

Online Appendix for: “Gendered Impacts of Covid-19 in Developing Countries”

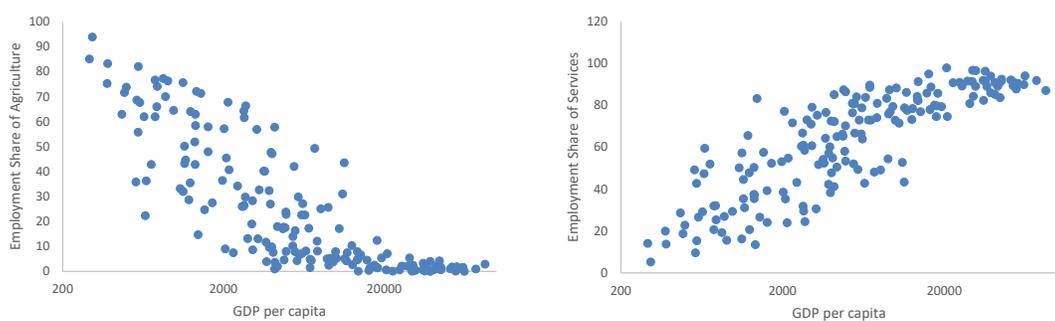
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A Data Sources

We use data from the Nigeria COVID-19 National Longitudinal Phone Survey (Covid-19 NLPS) implemented by the National Bureau of Statistics to track the impact of the pandemic. The survey was conducted for one year on a monthly basis starting from the end of April, 2020, and included households interviewed face-to-face in 2018/2019 for Wave 4 of the General Household Survey Panel (GHS-Panel), which was designed to be representative at national and zonal levels. The extensive information collected in the GHS-Panel just over a year prior to the pandemic provides a rich set of background information on Covid-19 NLPS households. 1,950 households were successfully interviewed in Round 1, and the same households were contacted by phone in subsequent rounds.¹ There are total 12 phone surveys conducted on a monthly basis starting from the end of April 2020 (see Figure B3).

We rely on data collected in Rounds 5 and 10 of Covid-19 NLPS and 2018/19 GHS-Panel. We choose these two surveys because they line up with the timing of the pre-pandemic information from GHS-Panel. Round 5 of Covid-19 NLPS was conducted in September 2020 and Round 10 in February, 2021. The post-planting part of the 2018/19 GHS-Panel was conducted in the period July–September 2018 and the post-harvest part in January–February, 2019. For the former, data on employment status and hours worked on a primary job in the week before the interview is collected for up to six randomly selected members of households age 15-64 plus the primary respondent. In GHS-Panel, employment status and hours

¹Households that do not have access to a phone and could not be interviewed despite several call attempts were excluded from the sample, which may introduce potential selection bias. To overcome this bias, a balanced sampling approach was adopted, and phone survey weights are available.



(a) Women’s Employment Share in Agriculture (b) Women’s Employment Share in Services

Figure B1: The Sectoral Composition of Women’s Employment Across Countries in 2015

Notes: Women’s employment in agriculture and services as a fraction of total women’s employment in 2015. Each dot is a country. Source: World Bank Development Indicators; accessed online on 12/21/2021.

worked on each job a week before the interview were collected for each member of household age five and above. For consistency with the Covid-19 NLPS data, we use hours worked on the primary job, defined as job were individual spent the most time during the last week, rather than all jobs.

B Additional Tables and Figures

Figure B1 plots the employment shares for women (out of all employed women) in agriculture and services in 2015 against GDP per capita for most countries in the world. The figure shows that in low-income countries, the majority of the female labor force is in agriculture, whereas services are relatively unimportant. The opposite pattern is observed in high-income economies, where the employment share of agriculture is negligible and most women work in services. The figure suggests that unlike in high-income countries, in low-income countries the specific impact of Covid-related shutdowns on contact intensive services does not play a substantial role for women’s employment losses during the pandemic.

Figure B2 depicts the cross-country relationship between income per capita and engagement of children in any learning activities during school closures. We use data from High Frequency Phone Surveys conducted by the World Bank to

identify the share of households with children engaged in any learning activity after schools were closed due to Covid-19. Only households with children who attended school prior to the pandemic are considered when this share is calculated. The figure shows that in countries with higher income per capita, on average, children were more likely to continue their education during the pandemic. In a number of countries in Sub-Saharan Africa, children continued with learning activities in less than half of households.

