# The Role of Cash Transfers in Smoothing the Income Shock of COVID-19 in the Arab Republic of Egypt

Romeo Gansey Maria Eugenia Genoni Imane Helmy



# Abstract

The COVID-19 pandemic impacted the Arab Republic of Egypt's economy and its people in many ways. By combining micro-simulations and imputation techniques, this paper models early impacts of the pandemic on household income and the role of cash transfers from the Government of Egypt in supporting households and workers. As expected, and consistent with other evidence, the estimates show that the pandemic shock decreased labor incomes and increased income poverty in Egypt. It was estimated that in fiscal year 2020, average household income per capita contracted by about 1.7 percent, and income poverty was about 2.2 percentage points higher, compared to a non-COVID-19 scenario for the same year, using the international poverty line of \$3.65 a day (2017 purchasing power parity). Labor income losses were widespread across the country, disproportionately affecting informal workers. The results also suggest that expanded social protection cash transfers and targeted cash assistance to Egypt's informal and tourism sectors played a substantial role in smoothing the initial labor income shock. In the absence of compensatory cash transfers, income poverty would have been 1.1 percentage points higher. The compensatory measures, in particular the cash transfer programs Takaful and Karama, preferentially protected rural households due to the programs' targeting rules. Thus, households in urban areas were significantly more likely to become income poor, compared to those in rural settings.

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# The Role of Cash Transfers in Smoothing the Income Shock of COVID-19 in the Arab Republic of Egypt<sup>1</sup>

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#### 1. Introduction

The COVID-19 pandemic has impacted the Arab Republic of Egypt's economy and the welfare of its people in many ways. Figure 1 shows that COVID-19 may have impacted welfare (monetary and non-monetary) through different channels, including changes in labor income, non-labor income sources, direct effects on consumption, and losses associated with service disruptions. The aim of this paper is to shed light on the following questions: (i) What were the early impacts of COVID-19 on household income and income poverty due to indirect employment and earnings losses? and (ii) What was the role of key fiscal measures, in particular targeted cash transfers, in minimizing the immediate negative income consequences of the crisis?

Due to limited data post-COVID, this paper combines micro-simulations and imputation techniques to create counterfactual household income distributions to assess the labor market impacts of COVID-19 in fiscal year 2020 (FY20). In addition, the analysis builds on an existing fiscal incidence model mapping taxes and transfers to the household income distribution to evaluate how the expansion of cash transfers via the Takaful and Karama social protection programs<sup>2</sup> and targeted transfers to workers in the informal and tourism sectors helped smooth negative income effects several months after the pandemic hit.<sup>3</sup>

The analysis contributes to a growing body of literature documenting the implications of the COVID-19 pandemic across countries. While the negative consequences for households and firms have been more extensively documented,<sup>4</sup> there is limited evidence on the role that government compensatory measures had in smoothing the shock. The results presented here aim to shed light on this question for Egypt by estimating the extent to which cash transfers were able to compensate for the immediate income losses associated with the pandemic.

The results confirm existing evidence of a large income shock due to the pandemic, particularly for urban households and those engaged in the informal sector. The analysis points to an average contraction in household income per capita of about 1.7 percent, driven by the poorest 50 percent of Egypt's urban households. The findings highlight the value of the cash transfers, especially via the Takaful and Karama programs, in partly compensating for those losses and limiting poverty increases in rural areas to modest levels, at least at the onset of the crisis. The importance of the Takaful and Karama transfers as compensatory measures results from the size of the transfer, compared to other measures, but also from the targeting rules that help reach relatively poorer households.<sup>5</sup> The patterns

<sup>&</sup>lt;sup>2</sup> Takaful and Karama (TKP) consist of conditional and unconditional cash transfers providing cash benefits, with the conditions being tied to health and education behaviors of recipients. The programs provide income support to households with children under 18 years of age (Takaful), and to the elderly poor, orphans, widows, and people living with disabilities (PWD) (Karama). The Takaful and Karama program and the social solidarity pension (Daman) are the primary cash transfer programs active in Egypt (World Bank 2022a).

<sup>&</sup>lt;sup>3</sup> Price changes are captured via changes in the Consumer Price Index. However, we do not explicitly model impacts on consumer behavior.

<sup>&</sup>lt;sup>4</sup> See Assaad and Krafft (2015); Breisinger et al. (2020a, 2020b); Buheji et al. (2020); Djankov and Panizza (2020); Eldeep and Zaki (2022).

<sup>&</sup>lt;sup>5</sup> Recent evidence shows that, notwithstanding strong targeting performance, exclusion errors remain, due to the size of the program relative to the poverty rate and because of errors inherent to the use of proxy means testing (PMT) in

also point to a challenge for the traditional targeting approach in periods of crisis or shocks. As the Takaful and Karama targeting rules focus on the poorest regions (more rural) and use a proxy-meanstesting (PMT) model (better to proxy chronic poverty), the program's expansion benefited rural households relatively more. This highlights the importance going forward of revising mechanisms to better identify households impacted by shocks, which may not necessarily be eligible for support under traditional targeting algorithms.

The next section of the paper provides context and describes the actions of the Government of Egypt (GoE) after the pandemic hit. The ensuing third section discusses methodology. The fourth section presents main findings. The final section concludes.



Figure 1: Channels of COVID-19 impact on welfare (monetary and non-monetary)

Note: Channels analyzed in this paper highlighted in green.

# 2. Pre-COVID context and government measures

The pandemic struck Egypt during a period of macroeconomic stability and economic growth, albeit marked by challenges for private-sector-led investment and growth. With the 2016 structural reform program, the country evidenced an improvement in the budget deficit and fiscal consolidation. Additionally, Egypt's foreign reserves account improved due to remittance and portfolio inflows, foreign borrowing, petroleum exports, and tourism revenues (Alnashar et al. 2020). Tourism, real estate, non-oil manufacturing, and the information and communication sectors saw a surge in their contributions to GDP before the pandemic. Nevertheless, the private sector still experienced limited growth compared to the public sector, hindering investment and job creation in productive activities (World Bank 2022b).

targeting practices. While about 30 percent of Egyptian households are poor, the program covers only 15 percent of the population (World Bank 2022a).

