Giza	1.046	0.025	1.056	0.014	-0.482	-0.235	-0.489	-0.198	1.268***	1.057***	1.284***	1.058***
	(0.880)	(0.955)	(0.880)	(0.958)	(0.416)	(0.413)	(0.411)	(0.419)	(0.269)	(0.200)	(0.268)	(0.199)
Beni-Suef	1.097*	1.039	1.158*	1.051	-0.652*	-0.535	-0.868**	-0.588	0.236	0.563***	0.240	0.539***
	(0.665)	(0.762)	(0.662)	(0.768)	(0.333)	(0.364)	(0.347)	(0.371)	(0.267)	(0.178)	(0.268)	(0.179)
Fayoum	2.221***	1.747**	2.279***	1.790**	0.873***	1.068***	0.809***	0.962***	-0.396	0.092	-0.314	0.116
	(0.635)	(0.788)	(0.629)	(0.790)	(0.294)	(0.340)	(0.292)	(0.345)	(0.281)	(0.187)	(0.283)	(0.191)
Menia	1.689**	1.694**	1.709***	1.635**	0.124	1.385***	-0.025	1.294***	-0.101	0.116	-0.196	0.062
	(0.657)	(0.754)	(0.659)	(0.754)	(0.328)	(0.315)	(0.335)	(0.320)	(0.270)	(0.173)	(0.270)	(0.174)
Asyout	1.515**	1.400*	1.539**	1.382*	0.673**	0.645*	0.586*	0.621*	-0.015	0.112	-0.064	0.072
	(0.652)	(0.817)	(0.649)	(0.824)	(0.320)	(0.330)	(0.324)	(0.337)	(0.281)	(0.175)	(0.282)	(0.176)
Suhag	1.786***	1.721**	1.897***	1.843**	0.117	0.486	-0.095	0.429	0.861***	0.574***	0.880***	0.569***
	(0.662)	(0.753)	(0.657)	(0.757)	(0.319)	(0.335)	(0.322)	(0.342)	(0.243)	(0.176)	(0.242)	(0.178)
Qena	2.426***	1.946**	2.496***	1.985***	1.280***	2.261***	1.135***	2.176***	0.926***	-0.026	0.902***	-0.040
	(0.628)	(0.764)	(0.625)	(0.768)	(0.297)	(0.311)	(0.296)	(0.317)	(0.247)	(0.185)	(0.245)	(0.186)
Aswan	0.124	0.448	0.058	0.408	-0.799*	-0.580	-0.744	-0.494	0.930***	-0.147	0.918***	-0.141
	(0.842)	(0.840)	(0.844)	(0.837)	(0.472)	(0.420)	(0.475)	(0.430)	(0.251)	(0.202)	(0.253)	(0.202)
Luxur	-21.524***	-21.477***	-21.451***	-21.428***	0.390	1.033	0.143	0.955	0.217	-0.370	0.119	-0.420
	(0.633)	(0.748)	(0.633)	(0.760)	(0.653)	(0.631)	(0.681)	(0.649)	(0.470)	(0.367)	(0.473)	(0.369)

Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019). Samples weighted using individual-level weights. Standard errors robust to heteroskedasticity in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Baseline category "Fully satisfied."

Table 5. Descriptive statistics of workers' demographics by their outcomes

Did you worry about food?	Never	Rarely	Sometimes/Often
Intermediate edu.	.365 (.482)	.335 (.472)	.335 (.472)
Above intermediate edu.	.273 (.445)	.136 (.344)	.078 (.268)
Female	.210 (.407)	.175 (.380)	.144 (.352)
Urban	.439 (.496)	.356 (.479)	.309 (.462)
Wealth score '12	.068 (.885)	-.269 (.704)	-.419 (.717)
Wealth score '18	.121 (1.008)	-.340 (0.686)	-.482 (.607)
Monthly wage (all jobs) '12	1,131 (1,199)	911 (645)	988 (1,104)
Monthly wage (all jobs) '18	3,031 (7,856)	2,313 (3,113)	2,176 (3,523)

