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The labour market impact of COVID-19 lockdowns

Evidence from Ghana

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Abstract: In this paper, we provide causal evidence of the impact of stringent lockdown policies on labour market outcomes at both the extensive and intensive margins, using Ghana as a case study. We take advantage of a specific policy setting, in which strict stay-at-home orders were issued and enforced in two spatially delimited areas, bringing Ghana's major metropolitan centres to a standstill, while in the rest of the country less stringent regulations were in place. Using a difference-in-differences design, we find that the three-week lockdown had a large and significant immediate negative impact on employment in the treated districts, particularly among workers in informal self-employment. While the gap in employment between the treated and control districts had narrowed four months after the lockdown was lifted, we detect a persistent nationwide impact on labour market outcomes, jeopardizing particularly the livelihoods of small business owners mainly operating in the informal economy.

Key words: COVID-19, lockdown, employment, informal economy, Ghana

JEL classification: I18, J46, J63, O55

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1 Introduction

To limit the spread of COVID-19, the infectious disease caused by the novel coronavirus, policymakers around the world have enacted stringent containment and closure policies. In April 2020, rules on hygiene and social distancing reshaped daily life, schools and businesses were closed, gatherings banned, and almost 2.7 billion workers, representing around 81 per cent of the world's workforce, were affected by partial or full lockdown regulations (ILO 2020a).

Stringent early confinement policies were implemented with the aim of reducing contagion and buy time for health systems to create additional testing and treatment capacity, but at a high cost. Beyond the drop in commodity prices and external demand, workplace closures and travel bans led to a reduction in economic activity. Simulating different scenarios for the impact of COVID-19 on global economic growth, the International Labour Organization (ILO) first warned in March 2020 against the risk of an economic and labour crisis that could increase global unemployment by between 5.3 million ('low' scenario) and 24.7 million ('high' scenario), from a base level of 188 million in 2019. Beyond job losses and business closures, underemployment was also expected to surge, as the economic consequences of the pandemic caused working hours and wages to decline, in combination leading to a sharp rise in working poverty (ILO 2020b). Informal self-employment, an activity of last resort that often serves to buffer the impact of economic shocks in developing countries, was generally not available due to the imposed restrictions. Workers in this sector, who need to earn a living on a day-to-day basis and have limited or no access to healthcare or social safety nets, were severely hit (Danquah et al. 2020; ILO 2020c).

In this paper, we investigate changes in labour market outcomes since the onset of the pandemic, using Ghana as a case study. We take advantage of a specific policy setting, in which strict stay-at-home orders were issued and enforced in two spatially delimited areas, bringing Ghana's major metropolitan centres to a standstill, while in the rest of the country less stringent regulations were in place. We exploit this geographic variation to estimate the differential impact of COVID-19-related confinement measures on labour market outcomes in Ghana—at both the extensive and the intensive margins—comparing the effects under the two alternative policy settings.

For this study, we conducted a rapid phone survey with a subsample of 662 workers drawn from the 2018/19 Ghana Socioeconomic Panel Survey (GSPS). The data were collected between 19 August and 17 September 2020 and comprised recall information for the months of February, before the coronavirus had reached Ghana, and April, when parts of Ghana were under lockdown, allowing us to construct a longitudinal dataset at the worker level. Using a difference-in-differences (DID) design, we estimate the causal short- and medium-term impact of the coronavirus pandemic and associated lockdown measures on employment, labour earnings, and working hours.¹

Overall, the results of this study indicate that legal shutdown orders induced a substantial decline in employment during the lockdown period in the affected districts. According to our preferred specification—which includes worker-fixed effects and limits control districts to those in a population density range that is comparable to the treated districts—workers in lockdown districts faced a 63.4 per cent risk of being out of work in the month of April, compared with a *ceteris paribus* risk of 28.3 per cent faced by workers located in districts not affected by the lockdown.

¹ Other studies that have used the DID design to analyse the causal effect of the COVID-19 pandemic on labour market outcomes and wellbeing are Bargain and Aminjonov (2020), Brodeur et al. (2021), and Fang et al. (2020).

This means that workers located in districts under lockdown had a 35.1 per cent lower chance of continuing to work throughout April than workers in districts not subject to lockdown policies.

Despite this strong and significant short-term effect, we also find evidence for a strong recovery in employment. Four months after the lockdown was lifted, we find no statistically significant difference in employment rates between lockdown and no-lockdown districts. Nonetheless, nationwide, workers' chances of employment remained 11.6 percentage points below the February 2020 benchmark, indicating a persistent impact of the pandemic on the labour market. Similarly, labour earnings and working hours remained significantly below pre-COVID levels.

Importantly, our analysis shows that the negative employment effect of the pandemic was not only significantly more sizable in districts affected by the lockdown but was also concentrated among workers in informal self-employment. In addition, across Ghana, the earnings of self-employed workers and of female workers remained more negatively affected in the medium term. This finding reinforces the results obtained by other studies in the Sub-Saharan African context, suggesting that micro and small enterprises have experienced a greater decline in activity due to the pandemic than medium and large enterprises (Lakuma and Sunday 2020), and informal workers have been at the highest risk, given the nature of their work and lack of financial means to buffer economic shocks (Balde et al. 2020; Bassier et al. 2020).

The paper is organized as follows. Section 2 provides relevant background information on the COVID-19-related policy environment in Ghana. Section 3 introduces the data, discusses our empirical approach and identification strategy, defines key variables of interest, and presents descriptive statistics. Section 4 presents our estimation results, while Section 5 provides the results of various robustness checks. Section 6 concludes.

2 Background and policy environment

The first two cases of COVID-19 were reported in Ghana on 12 March 2020. As a first response, on 15 March, all public gatherings exceeding 25 people were banned, all schools and universities were closed until further notice, and on 23 March all of the country's borders were closed. Urban market centres, providing essential services, were exempted from the suspension of public gatherings, but measures to disinfect and enhance conditions of hygiene in markets were implemented (Asante and Mills 2020). In addition, citizens were advised to strictly observe good personal hygiene and social distancing to prevent the spread of the disease.

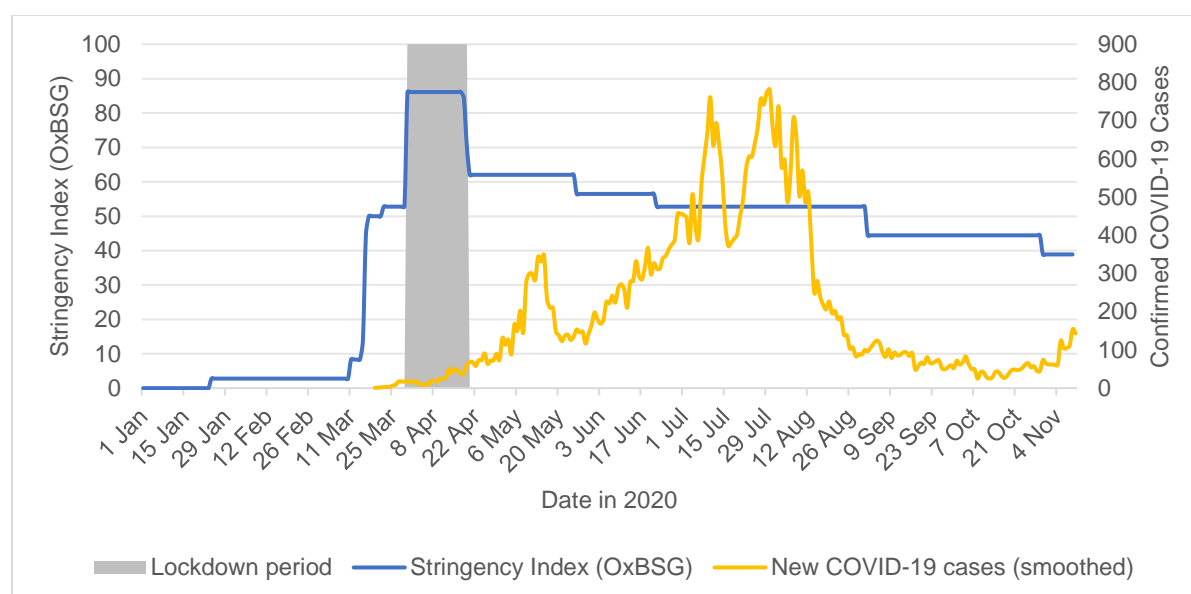
Despite these preventive measures, cases continued to rise and the two largest cities in Ghana, Accra and Kumasi, emerged as 'hotspots' of the disease. As a result, on 27 March, the President announced a partial lockdown of the Greater Accra and Greater Kumasi Metropolitan Areas and contiguous districts, which was to take effect from 30 March 2020, 48 hours after the announcement. The partial lockdown required that residents of the restricted districts stay at home, and all passenger travel between the restricted districts and other parts of the country was prohibited. Apart from essential workers, who continued their activities (including the production, distribution, and marketing of food, beverages, pharmaceuticals, medicine, paper, and plastic packages), people were allowed to leave home only to purchase essential goods, seek medical care, undertake banking transactions, or use public sanitation facilities. Officers of the Ghana Police Service and Ghana Armed Forces were tasked to strictly enforce the lockdown (Asante and Mills 2020). The partial lockdown was initially announced for a period of two weeks, but ultimately was extended to 21 April, lasting three weeks (21 days) in total. Although the partial lockdown was

then lifted, the suspension of all public and social gatherings remained in effect throughout May 2020.