Before the pandemic hit, the labor market in Egypt faced persistent challenges. While Egypt's GDP growth reached 5.6 percent in 2019, labor force participation continued to decline. This partly reflected challenges in absorbing the sustained growth in the country's working-age population. Egypt's unemployment rate was high, particularly for women, youth, and the most highly educated, signaling a difficulty in transitioning from school to work and in integrating women into the labor market. Furthermore, informality was high and increasing, reflecting the need to improve the quality of jobs. Jobs with no social security rose to encompass 67 percent of all jobs in 2018, up from 57 percent in 2010. These trends reflected difficulties from the demand side of the labor market, where the most productive sectors were not the most important in creating jobs. Pre-COVID labor market trends pointed to the importance of accelerating private sector job creation. While about 78 percent of jobs in Egypt were in the private sector, this share remained well below the global average of 90 percent, and about 3 in 4 private sector workers in Egypt were engaged in informal, low-quality activities characterized by low productivity and low pay (Cortes et al. 2022).

The COVID-19 pandemic exerted its greatest impact on Egypt during the final quarter of FY20, with the declaration of a national public health emergency in mid-March 2020. That quarter overlapped with the main lockdown implemented by the GoE. Mobility trends show how activity fell during the last quarter of FY20 and subsequently in workplaces, transit stations, and areas related to retail and trade. Mobility and economic activity started to recover during FY21 (Figure 2).





**Source:** Authors' calculations based on Google COVID-19 Community Mobility Trends (as of March 2022).

Following its mid-March 2020 emergency declaration, the GoE undertook immediate precautionary measures aimed to contain the spread of the virus and prevent and mitigate crisis impacts. Measures implemented included nighttime curfews, restrictions on gatherings and domestic and international travel, and decrees facilitating home-based work for civil servants. Educational institutions, including schools and universities, were closed, as were religious establishments. Sports and recreational activities were also suspended, and restaurants were shut. Businesses and shops were required to close by 5 p.m., in line with the national curfew, and were fully shuttered on weekends. Some villages and cities with a high number of COVID-19 cases were completely isolated. A national campaign for

the sterilization of key facilities was launched, in addition to a public campaign to raise awareness of the virus (IDSC 2020).

A gradual reopening of the economy supported partially resuming economic activities. In May 2020, the GoE announced a three-stage plan in preparation for the gradual return of economic activities. Hotels were allowed to operate at 25 percent capacity until June 2020 and at 50 percent capacity thereafter. A shorter nighttime curfew, restarting air travel, and re-opening restaurants at 25 percent capacity allowed for partially resuming activities while maintaining intensive risk-mitigation measures, including social distancing and mandatory mask wearing in public places (IDSC 2020).

To respond to the economic impacts of the crisis, the GoE also undertook a wide range of immediate and short-term measures.<sup>6</sup> The government deployed cash transfers as an important compensatory strategy. First, existing cash transfer program coverage was expanded. The flagship Takaful and Karama programs (see footnote 2) added 411,000 beneficiaries, an expansion equivalent to about 13 percent of their total beneficiary base in FY19.

Second, additional targeted cash transfers were deployed to workers in the tourism and informal sectors. The government distributed emergency cash support totaling EGP 4.6 billion to about 1.6 million informal workers. By the end of FY20, around EGP 200 million were disbursed to 200,000 workers in 3,237 establishments in the tourism sector, from a total of 3,800 such establishments.<sup>7</sup> Cash transfer support totaling EGP 17 million was provided to 9,000 touristic guides, and contributory pensions were increased by 14 percent. This set of measures is analyzed in the following pages.

<sup>&</sup>lt;sup>6</sup> In March 2020, a stimulus package of USD 6.13 billion (EGP 100 billion or 1.8 percent of GDP) was allocated to mitigate the impacts of COVID-19. Almost half of this package was directed to support the tourism sector, which comprised around 12 percent of GDP before the crisis. EGP 300 million were allocated to the construction sector, which employs a large share of informal workers. The government also provided preferential interest rates on loans, offered reduced energy costs, and provided loans with longer grace periods to the tourism, industry, agriculture, construction, and aviation sectors. EGP 5 billion flowed to the health care sector to fund medical equipment and supplies and offer bonuses to medical staff. Tax exemption limits increased from EGP 8,000 to EGP 15,000. In addition, a consumer spending initiative of EGP 10 billion was launched to provide citizens with low-interest loans over two years to pay for discounted consumer goods. The Central Bank of Egypt (CBE) also implemented a series of monetary easing actions. First, the CBE cut interest rates by 300 basis points. Second, it issued multiple decrees to facilitate automated teller machine (ATM) withdrawals and digital payments through mobiles and e-wallets by raising limits on cash withdrawals and waiving transaction fees. The cost of the response package was large, and a special Corona tax was introduced to finance the compensatory measures. The support provided to different sectors was mostly financed by Corona taxes of 1 percent on public and private sector salaries and 0.5 percent on pensioners (IMF 2022; Ministry of Planning and Economic Development 2022).

<sup>&</sup>lt;sup>7</sup> An emergency fund at the Ministry of Manpower issued salary payments for workers in impacted establishments (mostly in the tourism sector).

#### 3. Methodology

#### Constructing a non-COVID counterfactual household income distribution for FY20

The first part of the estimation strategy adopted in this paper aims to generate an updated baseline household income distribution for FY20, in the absence of the COVID-19 shock. The starting point is Egypt's Household Expenditure and Income Survey (HIECS) 2017/18, which collected information about households' incomes and consumption and is the official data source for poverty estimation. The survey is representative of the Egyptian population, and data were collected over a full year to capture seasonality in income patterns. The survey covers three quarters of FY18; data collection started in Q2 of 2017 and was completed in Q3 of 2018. For this analysis, we treat this baseline information as FY18.