Was there ever no food?	Never	Rarely	Sometimes/Often
Intermediate edu.	.365 (.481)	.356 (.479)	.247 (.432)
Above intermediate edu.	.259 (.438)	.086 (.280)	.089 (.285)
Female	.204 (.403)	.164 (.371)	.164 (.370)
Urban	.434 (.496)	.308 (.462)	.250 (.434)
Wealth score '12	.035 (.879)	-.398 (.723)	-.422 (.658)
Wealth score '18	.078 (.995)	-.437 (.575)	-.544 (.536)
Monthly wage (all jobs) '12	1,118 (1,187)	970 (854)	884 (765)
Monthly wage (all jobs) '18	2,892 (5,887)	3,984 (22,740)	1,848 (1,399)

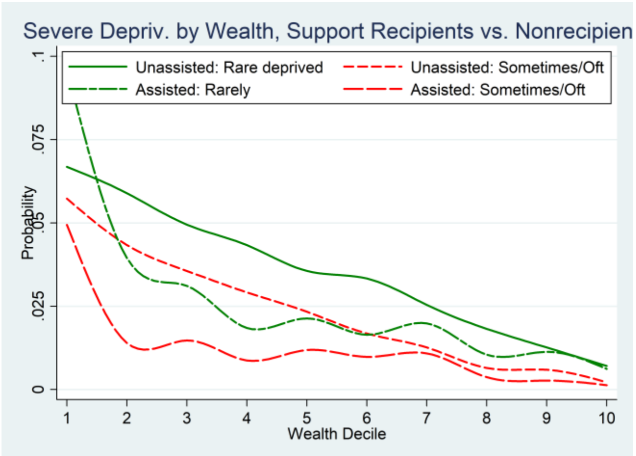
How satisfied with your job?	Fully satisfied	Rather satisfied	Non-satisfied
Intermediate edu.	.345 (.475)	.380 (.485)	.352 (.478)
Above intermediate edu.	.387 (.487)	.194 (.396)	.121 (.326)
Female	.219 (.413)	.110 (.313)	.321 (.467)
Urban	.485 (.500)	.391 (.488)	.378 (.485)
Wealth score '12	.257 (.951)	-.097 (.779)	-.218 (.805)
Wealth score '18	.376 (1.127)	-.092 (.854)	-.266 (.766)
Monthly wage (all jobs) '12	1,267 (1,408)	1,024 (986)	946 (891)
Monthly wage (all jobs) '18	3,300 (4,752)	2,813 (9,841)	2,065 (2,790)

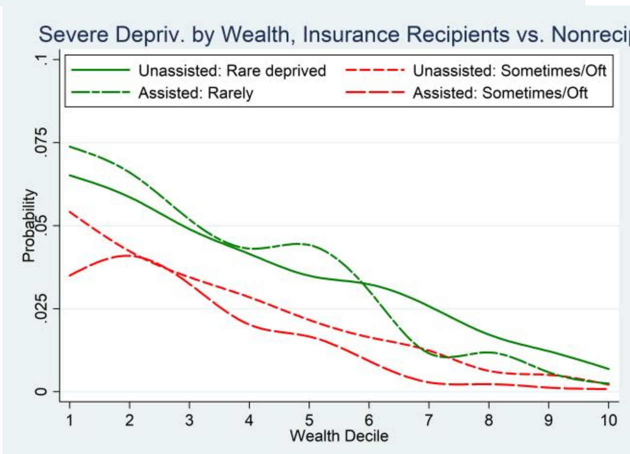
Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019). Samples weighted using individual-level weights.