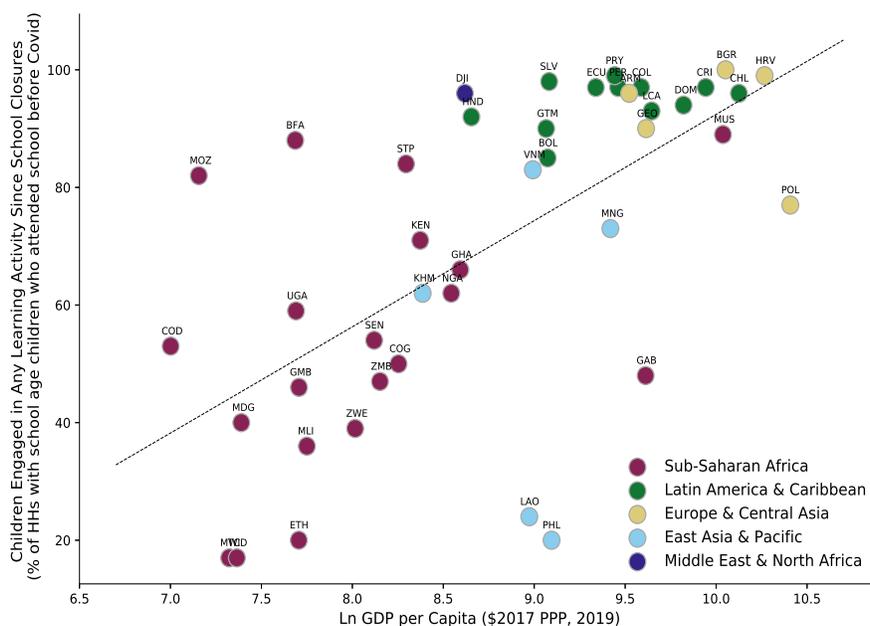


Figure B2: Learning Activities during School Closures and Income

Notes: This figure is generated using data from High Frequency Phone Surveys (World Bank). Data collected during first rounds of phone surveys for each country is used for the share of HHs where children engaged in any learning activity. In most countries, first rounds were conducted in May-June 2020.

Figure B3 provides a timeline of the stringency of government containment measures during the pandemic and of mobility data collected by Google. The figure also shows when each wave of the Covid-19 NLPS survey was conducted. The figure shows that restrictions were the most severe from April to July of 2020, and that by September (when the 5th wave that we use here was collected) restrictions were already more relaxed. There is little change overall between waves 5 and

10; however, most schools fully reopened in November of 2020, in between the data collection of these two waves.

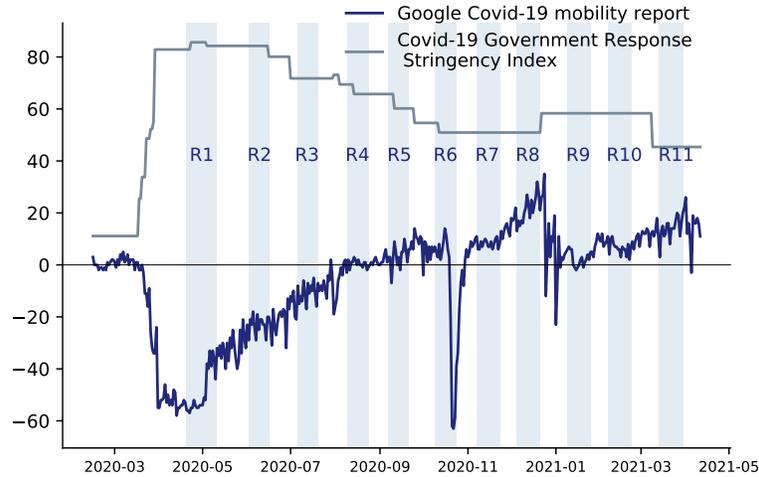


Figure B3: Timeline of Government Restrictions and Population Mobility

Notes: Google Covid-19 mobility report shows mobility trends for public transport hubs (subway, bus, and train stations) relative to a baseline value – median value for the corresponding day of the week during the 5-week period Jan 3 - Feb 6, 2020. Covid-19 Government Response Stringency Index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, re-scaled to a value from 0 to 100 (100 = strictest).

Figure B4 provides a timeline of school closures during the pandemic. The figure shows that schools were closed in March 2020 as a response to Covid-19 outbreak. School reopened partially for some students at the end of September 2020, and fully reopened for all students in November 2020.