To create a counterfactual income distribution for FY20, we start from the observed trends provided by the Labor Force Survey (LFS) for the period 2017 to June 2020. We take the trends in labor force participation, unemployment, and earnings across different sectors to update the HIECS 2017/18 employment and labor income distributions. This analysis focuses on the early pandemic impacts for FY20. That means that the income shock considered covers the last quarter (Q4) of FY20 (April to June 2020). The LFS data already captures the impact of COVID-19 in that last guarter. Therefore, to create the counterfactual non-COVID income distribution, we assume that, in the absence of the COVID-19 shock, labor market conditions would have been like those observed in Q3 of FY20. Projections done before the pandemic indicate that there was no expectation of another economic shock or break for Q4 (see Annex A, Figure A.1). Trends using LFS also show that the structure of Egypt's labor market changes little from quarter to quarter, so using employment and income measures for Q3 may be a sensible way to model the counterfactual labor market situation. However, one concern is seasonality. When we compare trends in FY19 across quarters, the indication is that Q4 employment composition and earnings are not very different from those observed in Q3 (Annex A, Table A.O). The ratio of monthly earnings between Q3 and Q4 in FY19 ranged between 1.02 and 1.06, depending on the sector, suggesting a positive and not a very large difference between the two quarters, on average.

We update workers' labor market status (extensive margin), based on the changes observed in activity status and employment by sector. Due to sample size limitations in modeling transitions, we use six states for males (not working, which combines out of the labor force and unemployed; working in agriculture; working in industry as an informal worker; working in industry as a formal worker; working in services as an informal worker; working in services as a formal worker). For females, we consider three states (not working, formal workers, and informal workers). Table 1 shows the percentage of workers across these states by gender in HIECS 2017/18.

To produce the most accurate update, workers had to be remapped into different labor market states to reflect the changes in labor force participation and unemployment and the increases in informality observed over the period. The transition model parameters are estimated using the Egypt Labor Market Panel Survey (ELMPS) for the period 2012 to 2018. The ELMPS is a key source of information for the Egyptian labor force, and main trends and patterns align closely with the LFS. The value added

of the ELMPS is the panel component, which allows for a better modeling of transitions into different labor market states, as it follows the same workers across time.<sup>8</sup>

#### Table 1.a: Labor states in FY18 (males)

	%	Obs.
Agriculture	13.2	4,764
Industry - Informal	14.3	5,161
Industry - Formal	5.8	2,081
Services - Informal	16.6	6,002
Services - Formal	18.0	6,515
Not working	32.1	11,603
Ν		36,126

#### Table 1.b: Labor states in FY18 (females)

	%	Obs.
Informal	10	3,524
Formal	8	2,944
Not working	82	29,282
Ν		35,750

**Source**: Authors' calculations using HIECS 2017/18.

Note: Unweighted percentages.

Using the panel data in ELMPS, a Mincer type multinomial logit regression for adults aged 15 and older was estimated to create a propensity score with the likelihood that an individual with a given set of observable characteristics (e.g., age, education, household size and demographics, location) would stay or transition to a different labor market state (Annex B). This propensity is then calculated for individuals in HIECS and used to remap them to match counterfactual FY20 states inferred from the LFS. This analysis was done separately by gender. Table 2 presents the two-year transition matrix used in the model, building on the LFS trends and ELMPS transition probabilities by gender to update the HIECS. About 18 percent of the sample of working-age males and 8 percent of the sample of working-age females are reallocated across states. Overall, the main transitions that needed to be modeled relate to stopping work and becoming informal. The adjustment also considers demographic changes by raking HIECS weights based on population estimates disaggregated by age categories and gender, as the working age population is growing.<sup>9</sup>

Once the labor market states are updated, labor income is adjusted to reflect earnings growth over the period. Incomes are updated based on the nominal growth rate of their destination (FY20) income source over two years. The income growth rates are computed by labor market state, gender, and age group (ages 15-24, 25-34, 35 and above).

<sup>&</sup>lt;sup>8</sup> Attrition in the ELMS is about 20 percent over the period 2012-2018.

<sup>&</sup>lt;sup>9</sup> Population projections were obtained from the UN Population Prospects.

To update non-labor income, we use administrative data<sup>10</sup> on the observed expansion of the main national cash transfer programs (Takaful and Karama) to simulate the expansions in coverage and amounts observed between FY18 and FY20 in the household survey. This adjustment is very important, as the cash transfers were introduced to compensate for some of the large economic reforms that started in 2016. The allocation rule is based on characteristics measured in the HIECS, which helps with allocation of the cash transfers. In addition, international remittances are adjusted by their observed growth rate using World Development Indicators (WDI) estimates of remittance flows (2.9 percent increase in FY20 compared to FY18). Domestic remittances are adjusted using growth rates in labor incomes.<sup>11</sup> Finally, other sources of income are updated by inflation.

Poverty rates are calculated based on the international poverty lines using household income per capita. The total household income per capita consumption aggregate is adjusted using 2011 purchasing power parity (PPP). Income poverty is estimated based on the \$3.65 per day poverty line in 2017 PPP. We prefer to analyze income poverty due to the complexities involved in modeling changes in consumption from changes in income due to COVID-19.

	opulated miles i rzo (no covid)						
HIECS 2018	Agriculture	Industry-	Industry-	Services-	Services-	Not	All
		Informal	Formal	Informal	Formal	working	
Agriculture	11.1	0.8	0.0	0.6	0.2	0.5	13.2
Industry - Informal	0.5	11.2	0.4	1.1	0.3	0.8	14.3
Industry - Formal	0.1	0.4	4.3	0.1	0.5	0.3	5.8
Services - Informal	0.3	1.1	0.3	12.9	1.3	0.8	16.6
Services-Formal	0.2	0.0	0.5	1.4	15.0	0.9	18.0
Not working	0.9	1.4	0.3	1.6	0.6	27.4	32.1
All	13.0	14.7	5.8	17.7	18.0	30.7	100.0

#### Table 2.a: Two-year transition matrix used to update HIECS (males) Updated HIECS FY20 (no COVID)

Note: Unweighted percentages based on a total sample size of working-age males of 36,126.