Figure 1. "In the past 4 weeks, was there ever no food to eat of any kind in your HH?"
Predicted probability of degree of food deprivation, by wealth decile

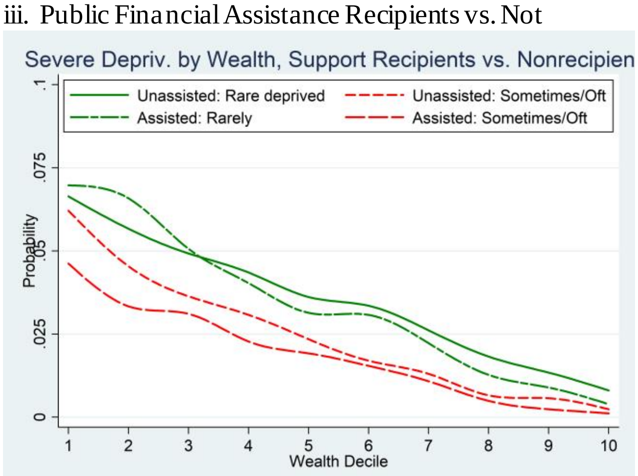
i. Public Vocational Training Recipients vs. Not

ii. Public Health Insurance Beneficiaries vs. Not





iii. Public Financial Assistance Recipients vs. Not

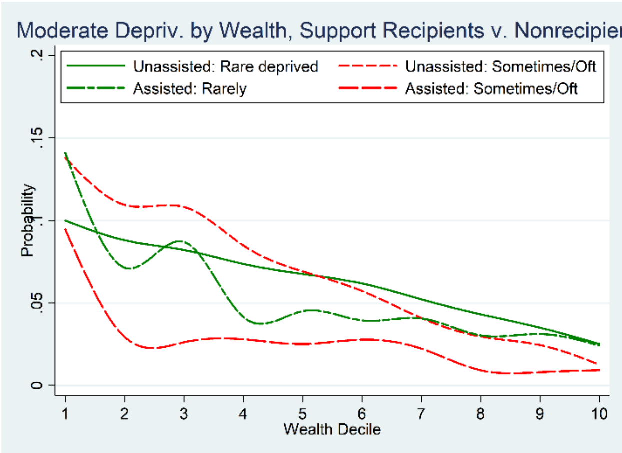


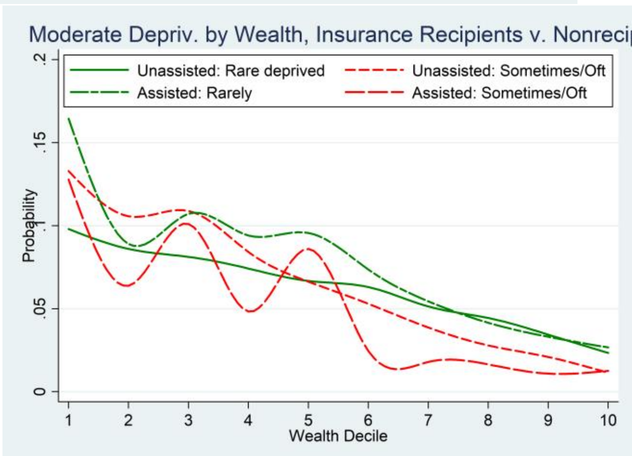
Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019).
Predicted probabilities from Model 2. Model 1 results near identical.

Figure 2. "In the past 4 weeks, did you worry that your HH would not have any food?"
Predicted probability of degree of food deprivation, by wealth decile