The first phase of the process of easing national restrictions began on 5 June. Provided social distancing restrictions were met, public gatherings of up to 100 people were allowed, and junior and senior high schools and universities re-opened from 15 June, so that older students could resume classes ahead of exams. Large sporting events, political rallies, festivals, and religious events remained suspended until 31 July. The second phase of re-opening started on 1 August, lifting restrictions on the number of people in public gatherings and opening tourist sites. However, beaches, pubs, cinemas, and nightclubs remained closed. International flights resumed from 1 September, subject to enhanced COVID-19 protocols. Land and sea borders remained closed to human traffic.

Figure 1 illustrates the stringency of policy measures that were in place in Ghana between January and November 2020 in response to the COVID-19 pandemic. The stringency index shows the response level in the national subregion with the strictest policies (districts subject to lockdown regulations) and the grey shaded area indicates the lockdown period.²

Figure 1: COVID-19 cases and government response stringency index in Ghana



Note: the grey shaded area demarcates the lockdown period from 30 March to 19 April. The stringency index is a composite measure based on nine response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (strictest); it shows the pandemic response level in the districts subject to the strictest lockdown measures.

Source: authors' illustration based on Hale et al. (2020) and Roser et al. (2020).

Considering the evolution of newly confirmed COVID-19 cases, the Ghanaian government was quick to implement stringent measures, when case numbers were still relatively low. From a public health perspective, the lifting of the partial lockdown may be considered premature. The number of confirmed COVID-19 infections continued to escalate during the lockdown and increased

² The Coronavirus Government Response Tracker (OxCGRT), published and managed by researchers at the Blavatnik School of Government at the University of Oxford (Hale et al. 2020), collects publicly available information on 17 indicators of government responses, spanning containment and closure policies (such as school closures and restrictions on movement); economic policies; and health system policies (such as testing regimes). The indicators are aggregated into a set of four common indices, one of which is the stringency index presented here.

exponentially after restrictions were lifted, reaching peak levels only in late July or early August, after which the pandemic curve flattened. The decision to lift the partial lockdown was largely influenced by mounting concerns regarding the severe economic burden that the restrictions posed, especially on the livelihoods of the urban poor, many of whom had by that time run out of money to buy food, due both to the hike in food prices and to the restricted possibilities to earn a living (Asante and Mills 2020).

3 Data, empirical strategy, and descriptive statistics

In this section, we present our data, including descriptive statistics, and outline our empirical strategy and approach to identification. As discussed in Section 2, to confine the spread of the coronavirus, the Ghanaian government implemented a geographically contained three-week lockdown covering the Greater Accra and Greater Kumasi Metropolitan Areas and contiguous districts from 30 March to 21 April 2020, while other areas were subject to less stringent regulations. In this study, we intend to exploit this geographic variation using a DID design to estimate the labour market impact of the pandemic under the two distinct policy settings, distinguishing between respondents in lockdown (treated) and no-lockdown (control) districts.

3.1 Data sources

The sample for this study was drawn from the most recent round of the Ghana Socioeconomic Panel Survey (GSPS), which is a joint effort between the Economic Growth Centre (ECG) at Yale University and the Institute of Statistical, Social and Economic Research (ISSER) at the University of Ghana. The first round of the GSPS was collected in 2009/2010, consisting of a nationally representative sample of 5,010 households in 334 enumeration areas containing 18,889 household members. Two follow-up rounds were conducted in 2013/14 and 2018/19.

To construct the sampling frame for this study, we focused on the GSPS Wave 3 (W3) adult population in urban areas who were heads of household and had been working (outside of smallholder agriculture) in the last survey round. From these we drew a random sample of 937 respondents, stratified by geographic location, occupational position (wage employee vs. self-employed) and formality status (formal vs. informal employment). Among those who were contacted, 187 could not be reached, 17 were no longer members of the same household, 10 could not be unequivocally identified, and in 8 cases the interview was not completed, leaving us with a sample of 662 respondents, of whom 612 reported having been working in February 2020. To those who were successfully contacted, a structured questionnaire was administered by trained local enumerators using phone interviews.

The GSPS-COVID survey asked multiple questions about the respondents' perception of and compliance with the pandemic response measures implemented by the national government, and the economic and labour market impact that they had experienced. Concerning the latter, respondents were asked retrospectively about their household's economic wellbeing and their own employment situation in February (i.e. before the coronavirus had reached Ghana), in April (the month when parts of Ghana were under lockdown), as well as in the seven days prior to the interview, which took place between 19 August and 17 September 2020.

3.2 Empirical strategy and identification

We centre our discussion around analysing the effect of COVID-19-related lockdown policies on labour market outcomes in Ghana. Lockdown here refers to a legally enforceable order for residents to remain in their homes except for essential trips. We take advantage of the Ghana-specific policy context, in which strict lockdown policies were issued and enforced in two spatially delimited areas, while in the rest of the country less stringent regulations were in place. We exploit this geographic variation to estimate the differential labour market impact of strict stay-at-home orders using a DID design.

In the first part of the analysis, we investigate the policy impact at the extensive margin, focusing on the employment status of the worker. Here, the dependent variable is a binary indicator that takes on a value of one if the respondent is working (actively working or on paid leave) and zero otherwise (either temporarily or permanently out of work). The second part of the analysis investigates the impact at the intensive margin. Here, we use working hours and labour earnings as relevant outcomes of interest. Labour earnings are deflated to constant 2018 prices using the Ghana Statistical Service (GSS) monthly consumer price index as of August 2020 (GSS 2020).

Our DID design builds on a basic comparison between changes in these labour market outcomes among respondents in lockdown districts, considered ‘treated’, and respondents in no-lockdown districts, considered ‘control’. Our analysis compares the changes in labour market outcomes between three points in time: (i) February 2020, the base period before the COVID-19 pandemic had reached Ghana; (ii) April 2020, when parts of Ghana were under lockdown; and (iii) August/September 2020, when the most stringent policy measures had been relaxed. Changes that occurred between February and April 2020 (first post-treatment period) will give an indication of the immediate short-term effects of the COVID-19 pandemic and related policy measures, while changes that occurred from February up to August/September 2020 (second post-treatment period) will give an indication of the medium-term implications. In addition, a backward-looking comparison of changes in labour market outcomes between 2018/2019 and February 2020 (pre-treatment period) will serve to verify the common trends assumption underlying the DID identification strategy (provided as a robustness check).

We write the DID regression model as:

$$Y_{idt} = \beta_0 + \beta_1 LOCKDOWN_d + \beta_2 (LOCKDOWN_d \times POST_{1t}) + \beta_3 (LOCKDOWN_d \times POST_{2t}) + \beta_4 X_i + \theta_t + \varepsilon_{idt} \quad (1)$$

where the dependent variable Y_{idt} is the labour market outcome of worker i in district d at time t . $LOCKDOWN_d$ is a dummy variable that defines the treatment status at the district level, taking on a value of one for districts that were subject to lockdown policies, and zero otherwise. $POST_{1t}$ and $POST_{2t}$ are dummy variables that take on a value of one for the first and second post-treatment period, respectively, and zero otherwise. The coefficients of the interaction terms, β_2 and β_3 , yield the DID estimates that capture the effect of the lockdown policies on the outcome variables. We also control for time-fixed effects, θ_t , to identify the period-specific impact on labour market outcomes across treated and control districts. X_{idt} is a vector of time-fixed worker-specific control variables, and ε_{idt} is the error term. The standard errors are clustered at the district level.

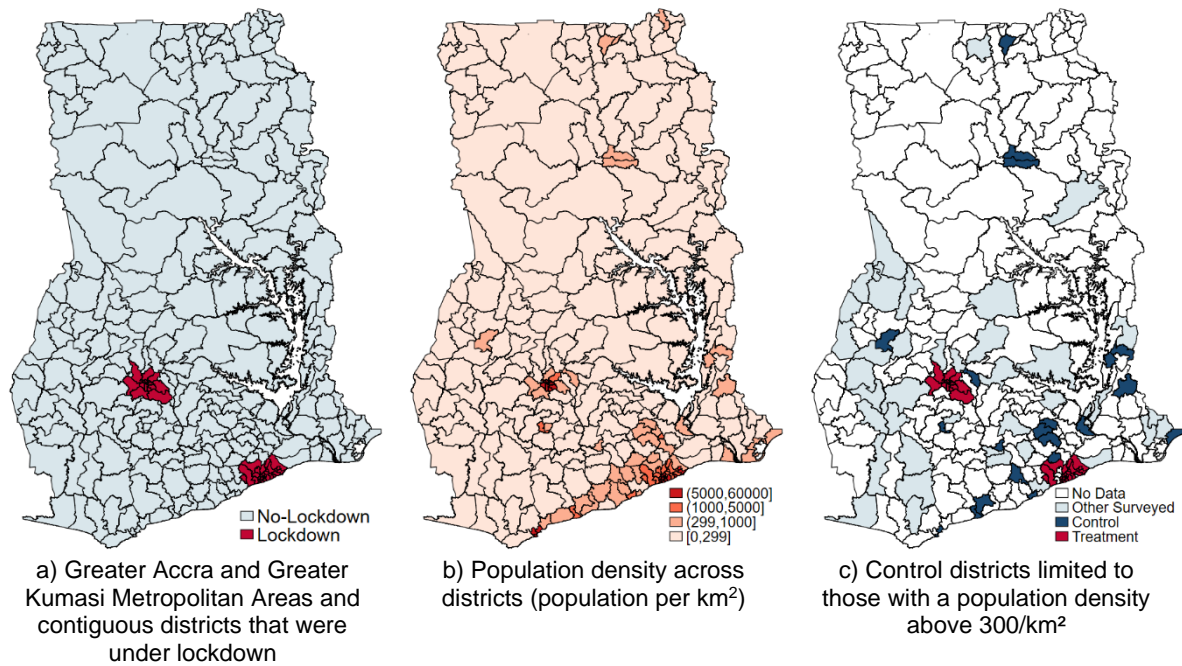
In the base specification, we estimate equation (1) using ordinary least squares (OLS) regression. Taking advantage of the panel structure of our data, we also estimate a second model that controls for worker-fixed effects, μ_i :

$$Y_{idt} = \delta_0 + \delta_1 (LOCKDOWN_d \times POST_{1t}) + \delta_2 (LOCKDOWN_d \times POST_{2t}) + \mu_i + \theta_t + \varepsilon_{idt}. \quad (2)$$