Table 2.b: Two-year transition matrix used to update HIECS (fema	les)
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	Updated HIECS FY20 (no COVID)					
HIECS 2018	Informal	Formal	Not working	All		
Informal	6	0	4	10		
Formal	0	7	1	8		
Not Working	2	1	79	82		
All	8	8	83	100		

**Note:** Unweighted percentages based on a total sample size of working-age females of 35,750.

<sup>&</sup>lt;sup>10</sup> The World Bank worked with Egypt's Ministry of Finance on a Commitment to Equity (CEQ) exercise to map taxes, transfers, and subsidies in the HIECS survey to understand the incidence of fiscal policies. This exercise used administrative data and allocation rules which allowed the authors to model the expansion in cash transfers over the period covered in this paper.

<sup>&</sup>lt;sup>11</sup> Very few households report income from remittances in HIECS, thus how we model remittances does not impact results. Yet it is important to keep in mind that remittance inflows were impacted by COVID-19, such that the income shock estimated in this paper may underestimate the total income loss.

#### Modeling the impact of COVID-19 in FY20

As the LFS 2020 covers the pandemic shock, we estimate from the data the size of job losses and who was more likely to stop working in Q4 of FY20. Figure 3 shows relative changes in labor force states between Q3 and Q4 of FY20. These figures are the ones used in the simulation of job losses. We model the likelihood of working using LFS data and generate a propensity score that we apply in the HIECS data. Working household members are selected to experience an employment shock in the last quarter of FY20 based on their ranked propensity score: those with the lowest score sequentially exit the pool of workers until the predicted number of workers who lost their jobs is matched in each relevant labor market state.

In addition to job losses, impacts occurred in terms of lower earnings. LFS asked workers if they experienced earnings losses due to COVID-19. Table 3 presents the share of workers in the LFS data who did not lose employment but reported a negative income shock due to COVID-19. Mean changes in earnings between Q3 and Q4 are used in each relevant labor force state, respectively, to adjust one-quarter of the workers' labor income.





Source: Authors' calculations using LFS 2020.

Table 3: Estimated	changes	in lat	oor ind	:ome
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Males	Workers reporting a decline in earnings due to COVID (percentage)	Average income change, Q4 versus Q3 FY20 (percent)
Agriculture	18	-33
Industry - Informal	46	-19
Industry - Formal	26	-4
Services - Informal	51	-28
Services - Formal	22	-5
Females		
Informal	22	-19
Formal	8	0

**Source**: Authors' calculations using LFS data.

**Note:** Income changes are based on a total monthly income variable in nominal terms.

As mentioned, an important objective of this analysis is to look at the role that cash transfers played in supporting households' incomes. For that purpose, we model the emergency expansion of the main cash transfer programs (Takaful and Karama) described in the previous section. We identify recipients of these programs in HIECS using the targeting rules and adjust the number of households receiving and the size of the transfer as a response to COVID-19. As noted, Takaful targets households with children under 18, while Karama targets the elderly poor, orphans, widows, and people living with disabilities. The selection of beneficiaries is conducted through geographical and categorical criteria, with proxy means testing (PMT).<sup>12</sup>

We also simulate the emergency cash transfer to informal workers that was paid starting in April 2020. The grant of EGP 500 per worker was paid monthly for three months to around 2 million informal workers registered in the workforce databases of the Ministry of Manpower across governorates.<sup>13</sup> A relative allocation using HIECS survey weights indicates that the grant was paid to about 12.1 percent of Egypt's informal workers. Since the distribution rules are not clear, we randomly selected informal workers in the updated HIECS dataset to reach the size of the informal worker population that benefited.<sup>14</sup>

<sup>&</sup>lt;sup>12</sup> The targeting rules are applied using the Fiscal Incidence Tool constructed with the Ministry of Finance. The PMT targeting formula relies on a set of household demographics and assets to identify poor households.

 $<sup>^{13}</sup>$  The first payment was processed in April 2020 via post offices (4,000 branches), the Agriculture Bank of Egypt (1,100 branches), and 600 schools that also served as payment sites – a total of 5,700 outlets. Beneficiaries received a free ATM card with their first payment to cash their second and third payments at post offices and/or banks. To avoid overcrowding and ensure safety, accepted beneficiaries were notified via SMS regarding the location and time to visit to collect their first payment and ATM card.

<sup>&</sup>lt;sup>14</sup> The following caveat concerning the analysis should be kept in mind. It is unclear from LFS data whether there could be some double counting of the targeted transfers to workers. This means that the income loss reported in LFS could have been bigger if respondents included those transfers, and the reported results may be overestimating the importance of the cash transfers in smoothing the impact.

The model incorporates payments of workers' salaries in non-performing establishments (mostly in the tourism sector) issued by the Emergency Fund at the Ministry of Manpower. Under this program, by April 27, 2020, around EGP 57 million were disbursed to 48,000 formal workers in 205 establishments in the tourism sector. To model this response, a one-time transfer of EGP 1,187.5 (57 million/48,000) is assigned to 22.8 percent of workers in the formal tourism sector to reflect a proportionate share using survey weights. We also include the cash transfer of EGP 500 per person allotted to 9,000 touristic guides to support their families during the Coronavirus pandemic (total cost: EGP 17 million).

Note that to limit the possible influence of an idiosyncratic random draw, we rely on 1,000 Monte Carlo replications of the random allocations (for informal workers and workers in the tourism sector), which are then averaged across working members at each household level. Other sources of non-labor income remain the same as in the non-COVID scenario.

