

The labor market implications of restricted mobility during the Covid-19 pandemic in Kenya. Evidence from nationally representative phone surveys in Kenya.

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Abstract

We use an instrumental variable approach to identify the causal impacts of mobility reduction induced by policy changes on labor market outcomes. We find that a 10% recovery of mobility leads to an 11% increase of labor force participation and an increase of 7% of household members being employed. At the same time, a 10% recovery of mobility causes an increase of 12 wage hours per week (formal and informal) with wage hours in urban areas increasing 3.2 hours per week. Among the factors influencing self-reported mobility and, thus, nationwide mobility levels, the trust in the government's ability to deal with the pandemic correlates with more self-reported mobility, while employed individuals tend to restrict mobility more. Finally, country wide policy stringency levels clearly reduce self-reported mobility. Given the demonstrated adverse impacts of a lockdown on important economic indicators, Governments need to explore options to limit the economic fall-out while protecting citizens from infections, e.g. by using partial or geographically constrained lockdowns.

Keywords – *Mobility; Labor Market; Covid-19*

1 Introduction

As response to the Covid-19 pandemic, many governments have imposed measures aimed at restricting mobility and social interaction to reduce the speed of further infection. The consequences from these measures and restrictions on personal mobility have severely disrupted economic activities, as between one and four in five workers reside in countries with required workplace closures (ILO, 2021).

Particularly for households in developing countries, the labor market implications of the pandemic can be dire. The lack of economic safety nets particularly in the informal sector but also increased risk of infection and related expenses, especially for poor people living in high density areas with daily hands-on income, can exacerbate the consequences of losing parts of the income or the job entirely (Bargain and Ulugbek 2021, Gupta et al. 2021). Given the additional challenges, households in developing countries face in coping with the crisis, it is elementary for policy makers to understand, which socio-economic consequences any countermeasures aimed at curbing the spread of the virus may have. A better understanding of the

causal relationships between mobility reductions and labor market outcomes is vital to crafting better, more effective, and targeted policies in future situations in which there is the joint goal of slowing down everyday life to save lives while minimizing the negative economic and societal effects.

We investigate the labor market impacts of the observed policy adherence by applying IV estimation using policy stringency as instrument for reduced mobility. This produces the causal effects the reduced mobility had on labor market outcomes for households working in agriculture, wage jobs and self-employment which we estimate for both urban and rural households. In a second step, we analyze which household specific factors determined policy adherence.

We aim to add to the literature by examining the labor market effects of mobility restriction imposed by the Kenyan Government, combining policy restrictions with insights from Google Mobility Reports and large-scale household surveys. As far as we are aware, this is the first paper specifically looking into causal effects of reduced mobility on labour market outcomes over the course of the pandemic in a developing country. To the best of our knowledge no study has empirically examined the socio-economic impacts of the restrictive measures via its effect on mobility before. Our findings will enable governments and policy makers to better understand the dynamics and impacts of mobility restrictions in a pandemic and as such, assist in efficiently setting-up adaptive measures that may continue to be important for developing countries in the long-term.

2, Experimental Design and Data Collection

2.1 Data

To conduct our analyses, we leverage multiple sources of data. Central to our analyses are the Kenya COVID-19 Rapid Response Phone Household Surveys (RRPS). They measure labor market effects of the pandemic on households on a county-level for multiple survey waves between 2020 and 2021. The Kenya COVID-19 RRPS was structured as a five-waves bi-monthly panel survey that targeted nationals, refugees and stateless persons and has representative weights for national as well as county (admin-1) levels. The sampling frame of telephone numbers was composed of two groups of households. The first was based on a randomly drawn subset of the 2015/16 Kenya Integrated Household Budget Survey (KIHBS) with 9,009 households which covered urban and rural areas and was designed to be representative of the population of Kenya using cell phones. Given that this sampling frame was five-year-old at the time of the first RRPS wave, an additional group was added by applying Random Digit Dialing (RDD). The questionnaire covered multiple topics, such as behavior in response to the COVID-19 pandemic and mobility, changes in employment, income, food security, subjective well-being, access to education and health services, knowledge of COVID-19 and mitigation measures as well as perceptions of the government's response and coping strategies. The questionnaire was translated into Swahili, Luo, Arabic, French, Kirundi, Luganda, Oromo, Somali, Kinyarwanda, Tigrinya, Nuer and Dinka to ensure all respondents can be interviewed in a language they are comfortable with.