This is our preferred specification, as the worker-fixed effects, μ_i , absorb any worker-specific heterogeneities that may contaminate our DID estimates (see Fang et al. 2020 for a similar specification used to quantify the causal impact of human mobility restrictions on the containment and delay of the spread of the novel coronavirus in China). Given that the location of workers is fixed in our data over the study period, the worker-fixed effects, μ_i , also absorb any time-constant differences between districts. To ensure the robustness of our results, we estimate several variants of both equations on different subsamples.

As can be seen from Figure 2 panels (a) and (b), the districts that were subject to lockdown policies in Ghana comprise the two most densely populated urban centres. To increase comparability between the treatment and control groups, in the empirical estimation, control districts will be limited to those with a population density above 300/km². This cut-off value is fixed in reference to the population density in the least densely populated treated district.

Figure 2: Lockdown versus no-lockdown study areas



Note: population projections for 2020 by the Ghana Statistical Service (GSS) based on the 2010 Population and Housing Census.

Source: authors' illustration based own GPS-COVID-19 survey.

3.3 Descriptive statistics

Table 1 reports the summary statistics of average worker characteristics by district treatment status. Our sample was drawn from the GPS W3 adult population, limited to those who were living in urban areas, were heads of household, and were working outside of agriculture in 2018/19. Accordingly, in the GPS-COVID sample, 82.1 per cent of respondents identified as heads of household and 92.6 per cent reported being employed in February 2020. Of the respondents in our sample, 48.3 per cent are female and the average age is 44 years. Among those respondents who were working in February 2020, 26.5 per cent were in formal employment, and 37.4 per cent

reported being in wage employment.³ Thus, despite the urban focus and exclusion of agriculture, the informality rate is above 70 per cent, and every second worker was in informal self-employment prior to the pandemic (both matching the shares observed in earlier GSPS rounds). We find no statistically significant differences in any of these dimensions between workers in treatment versus control districts (see Table 1).

Table 1: Average worker characteristics by district treatment status

Characteristics in Aug/Sep 2020 (unless otherwise specified)	(1) Lockdown	(2) No-lockdown	(3) No-lockdown size cut-off	(1) - (3) Difference	P-value Ha: diff != 0
Female	0.453 (0.030)	0.504 (0.026)	0.491 (0.038)	-0.038 (0.048)	0.4282
Age in years	45.4 (0.704)	43.4 (0.601)	43.7 (0.887)	1.679 (1.134)	0.1414
Head of household	0.833 (0.022)	0.813 (0.020)	0.838 (0.028)	-0.005 (0.036)	0.8938
Household size	2.609 (0.094)	3.434 (0.105)	3.428 (0.158)	-0.819*** (0.172)	0.0000
Moved since last interview	0.087 (0.017)	0.122 (0.017)	0.139 (0.026)	-0.052* (0.030)	0.0844
Married (2018/19) ^a	0.471 (0.030)	0.488 (0.026)	0.456 (0.038)	0.014 (0.048)	0.7671
Secondary education (2018/19) ^a	0.174 (0.024)	0.203 (0.021)	0.181 (0.031)	0.007 (0.039)	0.8593
Tertiary education (2018/19) ^a	0.143 (0.022)	0.144 (0.019)	0.194 (0.031)	0.050 (0.037)	0.1761
Working in Feb 2020	0.935 (0.015)	0.919 (0.014)	0.925 (0.020)	0.010 (0.025)	0.6872
Formal employment in Feb 2020	0.244 (0.027)	0.279 (0.024)	0.267 (0.035)	-0.023 (0.044)	0.6010
Wage employment in Feb 2020	0.422 (0.031)	0.341 (0.025)	0.385 (0.038)	0.037 (0.049)	0.4500
Number of observations	276	385	173	449	449

Notes: ^a Information not collected in the GSPS-COVID survey and therefore taken from GSPS Wave 3 (2018/19). Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Source: authors' calculations based on GSPS-COVID-19 survey.

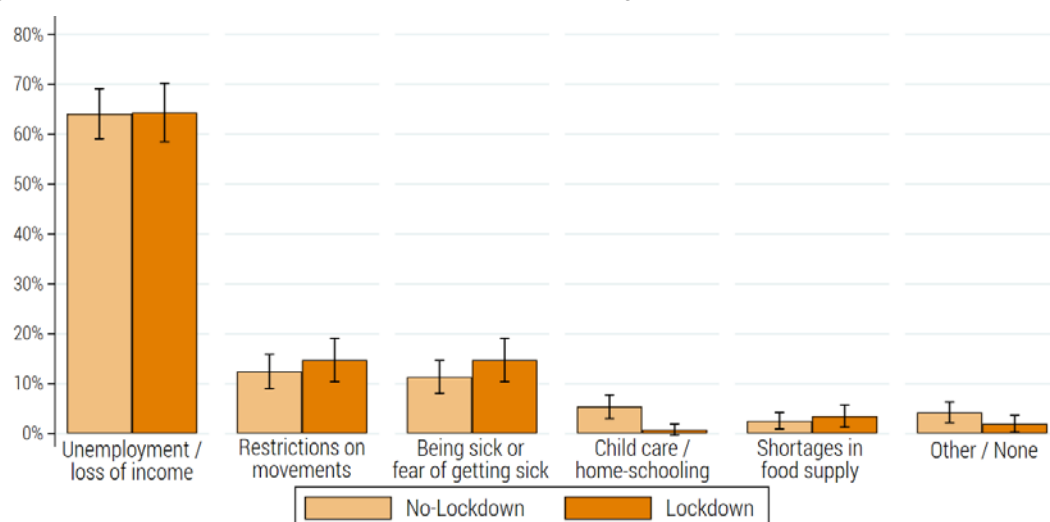
In the rapid GSPS-COVID phone survey, we did not collect information on the marital status and education levels of respondents. However, this information is available from earlier panel rounds. According to GSPS W3 data, close to half (48.1 per cent) of the respondents in our sample had been married in 2018/19. Moreover, 19.1 per cent reported completing secondary schooling as the highest level of education attained, and 14.4 per cent had attained tertiary education. Again, we find no statistically significant differences in these dimensions by treatment status.

³ Wage workers with written contracts and any social security withholdings from their salaries (for medical care or retirement provisions) are classified as formal. Self-employed workers are classified as formal if operating an enterprise that is officially registered with relevant national institutions.

While other worker characteristics are balanced between control and treated groups, we find that the average household size reported at the time of the interview (August/September 2020) among respondents in lockdown districts was significantly smaller than in districts not affected by the lockdown, and in fact had declined by 0.68 members on average compared with the 2018/19 estimate. Specifically, the average household size in the treated districts in February 2020 was 2.6 members, compared with 3.5 members in the control districts (see Table 1). The latter is close to the average household size of 3.4 members reported by the same respondents in 2018/19, for which we find no statistically significant difference by district treatment status. We also observe that a larger share of respondents in control districts had moved since the last interview round in 2018/19. Previous research has shown that, in anticipation of the lockdown restrictions and the expected consequences for doing business in affected districts, a non-negligible number of migrant workers in Ghana relocated to their hometowns between 28 and 29 March 2020 (Asante and Mills 2020; see also Lee et al. 2020 for similar evidence from India). If respondents with a higher risk of losing work during the lockdown were more likely to move out of treated districts and continue work in districts with no lockdown policies in place, this self-selection could cause our estimates to be biased. We check the robustness of our findings to the exclusion of movers in Section 5.

Figure 3 provides a ranking of aspects of the COVID-19 pandemic that, according to respondents, had the largest impact on them personally. Just under two-thirds of respondents selected unemployment or loss of income as the most important factor. Interestingly, this applies equally to respondents located in lockdown versus no-lockdown districts. In addition, 14.7 per cent of respondents in lockdown and 12.4 per cent of respondents in no-lockdown districts reported restrictions on movement as their primary concern. Similarly, 14.7 per cent of respondents in lockdown and 11.3 per cent of respondents in no-lockdown districts mentioned being sick or fear of getting sick as the aspect that impacted them the most. Yet, the differences in average shares between lockdown and no-lockdown districts are not statistically significant. With 5.4 versus 0.8 per cent, childcare and home-schooling were a significantly larger concern among respondents in no-lockdown versus lockdown districts. In both areas, a relatively small share of 2.5 to 3.5 per cent saw shortages in food supply as the biggest worry. Other concerns were raised by 1.7 and 0.4 per cent of respondents in no-lockdown and lockdown districts, respectively. In the former, 2.5 per cent of respondents said they had not been impacted by the pandemic at all, while the same applied to 1.6 per cent of respondents in lockdown districts.