## 4. Results

#### Estimated impact on household per capita income

Considering both the labor market impacts and the compensatory transfer channels, the results suggest that, at the national level, the pandemic reduced mean household per capita income in Egypt by about 1.7 percent in FY20, compared to a non-COVID situation (Figure 4a). The changes were driven by an average income contraction in urban areas of about 2.3 percent, while rural areas experienced a smaller decline in household income per capita. Upper Rural Egypt is the region with the smallest income declines, about -0.3 percent.

Income changes were widespread but larger for the poorest households in urban areas. Figure 4b shows an incidence curve presenting the change in household per capita income due to COVID-19 across income percentiles. The shaded lines mark the 95 percent confidence intervals. Income declined for most households, but the poorest households in urban areas experienced the largest losses, with the poorest 20 percent of urban households showing income reductions of about 5 percent, compared to an average of 3 percent for all urban households. In contrast, impacts were smaller and more evenly distributed in rural areas. As we will show later, this result is explained by the relatively larger expansion of government cash transfers in rural areas.

The income losses translate into a higher percentage of the population living with incomes below the international poverty line of \$3.65 day (2017 PPP). At the national level, income poverty is estimated to have been 2.2 percentage points higher due to COVID-19 in FY20, compared to a non-COVID scenario. The increase of 2.2 percentage points in the poverty rate led to around 2.2 million new poor because of the COVID crisis, as many Egyptian households live very close to the poverty line. Metropolitan areas and urban Lower Egypt show the highest rise in income poverty, about 3 percentage points, followed by rural areas in Lower Egypt (about 2.1 percentage points) (Figure 5).



#### Figure 4: Change in household income per capita due to COVID-19, by area

a. Average change across regions (%)



Source: Authors' calculations.

**Note:** Difference between household income per capita with and without COVID, FY20, percentages. BaU means refers to the no-COVID scenario



Figure 5. Change in income poverty by region, using poverty line of \$3.65 a day (2017 PPP)

**Source:** Authors' calculations.

**Note:** Difference between the income poverty rate with and without COVID-19, FY20, using the international poverty line of \$3.65 a day (2017 PPP). Difference in percentage points.

#### Characteristics of the new poor

By predicting levels of income for all households under the two alternative scenarios, the model enables us to examine the characteristics of those who became poor due to COVID-19, i.e., people who would not have been poor in FY20 had there been no crisis. The new poor differ from those poor apart from COVID-19 in several ways (Table 4). While 38.4 percent of the "always" poor reside in urban settings, around 45.8 percent of the new poor due to COVID-19 lived in urban areas. The new poor are more likely to reside in male-headed, younger, less educated, and smaller households than those always poor. The new poor are also disproportionately concentrated in households with heads who are informal workers (74.7 percent of the new poor), compared to all other households.

Table 4. Household characteristics by poverty stat	rable 4. Household characteristics by poverty status with and without COVID									
Characteristics	All	Poor with	New	Exited	Non-poor					
		and	poor	poverty	with and					
		without	with	with	without					
		COVID	COVID	COVID	COVID					
Households in urban areas	42.1	38.4	45.8	25.3	43.1					
Mean household size	5.0	6.0	5.6	5.8	4.7					
Mean dependency ratio	0.9	1.3	1.1	1.4	0.7					
Household head is male	88.0	92.2	95.0	89.8	86.6					
Mean age of household head	48.7	45.2	42.6	42.8	49.9					
Household head with basic education or lower	49.2	59.6	66.8	78.6	46.2					
Household head is informal worker	44.3	51.8	74.7	72.5	41.0					
Household head is not working	22.9	17.1	9.6	14.6	25.0					

# Table 4: Household characteristics by poverty status with and without COVID

**Source:** Authors' calculations.

To assess the relative importance of these household characteristics in the likelihood of becoming poor due to COVID-19, Figure 6 presents the odds from a logistic regression for the probability of becoming poor for households exhibiting specified characteristics versus all other groups (Annex B presents the regression results). An odds ratio above 1 indicates that a household with a particular characteristic is more likely to become poor due to COVID. We find two main features increasing the likelihood of becoming poor: living in metropolitan areas and working in the informal sector. The most prominent feature is informality, with households where the head was engaged in the informal sector being 2.2 times more likely to become poor due to the pandemic.

## The role of compensatory cash transfers

As discussed, the simulation models two channels of impact that play in opposite directions. On the one hand, there is a negative shock to labor income, while on the other hand there is an expansion in cash transfers. This sub-section quantifies the relative importance of the two channels. The overall estimated drop in income of about 1.7 percent stems from a 3.1 percent decline in labor income and a 1.4 percent increase in non-labor income (Table 5). The growth in non-labor income reflects the

combined expansion of Takaful and Karama and the other targeted cash assistance packages previously described. These results suggest that government responses helped dampen the immediate impact of the crisis to a large extent (counterbalancing about 45 percent of the labor income decline, on average). The significant expansion of Takaful and Karama is the most important transfer in counteracting income losses. Due to the program's targeting rules, its expansion markedly compensated income losses in the poorest rural areas of Lower and Upper Egypt. A decomposition for changes in the income-based poverty headcount using the \$3.65 international poverty line shows that, had cash transfers remained at their pre-COVID levels, the increase in poverty among Egyptian households would have been 3.3 percentage points, compared to the estimated 2.2 percentage points registered with the expanded cash transfers.

#### Figure 6: Odds of becoming poor due to COVID-19, households with specified characteristics



**Source:** Authors' calculations.

**Note:** Odds ratios from a logistic regression for becoming poor due to COVID-19. Reference group is all other households (always poor, exited poverty, and always non-poor); 95 percent confidence intervals in brackets.