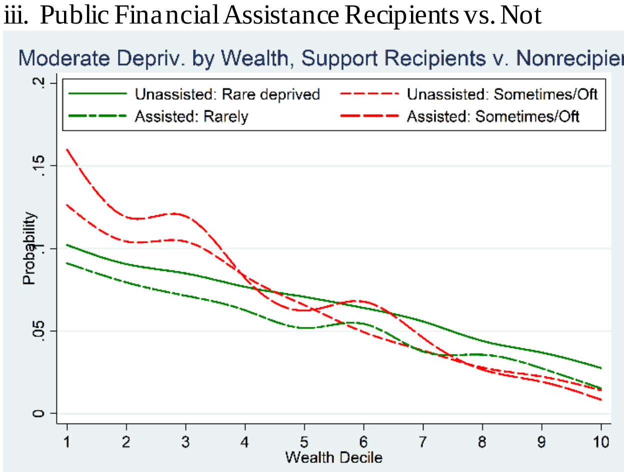
i. Public Vocational Training Recipients vs. Not

ii. Public Health Insurance Beneficiaries vs. Not





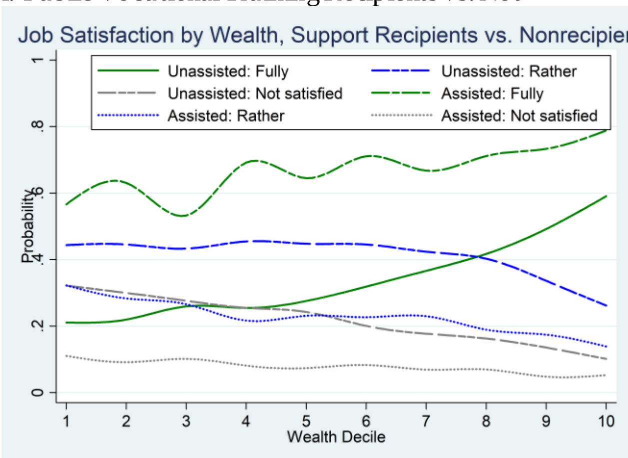
iii. Public Financial Assistance Recipients vs. Not



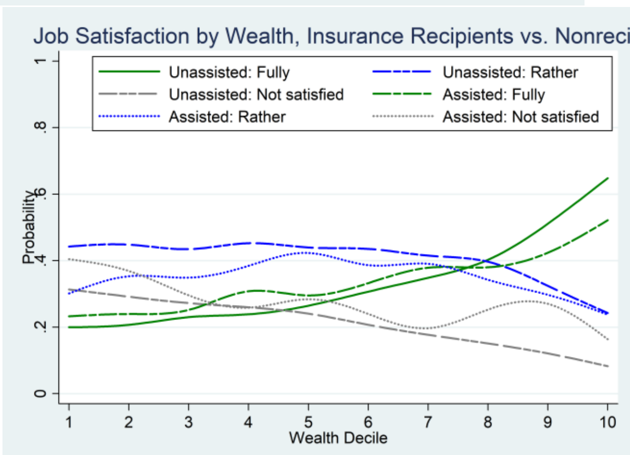
Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019).
Predicted probabilities from Model 2. Model 1 results near identical.

Figure 3. "How satisfied are you with your current job?" Predicted probability of degree of satisfaction, by wealth decile

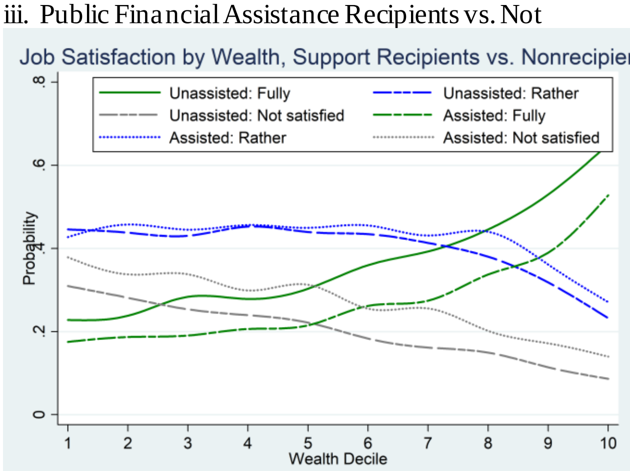
i. Public Vocational Training Recipients vs. Not