Figure 3: Aspects of the COVID-19 pandemic that had the largest impact on respondents

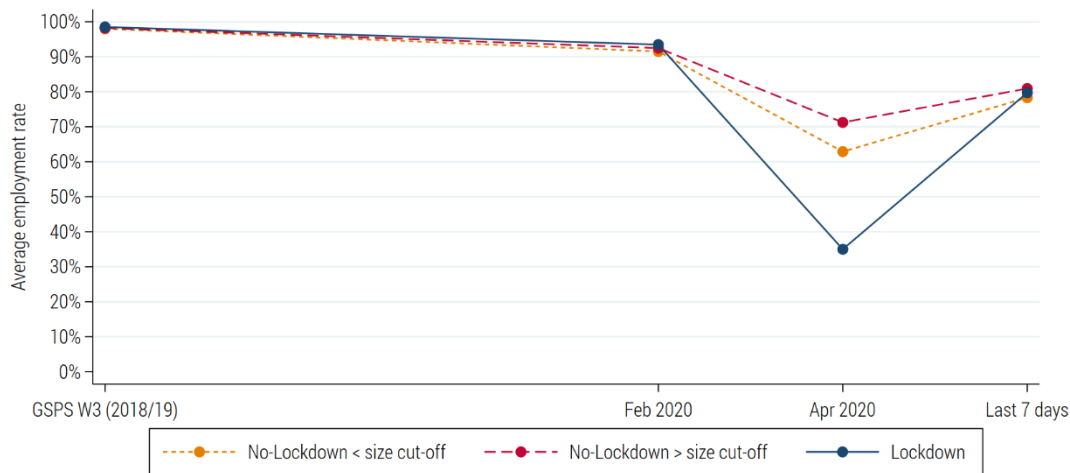


Note: sample limited to respondents who had been working February 2020. Average shares with 95% confidence intervals.

Source: authors' illustration based on GPS-COVID-19 survey.

Even though the type of worries expressed by respondents in treated and control districts are very similar, the extent to which these materialized differs considerably. Specifically, we observe a stark difference in short-term employment effects at the extensive margin. The trends displayed in Figure 4 reveal a much sharper drop in employment rates in treated versus control districts in the month of April, when treated districts were under lockdown. Overall, we observe a recovery in employment up to August/September 2020 throughout the country, with employment rates in our sample nevertheless remaining below the February average.

Figure 4: Time trends in employment, lockdown versus no-lockdown districts

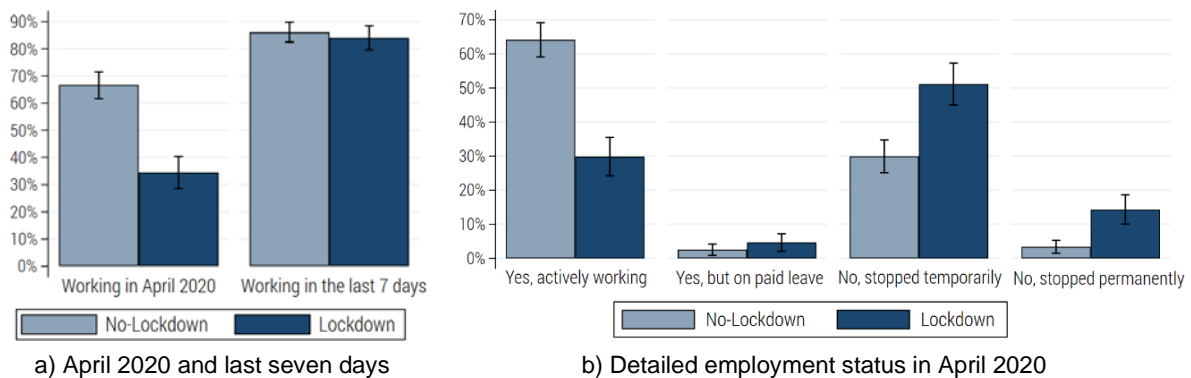


Note: the GSPS-COVID-19 sample was drawn from the GSPS W3 adult population in urban areas, limited to those who were heads of household and had been working in 2018/19. We distinguish no-lockdown districts below and above the population density cut-off value set at 300/km².

Source: authors' illustration based on GSPS-COVID-19 survey.

While respondents in both lockdown and no-lockdown districts worried about unemployment and loss of income as a result of the COVID-19 pandemic (see Figure 3), the descriptive evidence suggests that 66.7 per cent of respondents in no-lockdown districts continued working throughout the month of April, compared with 34.5 per cent of respondents in lockdown districts (Figure 5a). Importantly, the majority (51.2 per cent) of respondents in lockdown districts said that they had stopped working temporarily, while 14.3 per cent considered this break to be permanent (Figure 5b).

Figure 5: Employment status in lockdown and no-lockdown districts



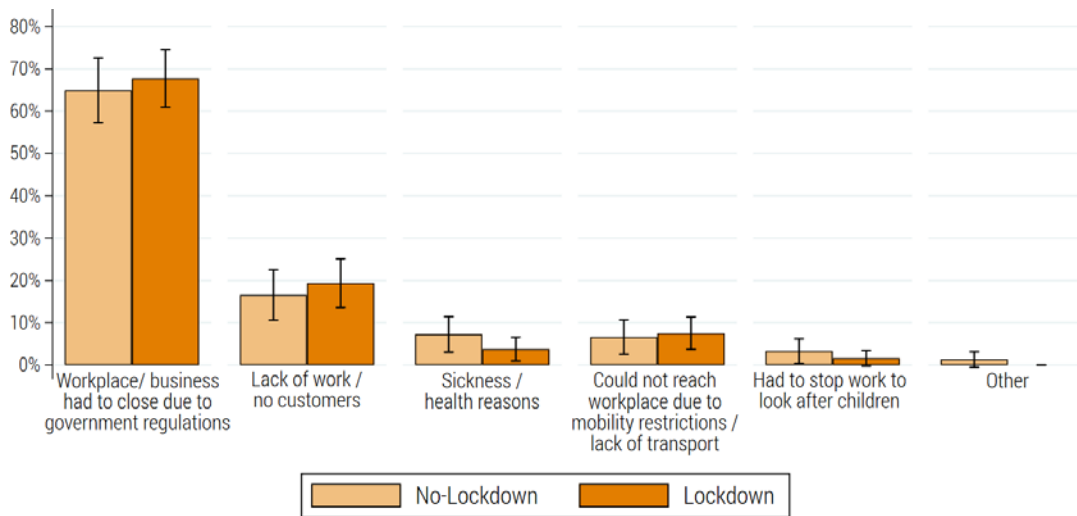
Note: sample limited to respondents who had been working February 2020. Average shares with 95% confidence intervals.

Source: authors' illustration based on GSPS-COVID-19 survey.

In line with this perception, we observe that at the time of the interview (August/September 2020), the gap in employment rates between lockdown and no-lockdown districts had closed. In districts that had been under lockdown, 84.1 per cent of respondents who had been working in February 2020 were observed to be working again, compared with 86.2 per cent of respondents in no-lockdown districts (Figure 5a).

While the immediate employment effect was significantly more pronounced in lockdown districts, the reasons for the break in employment reported by respondents who were out of work in April were largely similar between both areas (Figure 6). The vast majority of respondents (64.9 per cent in no-lockdown and 67.7 per cent in lockdown districts) reported workplace or business closures due to government regulations as the main reason for stopping work in April, followed by a lack of work or customers (16.6 per cent in no-lockdown and 19.4 per cent in lockdown districts).

Figure 6: Main reason for stopping work in April 2020

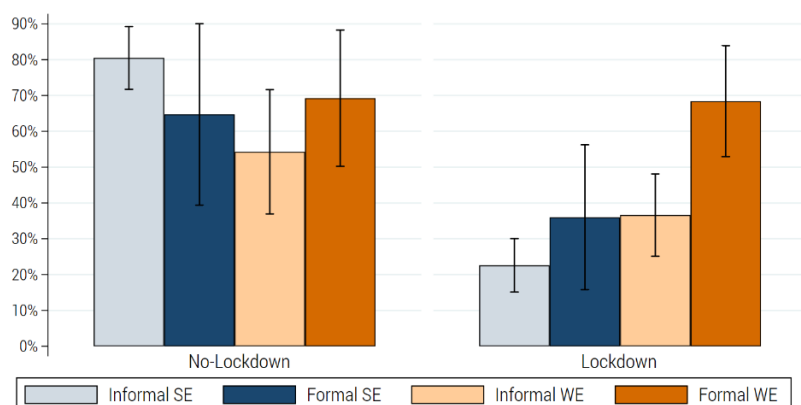


Note: sample limited to respondents who had been working February and out of work in April 2020. Average shares with 95% confidence intervals.

Source: authors' illustration based on GSPS-COVID-19 survey.