Table J. Change in nousenolu income bei cabila que lo covid-13 in Fizo (70)
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	National	Metropolitan	Lower Urban	Lower Rural	Upper Urban	Upper Rural
Total income	-1.7	-2.3	-2.5	-1.5	-2.3	-0.3
Labor income	-3.1	-2.8	-3.3	-3.1	-3.2	-3.1
Takaful and Karama	1.0	0.2	0.5	1.1	0.6	2.4
Other non-labor income	0.4	0.3	0.3	0.4	0.3	0.5

Source: Authors' calculations.

Note: Difference between household income per capita with and without COVID, FY20, percent.

#### 5. Conclusions

This paper has aimed to shed light on the following questions: (i) What was the impact of COVID-19 on household income and income poverty in Egypt? and (ii) What was the role of key fiscal measures, in particular targeted cash transfers, in minimizing the immediate negative income consequences of the crisis?

The results confirm existing evidence of a large income shock due to the pandemic, particularly for urban households and those engaged in the informal sector. The analysis points to an average contraction in household income per capita of about 1.7 percent, driven by the poorest 50 percent of urban households. It further suggests an increase of 2.2 percentage points in income poverty, pushing around 2.2 million more people into poverty, compared to a non-COVID-19 scenario for the same year, using the international poverty line of \$3.65 a day (2017 purchasing power parity). Two key features are correlated with Egyptians' likelihood of becoming poor due to COVID-19: living in metropolitan areas and being an informal worker.

Fiscal policy is a key instrument to protect households and firms from the negative impacts of economic crises and downturns, and to rekindle economic growth. When the COVID-19 pandemic hit, most countries implemented fiscal measures to minimize the immediate consequences of the economic shock, protect families from falling into poverty, and allow firms to weather the crisis. The GoE was no exception, implementing a rapid set of monetary and fiscal measures estimated to cost about 1.8 percent of GDP.

Our findings highlight the salience of cash transfers, especially via the Takaful and Karama programs, in partly compensating for household income losses and limiting poverty increases in rural areas, at least at the onset of the crisis. The importance of the Takaful and Karama transfers as a compensatory measure resulted from the size of the transfer compared to other measures, but also reflects the programs' targeting rules, which effectively target relatively poorer households.<sup>15</sup>

The observed patterns have also pointed to a challenge for the traditional targeting approach in periods of crisis or shocks. As the Takaful and Karama targeting rules focus on the poorest regions (more rural) and adopt a proxy-means-testing model to better proxy chronic poverty, the expansion of Takaful and Karama during COVID-19 preferentially benefited Egypt's rural households. This highlights the importance going forward of devising mechanisms to better identify households impacted by shocks that might not be eligible for support under traditional targeting algorithms.

<sup>&</sup>lt;sup>15</sup> Recent evidence shows that, notwithstanding strong targeting performance, exclusion errors remain due to the size of the program relative to the poverty rate, and because of errors inherent to the use of PMT in targeting practices. See footnote 5, above, and World Bank (2022a).

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Table A.O. Compositio	able A.o. composition of the Egyptian labor force by quarter (January 2015 to June 2020), males							
	LFS – 2019	LFS 2019 -	LFS 2019 -	LFS 2019 -	LFS 2020 -	LFS 2020 -		
	- Q1	Q2	Q3	Q4	Q1	Q2		
Agriculture	14.4	13.6	13.5	14.4	12.3	13.0		
Industry - Informal	13.6	14.4	14.6	13.6	14.8	13.0		
Industry - Formal	6.7	6.0	6.3	6.7	6.1	5.9		
Services - Informal	15.7	13.9	14.3	15.7	15.5	12.3		
Services - Formal	14.5	16.1	16.0	14.5	15.9	15.2		
Not working	35.2	36.0	35.4	35.2	35.3	40.6		

#### Annex A

Table A.0: Composition of the Egyptian labor force by quarter (January 2019 to June 2020), males

**Source:** Authors' calculations.

Table A.1: Composition of the Egyptian labor force by quarter (January 2019 to June 2020), females

	LFS 2019 – Q1	LFS 2019 – Q2	LFS 2019 – Q3	LFS 2019 – Q4	LFS 2020 – Q1	LFS 2020 – Q2
Informal work	6.0	5.6	5.4	6.8	6.6	3.7
Formal work	6.5	6.4	6.2	5.8	6.0	6.1
Not working	87.5	88.0	88.4	87.4	87.5	90.2

Source: Authors' calculations.



# Figure A.1: Projected GDP growth and GDP deflator before COVID-19 (using constant LCU, base year=2017) – Egypt

**Note**: Projection date: 07/19/19. LCU = local currency units. **Source**: Authors' calculations based on World Bank MPO AM2019.

# Annex B

Table B.C. Output of regressing destination labor force state on characteristics by origin labor force state, males
---