ii. Public Health Insurance Beneficiaries vs. Not



iii. Public Financial Assistance Recipients vs. Not

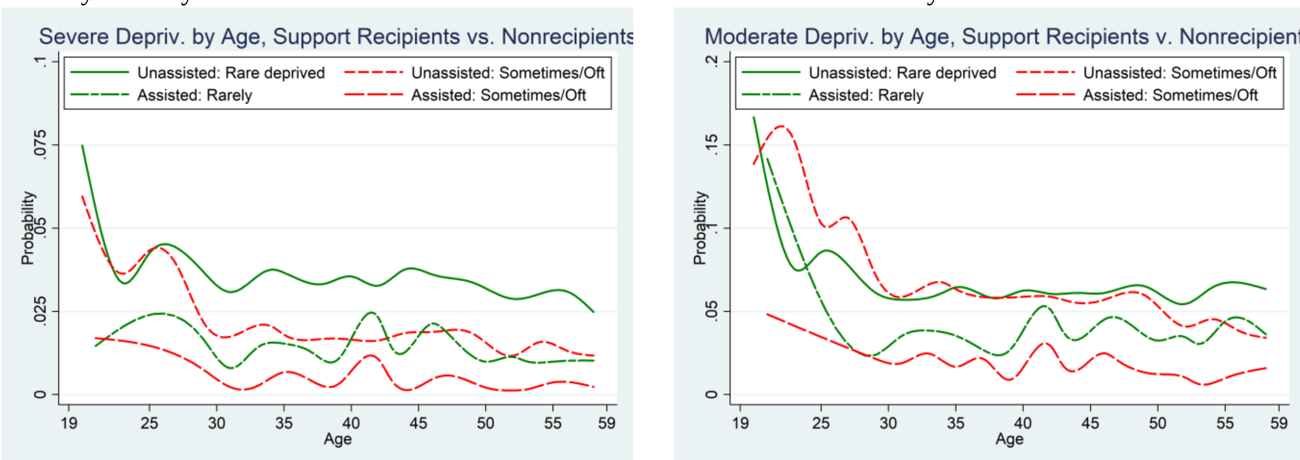


Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019).
Predicted probabilities from Model 3. Model 1 results near identical.

Figure 4. "In the past 4 weeks, was there ever no food to eat of any kind in your HH?"
Predicted probability of degree of food deprivation, 2012 public vocational training recipients vs. not, by age

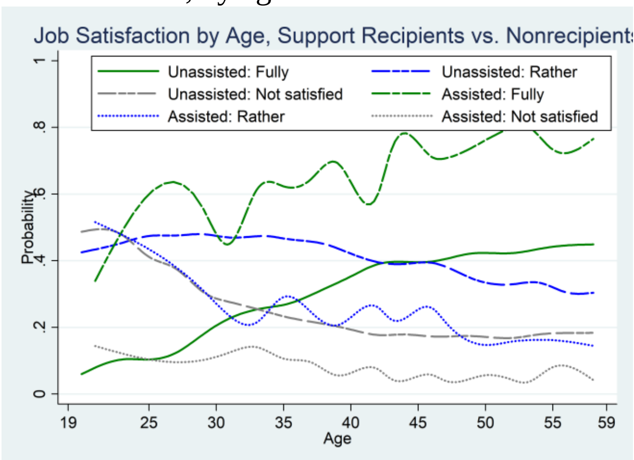
i. In the past 4 weeks, was there ever no food to eat of any kind in your HH?

ii. In the past 4 weeks, did you worry that your HH would not have any food?



Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019).
Predicted probabilities from Model 2. Model 1 results near identical.

Figure 5. "How satisfied are you with your current job?"
Predicted probability of degree of satisfaction, 2012 public vocational training recipients vs. not, by age



Notes: Authors' calculations based on ELMPS 2012 & 2018 (OAMDI, 2019).
Predicted probabilities from Model 2. Model 1 results near identical.