Importantly, while workers throughout Ghana reported government regulations and a lack of work or customers as the main reasons for stopping work in April 2020, the short-term employment effect of the pandemic was not only significantly more sizable in districts affected by the lockdown, but was also concentrated among workers in informal self-employment (Figure 7). This finding is in line with the evidence presented by other studies. For example, a recent rapid survey of businesses in Uganda suggests that lockdown measures have reduced business activity by more than half, and finds that micro and small enterprises have experienced a larger decline in activity than medium and large enterprises (Lakuma and Sunday 2020). Similarly, real-time survey data collected in Senegal, Mali, and Burkina Faso suggest that on average, by the end of April, one out of four workers had lost their jobs and one out of two workers had experienced a decline in earnings. Informal workers were at higher risk, as they generally rely on daily sales for their earnings, lack mechanisms for collective bargaining, and tend to be in activities that are contact-intensive and thus particularly affected by the pandemic response measures—such as restaurants, tourism businesses, small retail shops, hairdressing, and taxi driving (Balde et al. 2020). However, to the contrary, we also observe that workers in informal self-employment were most likely to continue working in no-lockdown districts. As indicated, most workers in this group are low-income earners with no or small savings, who need to earn a living on a daily basis (Danquah et al. 2019). Therefore, where possible, they would continue working in spite of the danger posed by the pandemic (Durizzo et al. 2021; Kazeem 2020).

Figure 7: Employment rates in lockdown and no-lockdown districts in April, by work status in February 2020



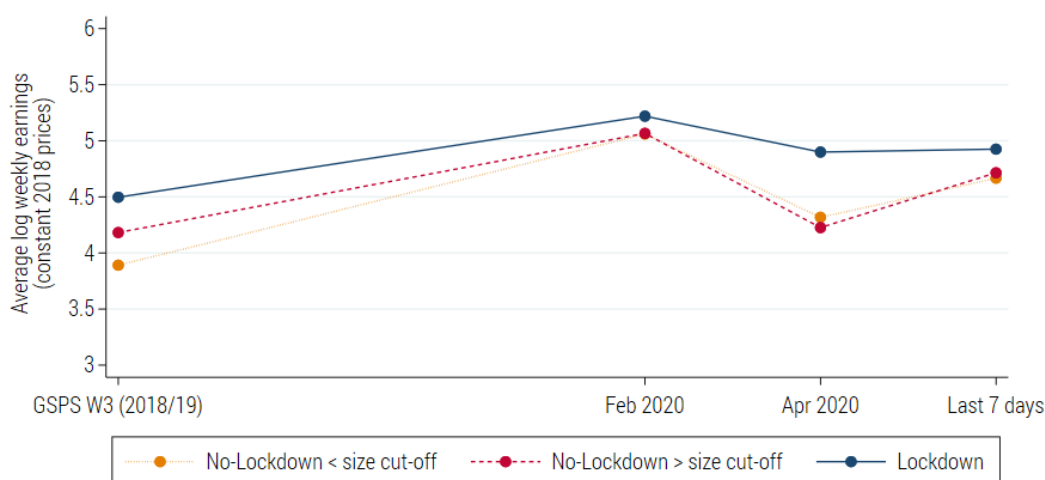
Notes: sample limited to respondents who had been working February 2020. SE = self-employed; WE = wage employed. Average shares with 95% confidence intervals.

Source: authors' illustration based on GSPS-COVID-19 survey.

In districts that were not subject to the lockdown, labour market dropout in April was highest among workers in informal wage employment. This is most likely explained by the low degree of employment security in these jobs, which lack basic contractual rights (Danquah et al. 2019). These workers were likely to be the first to be laid off in the face of the decline in economic activity caused by the pandemic. At the other extreme, workers in formal wage employment were the most likely to continue to work in spite of lockdown policies. This can be attributed to the higher level of job security and employment protection characterizing these jobs (Danquah et al. 2019). It may also be partly explained by the type of tasks performed in these jobs, which tend to be higher skilled and may more often be performed from home.

Lastly, at the intensive margin, Figure 8 documents the trends in average weekly earnings among those with non-zero labour incomes. The visual analysis suggests that the common trends assumption for the pre-treatment period is more likely to hold when defining the control group, which comprises no-lockdown districts with a population density above 300/km². This will be formally tested in the next section. We observe that average earnings tended to be higher in treated than control districts and followed relatively similar trends up to February 2020.

Figure 8: Time trends in weekly earnings, lockdown vs. no-lockdown districts



Note: sample in each period limited to respondents who reported non-zero (positive) labour incomes. We distinguish no-lockdown districts below and above the population density cut-off value set at 300/km².

Source: authors' illustration based on GSPS-COVID-19 survey.

According to Figure 8, the drop in average log weekly earnings was more pronounced in districts not affected by the lockdown. When interpreting this pattern, it is important to keep in mind that here we are considering only non-zero earnings of workers who continued working in April. As discussed above, in districts under lockdown, a substantially larger share of workers had stopped working completely (Figure 4 and Figure 5), and workers in informal self-employment were the worst affected (Figure 7). This implies that a larger share of low-income workers continued working in no-lockdown districts, while formal wage workers, who tend to hold higher paying jobs, were the most likely to continue working in April in lockdown districts. Overall, we observe a recovery in earnings up to August/September 2020 throughout the country, with earnings levels nevertheless remaining below the February average.

4 Estimation results

This section presents our estimation results. We first focus on the impact of coronavirus lockdown measures at the extensive margin, investigating the short- and medium-term impact on employment rates. Second, we examine the impact at the intensive margin, estimating the short- and medium-term impact on labour earnings and working hours. As discussed earlier, the sample was drawn from the GSPS W3 (2018/19) panel survey. The data were collected in August/September 2020, comprising recall information for April 2020 and February 2020, allowing us to construct a longitudinal dataset at the worker level and to estimate the effects using panel data methods. Our estimations employ robust standard errors clustered at the district level.

4.1 Impact of the lockdown on employment

Table 2 shows the linear probability estimates of working in April 2020 and in the seven days prior to the interview in August/September 2020, relative to the base period in February 2020, depending on the treatment status of the districts where workers are located. Column (1) presents the estimates for the full sample, while columns (2)–(4) present estimates for our preferred sample specification, limiting no-lockdown control districts to those with a minimum population density of 300/km². Column (3) controls for a set of worker-level covariates—including gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), and household size—while column (4) uses worker-level fixed effects in the regression. Given that the location of workers (recorded at the time of the interview, conducted in August/September 2020) is fixed over the 2020 study period, the worker-fixed effects also absorb any time-constant differences between districts.

Confirming the patterns observed in the descriptive analysis (see Section 3.3), we find that the lockdown measures implemented in parts of the country had a large and significant negative short-term impact on employment in the affected districts. In line with the patterns reported in Figure 4, we find a larger treatment effect of the lockdown on employment when limiting control districts to those with a population density equal to or higher than that observed in the least densely populated treated district. Without individual-level controls, our estimates suggest that workers located in districts under lockdown had a 37.2 per cent lower chance of continuing working throughout April 2020, compared with workers located in districts not subject to lockdown policies (column (2)). Controlling for observable time-constant individual-level covariates provides very similar estimates (column (3)).

Table 2: Impact of the coronavirus lockdown on employment

Dependent variable: Working in period t (=1 if YES)	(1) Full sample	(2) District size cut-off	(3) District size cut-off with covariates	(4) District size cut-off with worker FE
Post-period (base Feb 2020)				
April 2020	-0.253*** (0.034)	-0.212*** (0.046)	-0.216*** (0.046)	-0.283** (0.047)
Last 7 days	-0.125*** (0.019)	-0.116*** (0.026)	-0.116*** (0.026)	-0.116*** (0.026)
Lockdown	0.015 (0.029)	0.010 (0.033)	0.017 (0.036)	
Lockdown \times April 2020	-0.332*** (0.049)	-0.372*** (0.058)	-0.370*** (0.058)	-0.351*** (0.051)
Lockdown \times Last 7 days	-0.013 (0.024)	-0.022 (0.030)	-0.022 (0.030)	-0.022 (0.030)
Observations	1,936	1,318	1,318	1,318
Covariates	NO	NO	YES	NO
Worker-fixed effects (FE)	NO	NO	NO	YES

Note: covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), and household size. Linear probability model; FE = fixed effects (within) regression; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GPS-COVID-19 survey.

Our preferred specification, which controls for individual-fixed effects to absorb any worker-specific heterogeneities that may contaminate our DID estimates, yields a marginally smaller treatment effect, suggesting a 35.1 per cent drop in the chance of employment in April compared with February 2020, which is attributable to the lockdown (column (4)). We find that, on aggregate, workers in lockdown districts faced a 63.4 per cent risk of being out of work in April, compared with an average *ceteris paribus* risk of 28.3 per cent faced by workers in no-lockdown districts.