Figure B5 provides an impression of the intensive margin of employment changes by plotting for each survey wave and each gender the weekly hours worked conditional on being employed. For wave 5 (September 2020), hours changes compared to the pre-pandemic period are moderate, but weekly working hours of both women and men are considerably higher than previously in the wave 10 data (February 2021). A caveat is that average weekly working hours are computed for the primary activity only. Therefore, increase in working hours might reflect that some individuals shift from multiple jobs to the single one, which can drive up average weekly hours for primary activity.

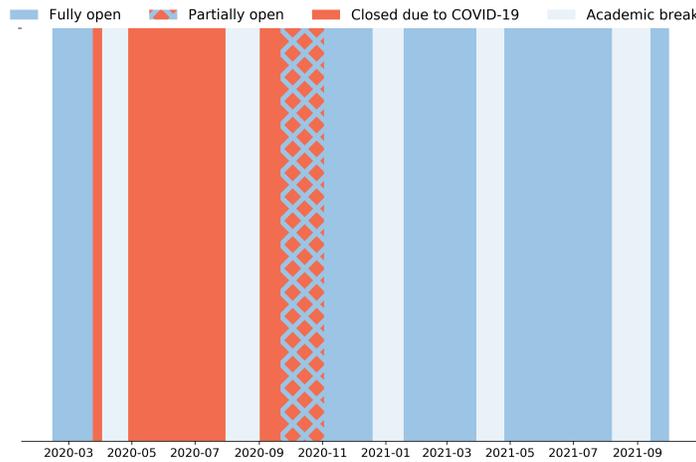


Figure B4: Timeline of Schools Closures in Nigeria

Notes: This figure is generated using UNESCO “Global monitoring of school closures” data.

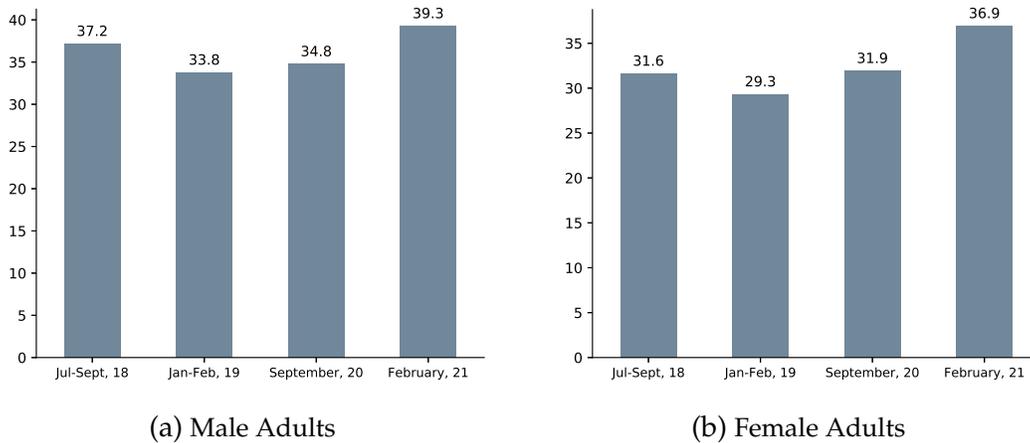


Figure B5: Average Weekly Working Hours by Gender

Notes: Average weekly working hours are computed for the primary working activity and conditional on individual to have a job. Primary working activity is defined as the job in which the individual worked the most hours.

Figure B6 depicts employment across different sectors for both women and men. The most notable change is a sharp rise in non-farm enterprise; for women, for example, we observe an increase from 30 percent in January-February 2019 to 44 percent in February 2021. The data is consistent with the view that households