	(1)	(2)	(3)	(4)	(5)
Variables	Informal	Formal	Informal	Formal	Not
	industry	industry	services	services	working
Origin state: Agrigulture					
Log-household size	0 907	0 400*	0 560**	0 907	0 971
Log-household size	[0.227]	[0 209]	[0 134]	[0 31/1]	10.2281
	0 989	1 084	1 011	1 016	0.936
190	[0 053]	10 1631	10 0501	[0 073]	[0 045]
Age squared	0,999	0.999	0.999	1,000	1.001
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
Education	[]	[]	[]	[]	[]
No education (ref.)			0 500	0 544.4	
Literacy	0.804	0.000	0.586	3.711**	0.392
The second state and the base	[0.478]	[0.004]	[0.352]	[2.401]	[0.289]
Lower intermediate	1.568	1.811	1.180	1.884	1.4/1
Techowers	[0.443]	[2.1/8]	[0.317]	[1.011] 7 4(5+++	[0.407]
Intermediate	1.800^^	12.904^^^	0.938	/.465^^^	0.851
University	[0.495]	[IZ.3UZ] 10 200**	[U.253] 2 445**	[3.33U] 7.227***	[U.263]
UNIVERSICY	10.000	10.390""	Z.44J^^	1.52/***	1.030
Household head	[0.000] 0.470**	[21.233]	[1.000]	[3.190]	[0.940]
nousenoid head	[0 153]	[0 321]	[0 233]	10 2861	10 3351
Urban	1 463	2 550	1 099	1 004	1 960*
	10 5221	[1 578]	10 4181	[0 511]	1.500
Constant	0.673	0.008*	0.859	0.028***	0.734
	[0.595]	[0.019]	[0.727]	[0.035]	[0.623]
Observations	1173.000	1173.000	1173.000	1173.000	1173.000
Origin state: Informal					
industry	0 072	0 004	0 000	0.000	0 501++
Log-nousenoid size	0.973	0.824	0.000	0.000	0.501^^
Aco	[0.301]	[U.341] 1 051	[0.200]	[0.370]	[U.170] 1 003
Age	1.021	1.0001	10 0801	1.230	1.003
lae squared	1 000	1 000	1 001	0 997	1 001
nge Squarea	10 0011	[0 001]	10001	[0 002]	1.001
Education	[0.001]	[0.001]	[0.001]	[0:002]	[0.001]
No education (ref.)					
Literacv	4.464**	2.034	5.505**	8.200*	4.359*
	[3.340]	[1.909]	[4.370]	[9.780]	[3.508]
Lower intermediate	1.789*	0.936	2.037*	9.721***	2.469**
	[0.556]	[0.430]	[0.741]	[6.858]	[0.888]
Intermediate	2.252***	2.460**	3.032***	12.650***	1.474
	[0.654]	[0.960]	[1.028]	[8.679]	[0.525]
University	1.905	1.188	3.463*	61.273***	1.886
	[1.276]	[1.113]	[2.480]	[55.522]	[1.432]
Household head	0.716	1.535	1.070	0.845	0.458*
	[0.259]	[0.736]	[0.428]	[0.397]	[0.189]
Urban	3.415***	5.216***	3.603***	8.425***	2.841***
	[1.119]	[2.041]	[1.260]	[3.327]	[1.027]
Constant	1.366	0.142	2.308	0.002***	1.592
	[1.621]	[0.237]	[3.017]	[0.005]	[2.101]
Observations	1157.000	1157.000	1157.000	1157.000	1157.000

	(1)	(2)	(3)	(4)	(5)
Variables	Informal	Formal	Informal	Formal	Not
	industry	industry	services	services	working
Origin state: Formal					
Industry Log-household size	1 531	0 906	2 209	1 263	1 764
log nousenoid size	[1 348]	[0 717]	[2.205	[1 074]	[1 453]
Age	1.250	1.914***	1.473	2.011***	1.078
	[0.335]	[0.473]	[0.426]	[0.540]	[0.294]
Age squared	0.996	0.991***	0.994*	0.991***	1.000
2 - 1	[0.003]	[0.003]	[0.003]	[0.003]	[0.003]
Education					
No education (ref.)					
Literacy	13.514*	2.687	5.043	2.853	1.709
	[20.954]	[3.907]	[8.610]	[4.420]	[2.693]
Lower intermediate	11.387**	9.868**	11.083*	8.762*	3.028
	[14.023]	[10.523]	[15.050]	[10.174]	[3.400]
Intermediate	2.222	2.830	3.006	1.870	3.774*
	[2.101]	[2.088]	[3.243]	[1.598]	[3.009]
University	1.223	1.690	0.973	3.022	4.043
-	[1.340]	[1.477]	[1.217]	[2.935]	[3.825]
Household head	0.588	0.672	1.119	0.868	0.413
	[0.584]	[0.625]	[1.190]	[0.851]	[0.440]
Urban	4.384**	4.069**	12.388***	8.104***	5.765***
	[2.837]	[2.432]	[8.636]	[5.132]	[3.700]
Constant	0.036	0.000**	0.000	0.000***	0.015
	[0.170]	[0.000]	[0.001]	[0.000]	[0.071]
Observations	512.000	512.000	512.000	512.000	512.000
Origin state: Informal					
services					
Log-household size	0.642	0.091***	0.662	0.869	0.685
	[0.267]	[0.045]	[0.244]	[0.350]	[0.282]
Age	0.998	1.414***	0.941	1.020	0.796***
	[0.094]	[0.173]	[0.070]	[0.087]	[0.064]
Age squared	0.999	0.996**	1.001	1.000	1.003***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
Education					
No education (ref.)					
Literacy	0.943	2.572	0.928	1.649	0.599
	[0.637]	[2.904]	[0.515]	[1.232]	[0.432]
Lower intermediate	1.248	6.762**	1.149	4.708***	2.405*
	[0.579]	[5.431]	[0.464]	[2.480]	[1.115]
Intermediate	1.003	5.156**	1.133	7.858***	1.797
	[0.438]	[4.113]	[0.427]	[3.896]	[0.801]
University	1.942	6.879**	1.881	21.498***	2.594
	[1.349]	[6.756]	[1.205]	[15.401]	[1.833]
Household head	2.384**	0.263***	1.889	1.667	1.940
	[1.026]	[0.133]	[0.732]	[0.697]	[0.853]
Urban	12.617***	12.089***	12.226***	8.813***	11.629***
	[6.116]	[6.754]	[5.626]	[4.205]	[5.631]
Constant	5.656	0.005**	25.060**	0.214	62.492***
	[9.150]	[0.011]	[33.596]	[0.332]	[90.639]
Observations	1327.000	1327.000	1327.000	1327.000	1327.000
Origin state: Formal					
services					
Log-household size	1.045	1.232	0.560	0.816	0.786
	[0.627]	[0.551]	[0.215]	[0.296]	[0.307]
Age	1.126	1.334**	1.040	1.589***	1.061