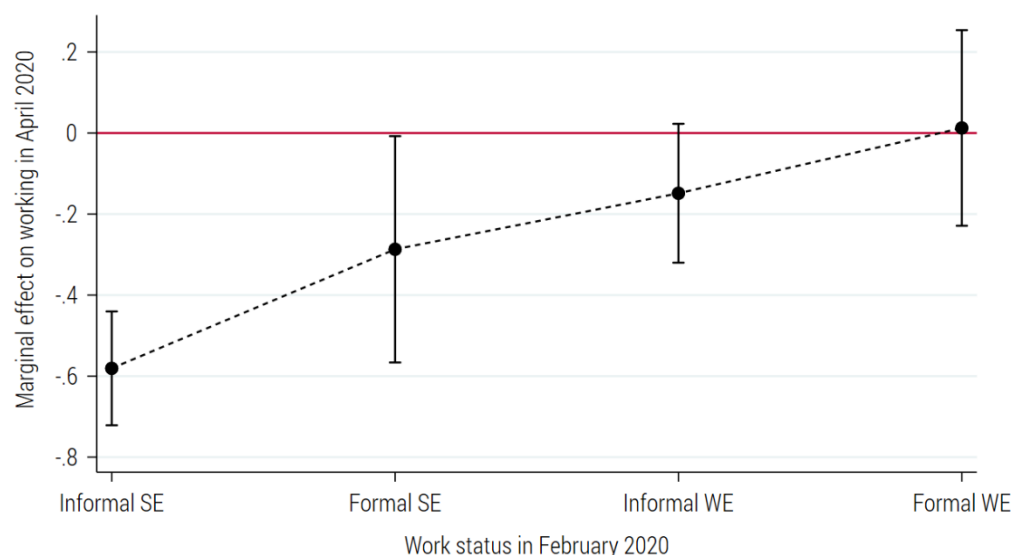
In addition, we find evidence for a strong recovery in employment about four months after the lockdown policies were lifted. As our estimates presented in Table 2 indicate, there was no statistically significant difference in chances of employment between lockdown and no-lockdown districts in August/September 2020. However, the average probability of being in work at the time of the interview was 11.6 per cent below the February 2020 level.

To check for potential heterogeneities in the treatment effect between different groups of workers, we focus on the first post-treatment period up to April 2020, for which we find a strong and significant impact of the lockdown on average employment rates. We limit the sample to respondents who were working in February 2020, and interact the treatment status, defined at the district level, with the workers' initial work status, defined by formality status (informal vs. formal) and occupational position (self- vs wage employment).

Figure 9 reports the average marginal effects of the lockdown on the chances of employment in April 2020, by initial work status in February. Confirming our descriptive results, we find that the negative employment effect of the lockdown was most pronounced for workers in informal self-employment, while workers in formal wage work did not face a higher risk of being out of work in lockdown versus no-lockdown districts. Interestingly, independent of the formality status, the

lockdown seems to have affected self-employed workers more than wage employees (Figure 9). This observation could be explained by a larger decline in the activity of micro and small enterprises (often operated by own account workers or family enterprises without no external employees) compared with medium and large enterprises (Lakuma and Sunday 2020).

Figure 9: Impact of the coronavirus lockdown on employment in April, by work status in February 2020



Note: regression fitted to 418 observations. Control districts limited to those with a population density above 300/km². Sample limited to respondents who had been working in February 2020. SE = self-employed; WE = wage employed. Covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), and household size. Each point shows the estimated average marginal effect of coronavirus lockdown measures on employment in April 2020, by work status in February 2020. The dashed lines show the 95% confidence intervals. Standard errors are clustered at the district level.

Source: authors' estimates based on GPS-COVID-19 survey.

As discussed earlier, the strong recovery of employment in districts where lockdown policies had brought much economic activity to a standstill in April 2020 can be attributed to the largely temporary nature of the workplace and business closures that caused the drop in employment. Table 3 explores this in more detail. Here, we again limit the sample to respondents who were working in February 2020. We investigate the impact of coronavirus lockdown measures on employment in the second post-treatment period up to August/September 2020, depending on the workers' reported detailed employment status in April 2020. Columns (1) and (2) present the estimates for the full sample, excluding and including worker-level controls, while in column (3) no-lockdown control districts are limited to those above the population density cut-off.

It is important to note that relatively fewer workers in districts not affected by lockdown policies had stopped work in April and a rather small share considered this break to be permanent (see Figure 5). Therefore, given the relatively low number of observations in this category, we consider the full sample estimates presented in column (2) preferable to the reduced sample estimates presented in column (3). These suggest that workers who experienced a permanent break in employment in April 2020 saw only modest chances of recovery. Compared with workers who had been able to continue working throughout April, they were still 45.5 per cent more likely to be out of work at the time of the interview in August/September 2020 (Table 3).

Furthermore, workers in no-lockdown districts who said they had stopped work temporarily in April 2020 were still 18.5 per cent more likely to be out of work in August/ September 2020 than workers who had continued working in April. In comparison, workers in lockdown districts who

had stopped work temporarily in April 2020 were only 1.7 (-18.5+16.7) per cent less likely still to be out of work in August/September 2020, suggesting a significantly stronger recovery (Table 3).

Table 3: Impact of the coronavirus lockdown on employment in last seven days, by work status in April 2020

Dependent variable: Working in last 7 days (=1 if YES)	(1) Full sample	(2) Full sample with covariates	(3) District size cut-off with covariates
Lockdown	-0.007 (0.024)	-0.018 (0.026)	-0.016 (0.032)
<i>Status in April 2020 (base: actively working)</i>			
On paid leave	0.070*** (0.016)	0.012 (0.028)	0.031 (0.029)
Temporarily stopped	-0.184*** (0.042)	-0.185*** (0.044)	-0.216*** (0.062)
Permanently stopped	-0.430** (0.172)	-0.455*** (0.167)	0.031 (0.036)
Lockdown × On paid leave	0.007 (0.024)	0.051* (0.031)	0.036 (0.030)
Lockdown × Temporarily stopped	0.149** (0.060)	0.167*** (0.060)	0.194** (0.078)
Lockdown × Permanently stopped	-0.033 (0.196)	0.015 (0.191)	-0.477*** (0.100)
Observations	612	612	418
Covariates	NO	YES	YES

Note: sample limited to respondents who had been working February 2020. Covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), household size. Linear probability model; standard errors in parentheses, clustered at the district level; *p<0.10, **p<0.05, ***p<0.01.

Source: authors' estimates based on GPS-COVID-19 survey.

4.2 Impact of the lockdown on earnings and working hours

We now turn to the analysis at the intensive margin. As indicated in Section 3.3, this part of the analysis focuses on the labour market outcomes of workers who continued working in the respective period. When interpreting the estimates, it is important to keep in mind that, in districts under lockdown, a substantially larger share of workers stopped working altogether.

Table 4 shows the estimates on log weekly earnings by period and district treatment status. In line with the descriptive trends (see Figure 8), we observe that from February to April 2020, earnings fell more sharply in no-lockdown districts. As discussed in Section 3.3, this is likely explained by the selection of workers who were able to continue work in spite of the lockdown. This hypothesis will be explored in more detail below.

Importantly, we find no statistically significant medium-term impact of coronavirus lockdown measures on earnings. However, across the sample, earnings in the seven days prior to the interview remained significantly below the pre-COVID level (Table 4). On average, depending on the specification, average weekly earnings in August/September were between 0.314 and 0.459 log points lower than in February 2020. These results imply a drop ranging from GH¢73.0 to GH¢99.8 relative to a base of GH¢271 in February 2020, equivalent to a decline of 26.8–36.8 per cent. It is important to note that in this estimation, all earnings have been deflated to constant

2018 prices, taking into account sharp price increases in consumer products and the falling purchasing power of earnings since the onset of the pandemic. Without accounting for inflation, a somewhat smaller decline in average weekly earnings of 21.7–32.3 per cent would have been estimated, depending on the specification.

Table 4: Impact of the coronavirus lockdown on log weekly earnings

Dependent variable: Log weekly earnings in period t (constant 2018 prices)	(1) Full sample	(2) District size cut- off	(3) District size cut- off with covariates	(4) District size cut-off with worker FE
Post-period (base Feb 2020)				
April 2020	-0.789*** (0.104)	-0.840*** (0.173)	-0.850*** (0.161)	-0.658*** (0.107)
Last 7 days	-0.373*** (0.057)	-0.352*** (0.079)	-0.314*** (0.083)	-0.459*** (0.067)
Lockdown	0.156* (0.091)	0.153 (0.124)	0.156 (0.102)	
Lockdown \times April 2020	0.458*** (0.137)	0.509** (0.195)	0.442** (0.185)	0.346*** (0.111)
Lockdown \times Last 7 days	0.077 (0.104)	0.055 (0.118)	0.003 (0.118)	0.135 (0.084)
Observations	1,061	710	710	710
Covariates	NO	NO	YES	NO
Panel effects	RE	RE	RE	FE

Note: covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), household size. FE = fixed effects (within) regression; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GPS-COVID-19 survey.

Table 5 shows the estimates of the lockdown impact on weekly working hours by period and district treatment status. The findings reflect largely similar patterns to those detected in the earnings estimation. Again, we find no statistically significant medium-term impact of coronavirus lockdown measures on working hours. However, across the sample, working hours in August/September 2020 remained significantly below pre-COVID levels. On average, depending on the specification, we estimate a decline of 4.8–6.9 hours per week since February 2020, equivalent to a decline of 10.0–14.3 per cent.