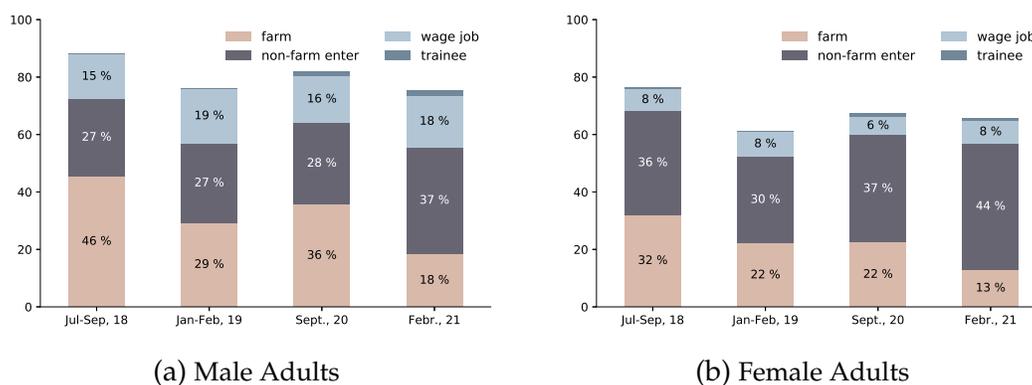


Figure B6: Share of Working Adults by Sector

Notes: The share of adults of age 21-55 that worked in the past week (at time when interview was conducted) at a given sector as a primary employment. Non-farm enterprise stands for the enterprise that belongs to a member of household. Sample includes $\approx 9,000$ and $\approx 4,000$ individuals for pre-Covid and Covid interviews, respectively.

responded to income losses by increasing self-employment and small-scale entrepreneurship. We also observe a decline in agricultural employment; because only the sector of the primary job is reported, this may reflect that some households members took on a new job as primary employment, leaving agriculture as a secondary activity.

Table B1 displays individual-level regression results of the impact of the pandemic on both extensive and intensive margin of employment by gender that include individual and household controls and geographic fixed effects (LGA). The regressions confirm that individuals worked less in the early phase of the pandemic, but experienced an expansion of working hours later in the recovery, driven primarily by female working hours.

The combination of school closures and the socioeconomic impact of the pandemic might have induced some adolescents, especially from poor households, to stop their education and start working. Table B2 displays regression results for the impact of the pandemic on the employment of individuals at ages 15 to 20. Panel A displays the results for all individuals aged 15-20 years old, while Panels B and C show the results for those who are supposed to be in secondary school or receive tertiary education, based on their age. We find that the pandemic led

Table B1: Impact of Covid-19's Weekly Working Hours for Adults

| | Weekly Working Hours | | | | log (Weekly Working Hours) | | | |
|-------------------|----------------------|-------------------|------------------|------------------|----------------------------|-------------------|------------------|------------------|
| | Sept. | Sept. | Febr. | Febr. | Sept. | Sept. | Febr. | Febr. |
| Covid | -4.156 (0.980) | -4.926 (1.297) | 4.251 (1.739) | 2.573 (1.935) | -0.356 (0.067) | -0.298 (0.082) | 0.154 (0.135) | 0.022 (0.152) |
| Covid × Female | | 1.414 (1.073) | | 3.096 (1.252) | | -0.107 (1.264) | | 0.243 (0.010) |
| # Obs | 12,094 | 12,094 | 12,404 | 12,404 | 12,094 | 12,094 | 12,404 | 12,404 |
| R-squared | 0.21 | 0.21 | 0.23 | 0.23 | 0.21 | 0.21 | 0.24 | 0.24 |
| Mean Pre-Covid | 28.0 | 28.0 | 21.5 | 21.5 | | | | |
| Age FE | Y | Y | Y | Y | Y | Y | Y | Y |
| LGA FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Control Variables | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: Robust standard errors (in parentheses) are clustered at the state level. Controls include gender, urban, number of HH members, access to electricity & internet, ownership of different assets (radio, car, land, etc.), access to finance, consumption quantile before the pandemic, education and literacy of the individual, marriage status, whether individual is a head of household, and a dummy for pre-covid interview held in January. Results for weekly working hours that combine both intensive and extensive margins and we apply inverse-hyperbolic sine transform of hours worked last week for the logarithm.

both to a higher probability for adolescents to work and more weekly working hours. While we observe an increase in the probability of performing some work for all age groups, weekly hours are higher only for the older cohort. Additionally, we find that the probability of work increased more for those living in urban areas compared to rural. We find no significant differences in the effects of the pandemic between women and men.