	(1)	(2)	(3)	(4)	(5)
Variables	Informal	Formal	Informal	Formal	Not
	industry	industry	services	services	working
	[0.220]	[0.196]	[0.128]	[0.189]	[0.137]
Age squared	0.997	0.995***	0.999	0.994***	1.000
	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Education					
No education (ref.)					
Literacy	0.000	0.419	1.670	1.223	1.552
	[0.002]	[0.659]	[1.128]	[0.796]	[1.090]
Lower intermediate	1.333	1.162	0.316**	0.617	0.678
	[1.257]	[0.814]	[0.152]	[0.270]	[0.342]
Intermediate	1.272	2.574	0.791	1.747	1.502
	[1.163]	[1.674]	[0.340]	[0.700]	[0.672]
University	1.717	4.107**	0.717	3.095**	3.782***
	[1.656]	[2.865]	[0.359]	[1.444]	[1.913]
Household head	2.100	1.259	0.730	1.553	0.503
	[1.487]	[0.701]	[0.373]	[0.760]	[0.280]
Urban	6.297***	7.763***	7.464***	4.091***	4.814***
	[3.059]	[3.005]	[2.636]	[1.376]	[1.719]
Constant	0.167	0.006*	18.543	0.004**	0.174
	[0.601]	[0.017]	[43.631]	[0.008]	[0.445]
Observations	1738.000	1738.000	1738.000	1738.000	1738.000
Origin state: Not working					
Log-household size	0.462***	0.173***	0.412***	0.407***	0.296***
2	[0.113]	[0.058]	[0.098]	[0.117]	[0.064]
Aqe	1.071	1.112	1.121**	1.191**	0.741***
-	[0.061]	[0.101]	[0.061]	[0.088]	[0.038]
Age squared	0.999	0.998	0.998***	0.997***	1.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Education					
No education (ref.)					
Literacy	0.868	246924.919	1.661	6.872	1.624
-	[0.432]	[1.642e+08]	[0.818]	[12.162]	[0.718]
Lower intermediate	1.394	2960753.180	2.267**	33.512**	2.595**
	[0.574]	[1.969e+09]	[0.942]	[56.155]	[0.996]
Intermediate	1.635	8074346.227	2.665**	96.112***	2.189*
	[0.689]	[5.370e+09]	[1.135]	[160.617]	[0.894]
University	0.528	10553000.409	2.536	141.602***	2.872*
-	[0.350]	[7.019e+09]	[1.488]	[243.257]	[1.664]
Household head	0.365	1.100	1.148	2.221	1.007
	[0.262]	[0.839]	[0.711]	[1.486]	[0.660]
Urban	4.458***	13.158***	12.685***	14.316***	13.261***
	[1.331]	[4.548]	[3.640]	[4.440]	[3.678]
Constant	1.904	0.000	0.679	0.006**	595.701***
	[1.878]	[0.000]	[0.651]	[0.012]	[516.645]
Observations	2963.000	2963.000	2963.000	2963.000	2963-000
	2200.000	2303.000	2000.000	2300.000	2200.000

Robust standard error in brackets \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Variables	(1)	(2)	(4)	(5)	(7)	(8)
					Not	
			Formal		working	
Informal						
Log-household						
size	0.567	1.403	0.711	0.755	0.245***	0.850
	[0.330]	[0.303]	[0.329]	[0.371]	[0.054]	[0.097]
Age	1.210	0.856***	1.551***	0.732**	0.952	0.872***
	[0.215]	[0.044]	[0.217]	[0.107]	[0.051]	[0.019]
Age squared	0.997	1.002***	0.995***	1.004**	1.001	1.002***
	[0.002]	[0.001]	[0.002]	[0.002]	[0.001]	[0.000]
Education						
No education	(ref.)					
Literacy	0.000	0.481	11.598	62110498.022	0.588	1.634**
	[0.004]	[0.253]	[18,952.155]	[9.747e+10]	[0.752]	[0.333]
Lower						
intermediate	2.244	1.577	1.971	7.101	9.179***	2.065***
	[1.903]	[0.494]	[2.446]	[8.702]	[4.871]	[0.294]
Intermediate	4.724**	1.423	21.636***	7.673**	31.014***	2.016***
	[3.078]	[0.365]	[18.558]	[7.114]	[15.227]	[0.249]
University	27.373***	1.534	32.840***	11.288**	32.473***	3.092***
	[20.840]	[0.752]	[28.559]	[10.624]	[18.244]	[0.750]
Household head	0.961	0.659	0.629	1.517	0.211***	1.224
	[0.640]	[0.174]	[0.330]	[0.837]	[0.103]	[0.225]
Urban	2.984**	1.167	3.050***	4.071***	2.146***	1.137
	[1.361]	[0.245]	[1.059]	[1.547]	[0.403]	[0.114]
Constant	0.004*	22.788***	0.000***	31.213	0.339	60.230***
	[0.012]	[22.742]	[0.000]	[86.174]	[0.329]	[24.455]
Observations	625.000	625.000	820.000	820.000	7497.000	7497.000

Table B.1: Output of regressing	g destination labor for	ce state on characteristics	by origin	labor force state,	females

Robust standard error in brackets \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

Characteristics	Poor with COVID
Household head is male	1.008***
	[0.003]
Age of household head	0.937***
	[0.005]
Household size	1.336***
	[0.033]
Household head is informal worker	2.178***
	[0.348]
Household head is not working	1.006**
	[0.003]
Education of household head	
Basic education or lower	
Secondary	0.323***
The set of a second set of a large set	[0.042]
Tertiary or higher	0.141***
Dester	[0.045]
Region	
Metropolitan	
Lower Egypt Orban	1.095
Louise Fount Dural	[0.205]
Lower Egypt Rurai	0.561***
Upper Faunt Urban	[0.081]
opper Egypt ofban	0.556***
Uppor Faunt Pural	[0.109]
opper mgypt Kurar	U.352***
Constant	[0.058]
Constant	***880.0
	[0.038]
N	24,185

Table B.2: Output of regression of being new poor on selected household characteristics (household level)

Robust standard errors in brackets \*\*\* p<0.01, \*\* p<0.05, \* p<0.1