Table 5: Impact of the coronavirus lockdown on weekly working hours

Dependent variable: Weekly hours worked in period t	(1) Full sample	(2) District size cut- off	(3) District size cut- off with covariates	(4) District size cut-off with worker FE
Post-period (base Feb 2020)				
April 2020	-19.320*** (3.297)	-19.197*** (3.905)	-15.752*** (4.772)	-14.226*** (4.581)
Last 7 days	-6.474*** (1.661)	-8.278*** (2.413)	-4.861*** (1.681)	-6.955*** (1.811)
Lockdown	2.402 (2.121)	2.529 (2.668)	2.723 (2.600)	
Lockdown \times April 2020	12.106** (4.974)	11.983** (5.416)	12.539* (6.592)	8.902* (5.147)
Lockdown \times Last 7 days	-3.751* (2.134)	-1.947 (2.765)	-0.534 (2.038)	0.631 (2.059)
Observations	1,177	809	761	761
Covariates	NO	NO	YES	NO
Panel effects	RE	RE	RE	FE

Note: covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), household size. FE = fixed effects (within) regression; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GPS-COVID-19 survey.

Lastly, we explore the characteristics of workers who experienced a sharper, lasting decline in earnings. The results are reported in Table 6. We find that the earnings of self-employed workers and the earnings of women remain more heavily affected in the medium term. Given that women generally have lower earnings than men, and most self-employed workers are in the informal sector in Ghana, this finding gives rise to concerns that the pandemic may have aggravated existing labour market inequalities, leaving workers who had already been in a more vulnerable position prior to the pandemic in a yet more precarious position (see Crossley et al. 2020 for similar findings for the UK).

Table 6: Changes in log weekly earnings by employment status in February 2020

Dependent variable: Log weekly earnings in period t (constant 2018 prices)	(1) Full sample	(2) Full sample with covariates	(3) Full sample with covariates	(4) Full sample with worker FE
Post-Period (base Feb 2020)				
Last 7 days	-0.227** (0.101)	-0.230** (0.089)	-0.187** (0.087)	-0.222*** (0.055)
Self-employed in Feb 2020	0.126 (0.121)	0.289*** (0.103)	0.271*** (0.099)	
Formal work in Feb 2020	0.301*** (0.102)	0.181* (0.101)	0.187* (0.101)	
Female		-0.290*** (0.091)	-0.230** (0.101)	
Last 7 days \times Self-employed in Feb 2020	-0.265*** (0.091)	-0.263*** (0.089)	-0.222** (0.106)	-0.170** (0.076)
Last 7 days \times Formal in Feb 2020	0.088 (0.120)	0.114 (0.122)	0.099 (0.119)	0.067 (0.089)
Last 7 days \times Female			-0.144 (0.115)	-0.205** (0.087)
Observations	876	876	876	876
Covariates	NO	YES	YES	NO
District fixed effects	YES	YES	YES	NO
Panel effects	RE	RE	RE	FE

Note: sample limited to respondents who had been working February 2020. Covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), household size. FE = fixed effects (within) regression; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GSPS-COVID-19 survey.

5 Robustness checks

In Section 4, we estimated the impact of the coronavirus lockdown on different labour market outcomes at the extensive and intensive margins. To ensure the robustness of our findings, in this section, we estimate several variants of our preferred model specification on different subsamples, including worker-fixed effects to absorb any worker- and location-specific heterogeneities and limiting control districts to those above the defined population density cut-off. To ease comparison, Table 7 summarizes the results from our preferred specification (see Section 4 for details). Column (1) presents the impact on employment, while columns (2) and (3) show the estimated impact on log labour earnings (at constant 2018 prices) and working hours, respectively.

Table 7: Impact of the coronavirus lockdown on labour market outcomes

	(1) Working in period t (=1 if YES)	(2) Log weekly earnings (constant 2018 prices) in period t	(3) Weekly hours worked in period t
Post-period (base Feb 2020)			
April 2020	-0.283** (0.047)	-0.658*** (0.107)	-14.226*** (4.581)
Last 7 days	-0.116*** (0.026)	-0.459*** (0.067)	-6.955*** (1.811)
Lockdown \times April 2020	-0.351*** (0.051)	0.346*** (0.111)	8.902* (5.147)
Lockdown \times Last 7 days	-0.022 (0.030)	0.135 (0.084)	0.631 (2.059)
Observations	1,318	710	761
Panel effects	FE	FE	FE

Note: FE = fixed effects (within) regression; control districts limited to those with a population density above 300/km²; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GSPS-COVID-19 survey.

First, we test whether our data support the assumption of common pre-treatment trends in labour market outcomes of treated and control groups, underlying the DID identification. Second, to test for potential bias due to self-selection, we examine whether our results are robust to the exclusion of workers who have moved since the 2018/19 panel round. Third, to ensure that our results are not driven exclusively by the two major metropolitan districts, which together account for 65.6 per cent of the treated observations, we re-estimate the impact excluding the Accra Metropolitan district and the Kumasi Metropolitan district.⁴ In addition, we estimate a specification defining a randomly generated set of districts as the treatment districts.

5.1 Testing the parallel trends assumption

To validate the parallel pre-trends assumption underlying our DID design, we use information on the labour market outcomes of respondents reported in GSPS W3 (2018/19) and February 2020, before the coronavirus pandemic had reached Ghana. Table 8 reports the results. As explained before, our sample was drawn from the GSPS W3 adult population, limited to those who had been working in 2018/19. As indicated in column (1), across the sample, about 6 per cent of respondents had dropped out of employment by February 2020. Moreover, as reported in column (2), we find a positive trend in real earnings between 2018/19 and February 2020, while we find no significant change in average working hours, as can be seen from column (3). Importantly, we find no evidence of a statistically significant difference in pre-treatment trends between workers in treated and control districts in any of three outcomes measures. That is, the coefficient estimates for the interaction terms $LOCKDOWN_d \times PRE_t$ are statistically insignificant, suggesting that the parallel pre-trend assumption is plausible.

⁴ The Greater Accra and Greater Kumasi Metropolitan Areas are administrative regions that comprise the respective nucleus city centres (i.e. the Accra Metropolitan and Kumasi Metropolitan districts) as well as adjoining districts.

Table 8: Pre-treatment trends in labour market outcomes by treatment status

	(1) Working in period t (=1 if YES)	(2) Log weekly earnings (constant 2018 prices) in period t	(3) Weekly hours worked in period t
Pre-period (base Feb 2020)			
GSPS W3 (2018/19)	0.0602*** (0.022)	-0.799*** (0.188)	-0.338 (3.164)
Lockdown \times GSPS W3	-0.008 (0.027)	0.096 (0.220)	0.258 (3.537)
Observations	884	734	846
Panel effects	FE	FE	FE

Note: FE = fixed effects (within) regression; control districts limited to those with a population density above 300/km²; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GSPS-COVID-19 survey.

As explained above, the results reported in Table 8 use our preferred model specification. For completeness, we also estimated the regression model using alternative specifications, and compared the labour market outcomes in the baseline period, fixed in February 2020, with both the pre-treatment period and the two post-treatment periods combined in the same estimation. The results, reported in Appendix Tables A1 to A3, reconfirm the above result. As can be seen from Tables A2 and A3, we fail to reject that labour earnings and working hours in years prior to treatment exhibit parallel trends when we estimate the regression for the full sample, as shown in column (1). However, as shown in columns (2)–(4), we find no statistically significant difference in pre-treatment trends between workers in treated and control districts once limiting no-lockdown control districts to those with a minimum population density of 300/km².

5.2 Exclusion of movers

As discussed in Section 3.3, one possible concern with our DID approach is self-selection out of treatment as workers move between treated and control districts. To test for potential bias due to self-selection, we re-estimate the impact of the lockdown on labour market outcomes excluding respondents who reported having moved since the 2018/19 panel round. Importantly, not all of these respondents moved between treated and control districts. The coefficient estimates on the reduced sample of stayers are reported in Table 9.

Compared with the base specification reported in Table 7, when reducing the sample to respondents who remained in the same geographic location between 2018/19 and August/September 2020, we find no significant difference in the impact of the lockdown on employment (column (1)). However, we find weak evidence for a somewhat larger gap in average post-treatment earnings between workers in treated versus control districts (column (2)). This is mainly explained by the lower earnings reported by workers in lockdown districts who had moved since the last round of interviews in 2018/19, who were excluded in this estimation.

Table 9: Impact of the coronavirus lockdown on labour market outcomes, exclusion of movers

	(1) Working in period t (=1 if YES)	(2) Log weekly earnings (constant 2018 prices) in period t	(3) Weekly hours worked in period t
Post-period (base Feb 2020)			
April 2020	-0.282*** (0.038)	-0.710*** (0.121)	-13.476**** (3.959)
Last 7 days	-0.114*** (0.026)	-0.507*** (0.085)	-10.188*** (2.949)
Lockdown \times April 2020	-0.349*** (0.050)	0.386*** (0.126)	3.604 (5.339)
Lockdown \times Last 7 days	-0.0208 (0.035)	0.216** (0.100)	-0.294 (3.146)
Observations	1,178	636	724
Panel effects	FE	FE	FE

Note: FE = fixed effects (within) regression; control districts limited to those with a population density above 300/km²; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GSPS-COVID-19 survey.

5.3 Exclusion of major metropolitan districts and random treatment assignment

The lockdown in Ghana was implemented in the two largest cities, Accra and Kumasi, which had emerged as 'hotspots' of the pandemic. It affected the immediate Accra Metropolitan and Kumasi Metropolitan districts as well as the Greater Metropolitan Areas and contiguous districts. To ensure that our results are not driven exclusively by the two major city centres, which together account for 65.6 per cent of the treated observations, we re-estimate the impact of the lockdown on labour market outcomes, excluding the Accra Metropolitan and Kumasi Metropolitan districts.