To examine the possible role of the income channel for employment changes, we split the sample into the top 40% vs. the bottom 60% of households defined by consumption prior to the pandemic. Table B3 displays regression results for the impact of the pandemic on the employment by gender in February for the two groups. We find that the positive effect of the pandemic on women's labor supply in February 2021 is concentrated among poorer households. In fact, there is no effect for those households in the top 40% of the (pre-pandemic) consumption

Table B2: Impact of Covid-19's on Employment and Hours of Work for Adolescents

| | Employment Status | | | Weekly Working Hours | | |
|--|-------------------|-------------------|------------------|----------------------|-------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Panel A: All individuals aged 15-20 | | | | | | |
| Covid | 0.075 (0.013) | 0.078 (0.014) | 0.056 (0.008) | 4.515 (1.546) | 4.087 (2.185) | 4.830 (1.741) |
| Covid × Female | | -0.006 (0.016) | | | 1.062 (2.652) | |
| Covid × Urban | | | 0.051 (0.016) | | | -1.121 (3.095) |
| # Obs | 4,997 | 4,997 | 4,997 | 1,639 | 1,639 | 1,639 |
| R-squared | 0.93 | 0.93 | 0.93 | 0.44 | 0.45 | 0.44 |
| Mean Pre-Covid | 0.301 | | | 23.7 | | |
| Panel B: All individuals aged 15-16 | | | | | | |
| Covid | 0.056 (0.011) | 0.061 (0.015) | 0.043 (0.008) | -0.431 (2.977) | 0.014 (3.305) | -0.797 (3.009) |
| Covid × Female | | -0.008 (0.022) | | | -1.094 (3.214) | |
| Covid × Urban | | | 0.042 (0.020) | | | 1.870 (5.639) |
| # Obs | 1,828 | 1,828 | 1,828 | 457 | 457 | 457 |
| R-squared | 0.95 | 0.95 | 0.95 | 0.59 | 0.59 | 0.59 |
| Mean Pre-Covid | 0.250 | | | 20.2 | | |
| Panel C: All individuals aged 17-20 | | | | | | |
| Covid | 0.087 (0.016) | 0.091 (0.018) | 0.067 (0.012) | 5.763 (1.579) | 5.143 (2.261) | 6.714 (1.823) |
| Covid × Female | | -0.011 (0.017) | | | 1.566 (3.592) | |
| Covid × Urban | | | 0.055 (0.019) | | | -3.184 (3.406) |
| # Obs | 3,115 | 3,115 | 3,115 | 1,095 | 1,095 | 1,095 |
| R-squared | 0.93 | 0.93 | 0.93 | 0.47 | 0.47 | 0.47 |
| Mean Pre-Covid | 0.333 | | | 25.4 | | |
| Age FE | Y | Y | Y | Y | Y | Y |
| Occupation FE | Y | Y | Y | Y | Y | Y |
| LGA FE | Y | Y | Y | Y | Y | Y |
| Control Variables | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: Robust standard errors (in parentheses) are clustered at the state level. Controls include gender, urban, number of HH members, access to electricity & internet, ownership of different assets (radio, car, land, etc.), consumption quantile before the pandemic, education and literacy of the HH's head, and dummy for pre-covid interview held in January. In regressions for weekly working hours only working adolescents are included.

Table B3: Impact of Covid-19's on Employment in February for Different Income Groups

| | Employment Status | | | | Weekly Working Hours | | | |
|-------------------|-------------------|------------------|-------------------|-------------------|----------------------|------------------|------------------|-------------------|
| | Bottom 60% | | Top 40% | | Bottom 60% | | Top 40% | |
| Covid | 0.100 (0.043) | 0.049 (0.044) | -0.037 (0.041) | -0.036 (0.042) | 6.635 (2.331) | 4.565 (2.710) | 0.387 (2.211) | -0.671 (2.207) |
| Covid × Female | | 0.086 (0.033) | | -0.003 (0.024) | | 3.462 (1.747) | | 2.145 (1.375) |
| # Obs | 8,243 | 8,243 | 4,162 | 4,162 | 8,222 | 8,222 | 4,142 | 4,142 |
| R-squared | 0.23 | 0.21 | 0.30 | 0.30 | 0.24 | 0.24 | 0.28 | 0.28 |
| Mean Pre-Covid | 0.67 | 0.67 | 0.71 | 0.71 | 28.9 | 28.9 | 36.8 | 36.8 |
| Age FE | Y | Y | Y | Y | Y | Y | Y | Y |
| LGA FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Control Variables | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: Robust standard errors (in parentheses) are clustered at the state level. Controls include gender, urban, number of HH members, access to electricity & internet, ownership of different assets (radio, car, land, etc.), access to finance, consumption quantile before the pandemic, education and literacy of the individual, marriage status, whether individual is a head of household, and a dummy for pre-covid interview held in January. Consumption quantiles are computed for pre-pandemic quantities.

distribution. These findings provide suggestive evidence for the income channel.