Impact of Twin Lockdowns on Hunger, Labor Market Outcomes, and Household Coping Mechanisms: Evidence from Uganda

Summary

The paper seeks to estimate the impact of two COVID-19-related lockdowns in Uganda, over both the short and medium term. This is done by comparing household- and individual-level outcomes from a phone survey conducted in Uganda in 2020 and 2021. The main outcome of interest is food insecurity, as captured by questions included in the Food Insecurity Experience Score (FIES) module. Food insecurity is found to be significantly worse during the lockdowns. The paper looks at labor-market outcomes to try and unpack why these drops in food insecurity arose and for which types of households.

Contribution

The paper purports to make two broad contributions. First, the paper claims to contribute "to the literature on understanding the impact of lockdowns", doing so in three ways: (1) estimating the results using a country-wide panel, (2) estimating short- and medium-term effects of lockdowns, and (3) using additional data over and above reported lockdowns (including a stringency index and Google mobility data). Second, the paper claims to contribute to "the small but growing body of research on the effects of aggregate shocks and how households cope with these shocks".

The literature on the effects of lockdowns is extensive, and many of these existing results come from large country-wide panels already. The paper's idea of disentangling short- and medium-term effects is a good one, but the authors are limited by the frequency of the data in trying to do this. The use of the stringency index and Google mobility data is a helpful addition. This is something the authors could highlight more in future revisions of the paper. The paper's use of multinomial and ordered logits to look at the likelihood of different labor market statuses is also an interesting additional contribution, which could also merit further exploration and emphasis – nesting and condensing labor market decisions to create binary dependent variables may be too restrictive.

The exact ways in which the paper contributes to the literature on aggregate shocks and coping mechanisms need to be made clearer in future revisions of the paper. It was not obvious from the paper how lockdowns should be regarded relative to other aggregate shocks, which makes it difficult to know how far the results can be generalized.

Essential points

The three following essential points would need to be fixed in the paper.

First, it is not clear how the paper is identifying the impact of Uganda's lockdowns. It appears that the identification strategy relies on the only difference between survey waves being whether or not a lockdown was in place. However, there are many other factors changing over these periods, only some of which are addressed in the paper. The paper makes a good attempt to rule out the impact of seasonality in the robustness checks (although this should come much earlier, as it is essential for identification). However, many other factors are changing over this period. In particular, the paper explicitly talks about the concurrent drought "compounding" the effects of the second lockdown, but this makes it difficult to know what is being captured by the coefficient on L_7 – is this coefficient mainly capturing the drought or the second lockdown? There may also be other confounding events including the Ugandan elections in 2021, internet blackouts, the lockdown policies of other countries (especially as remittances are an outcome variable), and so on. This is also especially important because the survey waves (3, 4, 5, and 6) in the excluded category contain a big mix of seasons. Other papers in the literature use identification across space (such as different districts having different lockdown policies) and time for identification. It would be important for the authors to address this identification issue more directly.

Second, and relatedly, the paper uses a fixed effects regression "to control for unobservable household characteristics". It would be helpful for the authors to explain what including household- or individual-level fixed effects does when the identification is based on comparing different points in time. Is this really about controlling for differences in the sample composition between different waves of the survey? Is this improving the efficiency of the estimates? Or is there some other way in which this is helping? Looking at the descriptive statistics in Table 1, it appears that the results mainly hinge on just comparing the means between different survey waves, so it would be important to explain how the fixed effects regressions are going beyond this. Similarly, it would be helpful to understand how much the fixed effects are adding over and above a simple OLS (perhaps through a Hausman test). If there is no clear answer to this, then perhaps one idea for shortening the paper would be to frame it more as conducting a descriptive exercise – well done descriptive statistics can still be extremely useful. This would also alleviate some of the difficulties including fixed effects in the multinomial/ordered logit models.

Third, as hinted at in the "Contribution" section of this report, it would be useful for the paper to explain what additional points we learn from looking at lockdowns in Uganda, compared to other places. Having two lockdowns is not unusual in itself, and indeed happened in many countries, even in Sub-Saharan Africa. Is there something particularly revealing about the Uganda case, especially now the lockdowns in question are almost two years in the past? Additionally, explaining how the Uganda lockdowns provide extra information on aggregate shocks would be particularly important.

Suggestions

A few smaller suggestions may also strengthen the paper.

The paper would benefit from explaining why it does not use the "raw score" – potentially with some cutoff à la Wambogo et al. (2018, see https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6121128/) – to aggregate across the FIES questions. Following Food and Agriculture Organization guidelines (see https://www.fao.org/3/i4830e/i4830e.pdf) this would also depend on checking the Rasch model infit statistics, to ensure it is valid. This would be slightly more standard than just taking the maximum across the eights FIES questions.

The paper at various points refers to "unemployment". Unemployment has a very clear definition, meaning someone who is not working (or not employed, more accurately), who is actively searching, and who is available for work/employment. If this is what the authors mean, then it would be helpful to understand how those individuals out of the labor force are being treated in these regressions. If not, a different term like "not employed" or "not working" would be more accurate.

The paper uses a multinomial logit approach to look at switches between labor market statuses. This is an interesting approach, but it might be helpful to complement this by looking at use transition matrices to better understand labor market switches.

In Table 5 the paper is interacting the impact of lockdowns with a dummy variable capturing whether the household was an agricultural household. It would be helpful for the authors to explain how the paper avoids the critiques of including interactions or doing sub-group comparisons in linear probability models, as outlined in Holm et al. (2015, see https://link.springer.com/article/10.1007/s11135-014-0057-0).

It would be useful for the authors to show how the results would be affected by multiple hypothesis testing corrections, since there are many outcome variables being considered. Alternatively, the authors should provide a qualitative explanation of why this is not needed.