The results are reported in Table 10. Compared with the base specification reported in Table 7, we find a somewhat smaller short-term treatment effect on employment in April 2020. At the intensive margin, for the first post-treatment period, we observe a slightly smaller differential trend in earnings between treated and control groups, and a larger temporary gap in working hours. However, none of these differences in coefficient estimates is statistically significant and the overall patterns remain robust across specifications.

In addition, as a final robustness check, we estimate a specification with random treatment assignment at the district level.⁵ Out of 78 districts covered in our data, 39 exceed the defined population density cut-off, of which 19 districts had lockdown policies in place. In this final specification, we randomly assign treatment status to 19 out of the 39 districts. As the results reported in Table 11 indicate, we find no statistically significant effect for this placebo treatment.

⁵ See Bertrand et al. (2004) for a discussion of this robustness test, where we are in effect enacting 'placebo' lockdowns on 'treatment' districts that are chosen at random.

Table 10: Impact of the coronavirus lockdown on labour market outcomes, exclusion of major metropolitan districts

	(1) Working in period t (=1 if YES)	(2) Log weekly earnings (constant 2018 prices) in period t	(3) Weekly hours worked in period t
Post-period (base Feb 2020)			
April 2020	-0.283*** (0.036)	-0.658*** (0.107)	-14.226*** (4.592)
Last 7 days	-0.116*** (0.024)	-0.459*** (0.067)	-6.955*** (1.816)
Lockdown \times April 2020	-0.319*** (0.063)	0.300** (0.127)	12.401** (6.080)
Lockdown \times Last 7 days	-0.032 (0.044)	0.135 (0.136)	3.394 (2.265)
Observations	785	444	467
Panel effects	FE	FE	FE

Note: FE = fixed effects (within) regression; control districts limited to those with a population density above 300/km²; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GPS-COVID-19 survey.

Table 11: Impact of the coronavirus lockdown on labour market outcomes, random treatment assignment

	(1) Working in period t (=1 if YES)	(2) Log weekly earnings (constant 2018 prices) in period t	(3) Weekly hours worked in period t
Post-period (base Feb 2020)			
April 2020	-0.489*** (0.037)	-0.504** (0.142)	-13.575* (5.855)
Last 7 days	-0.121*** (0.024)	-0.386*** (0.079)	-7.790*** (0.950)
Placebo \times April 2020	-0.022 (0.050)	-0.001 (0.162)	6.472 (6.148)
Placebo \times Last 7 days	-0.016 (0.034)	0.018 (0.092)	2.205 (1.747)
Observations	1,318	710	761
Panel effects	FE	FE	FE

Note: FE = fixed effects (within) regression; control districts limited to those with a population density above 300/km²; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GPS-COVID-19 survey.

6 Conclusions

In this paper, we provide valuable causal evidence that stringent lockdown policies impact on labour market outcomes, using Ghana as a case study. We find that the three-week lockdown of the Greater Accra and Greater Kumasi Metropolitan Areas and contiguous districts, which was in

effect from 30 March to 21 April 2020, had a large and significant immediate negative impact on employment in the affected districts.

While the gap in employment between workers located in treated versus control districts had narrowed four months after legal shutdown orders had been lifted, we find a persistent nationwide effect of the pandemic on labour market outcomes in Ghana, at both the extensive and the intensive margins. This effect, however, does not seem to depend on the stringency level of confinement policies, but may rather be attributable to an overall economic decline, which in the case of Ghana has been driven by the global drop in commodity prices and external demand from the main trading partners—including China, India, the United States, and several European countries—amongst other factors.

Importantly, we find that the short-term employment effect of the lockdown was felt most by workers in informal self-employment and, across the country, the earnings of self-employed workers and women remained more negatively affected in the medium term. To this extent, our results also echo concerns regarding the poverty and livelihoods implications of the COVID-19 pandemic. As Bassier et al. (2020) point out in their analysis on South Africa, not only were informal workers and their households particularly vulnerable to the negative economic consequences of the pandemic and associated lockdown measures, considering their need to earn a living on a daily basis, but the very fact of their informality also presented a challenge for governments to provide targeted economic relief. To prevent a persistent deepening of existing vulnerabilities and labour market inequalities, our results point to a continued need for effective strategies to address the business and livelihood needs of small business owners, especially women and those operating in the informal sector.

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Appendix

Table A1: Impact of the coronavirus lockdown on employment, pre- and post-treatment periods

Dependent variable: Working in period t (=1 if YES)	(1) Full sample	(2) District size cut- off	(3) District size cut- off with covariates	(4) District size cut-off with worker FE
Pre-period (base Feb 2020)	0.061***	0.057**	0.056**	0.055**
GSPS W3 (2018/19)	(0.015)	(0.022)	(0.023)	(0.024)
Post-period (base Feb 2020)				
April 2020	-0.253***	-0.212***	-0.215***	-0.261***
	(0.034)	(0.046)	(0.046)	(0.046)
Last 7 days	-0.125***	-0.116***	-0.116***	-0.116***
	(0.019)	(0.026)	(0.026)	(0.026)
Lockdown	0.015	0.010	0.013	
	(0.029)	(0.033)	(0.035)	
Lockdown \times GSPS W3	-0.011	-0.007	-0.005	-0.006
	(0.025)	(0.030)	(0.030)	(0.031)
Lockdown \times April 2020	-0.332***	-0.372***	-0.371***	-0.358***
	(0.049)	(0.058)	(0.058)	(0.052)
Lockdown \times Last 7 days	-0.013	-0.022	-0.022	-0.022
	(0.024)	(0.030)	(0.030)	(0.030)
Observations	2,571	1,753	1,753	1,753
Covariates	NO	NO	YES	NO
Panel effects	RE	RE	RE	FE

Note: covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), household size. FE = fixed effects (within) regression; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GSPS-COVID-19 survey.

Table A2: Impact of the coronavirus lockdown measures on log weekly earnings, pre- and post-treatment periods

Dependent variable: Log weekly earnings in period t (constant 2018 prices)	(1) Full sample	(2) District size cut- off	(3) District size cut- off with covariates	(4) District size cut-off with worker FE
Pre-period (base Feb 2020)				
GSPS W3 (2018/19)	-1.003*** (0.103)	-0.833*** (0.142)	-0.848*** (0.144)	-0.809*** (0.179)
Post-period (base Feb 2020)				
April 2020	-0.789*** (0.104)	-0.840*** (0.173)	-0.847*** (0.160)	-0.799*** (0.139)
Last 7 days	-0.373*** (0.057)	-0.352*** (0.079)	-0.307*** (0.087)	-0.441*** (0.067)
Lockdown	0.156* (0.090)	0.153 (0.124)	0.154 (0.104)	
Lockdown \times GSPS W3	0.302** (0.138)	0.132 (0.169)	0.135 (0.168)	0.092 (0.209)
Lockdown \times April 2020	0.458*** (0.137)	0.509** (0.195)	0.375** (0.181)	0.396*** (0.143)
Lockdown \times Last 7 days	0.077 (0.104)	0.055 (0.118)	-0.020 (0.121)	0.137 (0.099)
Observations	1,624	1,097	1,097	1,097
Covariates	NO	NO	YES	NO
Panel effects	RE	RE	RE	FE

Note: covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), household size. FE = fixed effects (within) regression; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GSPS-COVID-19 survey.

Table A3: Impact of the coronavirus lockdown measures on weekly working hours, pre- and post-treatment periods

Dependent Variable: Weekly hours worked in period t	(1) Full sample	(2) District size cut- off	(3) District size cut- off with covariates	(4) District size cut-off with worker FE
Pre-period (base Feb 2020)				
GSPS W3 (2018/19)	-1.912 (2.001)	-1.091 (3.251)	0.793 (2.984)	0.993 (2.862)
Post-period (base Feb 2020)				
April 2020	-19.320*** (3.296)	-19.197*** (3.904)	-15.487*** (4.881)	-13.956*** (5.143)
Last 7 days	-6.474*** (1.660)	-8.278*** (2.413)	-4.964*** (1.676)	-6.220*** (1.717)
Lockdown	2.402 (2.120)	2.529 (2.667)	2.932 (2.459)	
Lockdown \times GSPS W3	2.433 (2.715)	1.612 (3.740)	0.166 (3.954)	-0.379 (3.507)
Lockdown \times April 2020	12.106** (4.973)	11.983** (5.414)	12.326* (6.557)	7.609 (6.448)
Lockdown \times Last 7 days	-3.751* (2.134)	-1.947 (2.765)	-0.457 (2.040)	0.018 (2.103)
Observations	1,802	1,237	1,176	1,176
Covariates	NO	NO	YES	NO
Panel effects	RE	RE	RE	FE

Note: covariates include gender, head of household, age categories (<25; 25–34; 35–44; 45–54; 55–64; 65+), marital status (married in 2018/19), education levels (pre-primary; primary; basic; secondary; tertiary; missing in 2018/19), household size. FE = fixed effects (within) regression; standard errors in parentheses, clustered at the district level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' estimates based on GSPS-COVID-19 survey.