To determine mobility trends during the time of the pandemic, we use Google data which is recorded by tracking mobile phone devices with their respective GPS signals from users who have opted-in/ have not opted out

of location history tracking for their Google account (Google LLC 2021). Community mobility reports provide insights into how mobility changes during the pandemic and into policies' effectiveness aimed at reducing mobility.

To determine the degree of mobility restrictions in Kenya, we use the COVID-19 Government Response Tracker from the Blavatnik School of Government which tracks policy responses from governments during the Pandemic for multiple countries (Hale et al. 2021). The tracker traces health policies, economic policies and containment and closure policies of governments and assigns them an ordinal value ranging from 0 to 100 depending on severity and penetration across the country. We consider the latter type i.e., containment and closure policies enacted by the Government of Kenya. The policy stringency index in Kenya is recorded daily as a national average taking on values between 0 and 100.

We also include confirmed Covid-19 cases in Kenya, both national aggregates and county cases. National confirmed Covid-19 cases were obtained from published Government briefs. For state specific confirmed cases, we used regular updates by the Kenyan Ministry of Health from the respective homepage and Twitter.

2.2 Study Population and Sample Size

Our analysis focuses on working adults between 14 and 65 years old. We attain nationally representative RRPS data for 59,987 adults that were part of 24,340 households. Out of these, 17,709 households have complete information on employment status, 8,428/ 7,736 households on agricultural hours/income, 4,319/2,896 households on wage hours/income and 1,313 households on self-employment hours as well as the other covariates we consider. Sample characteristics are consistent across

survey waves. For the analyses of determinants of self-reported mobility reduction, we attain complete data for a total of 12,563 households.

2.3 Outcomes of Interest

Our labor market outcomes from the RRPS can be allocated into: A) employment status, B) hours worked in past 7 days and C) income earned in past 14 days per adult household member and thus combine both extensive margins of employment (category A) and intensive margins of employment (categories B and C). Within these categories, we look at a total of 8 different labor market outcomes (Supplement Table 2). We take weekly averages for all adults for which we have data available and aggregate them on a per county per-week level, which reflects the sampling and data collection strategy of the RRPS.

Our second analysis looks at whether households self-reported any behavioral change that could be attributed to self-restricting mobility and interaction. The outcome variable is a binary variable "Any self-reported mobility restriction" that was given a value of 1, if respondents stated that due to Covid-19, they had either avoid groups more often, stay at home more, traveled outside less, gone to work less, or returned home earlier at night (Supplement Table 3).

3. Statistical analyses and estimation strategies

In addition to labor market outcomes, we also have representative data on fear of the illness as well as self-perceived economic uncertainty. Hence, we can examine the causal effect of reduced mobility on labor market outcomes via an IV estimation. Given that mobility levels

are highly interlinked with economic activity as well as overall sentiment of security, we leverage policy stringency as exogenous shock in an IV estimation framework to determine the causal impact of mobility reductions on labor market outcomes in Kenya. We assume that policies aimed at restricting mobility were enacted without consideration of current economic activity, as in parallel to these measures, economic relief policies were introduced (see Presidential Announcement from April 16th, 2020). We apply the following first stage regression controlling for the percentual change of confirmed national cases:

$$M_{tc} = PSI_t + C_{tc} + \omega_{tc},$$

where M_{tc} refers to the average mobility change, PSI_t to the Policy Stringency Index and C_{tc} to the change in confirmed cases in week t and county c .

The second stage of our analysis is a county fixed effects regression at the county-week level that includes variables about economic uncertainty, fear of illness, the overall progress of the pandemic and socioeconomic factors such as average age and education levels of respondents in the county specific week captured in X_{tc} .

$$Y_{tc} = \widehat{M}_{tc} + X_{tc} + C_{tc} + \delta_c + \varepsilon_{tc}$$

With δ_c denoting the county fixed effect.

To determine factors that influence any self-reported mobility reducing behavior, we run a logit model at the household level:

$$m_{it} = x_{it} + PSI_t + C_{tc(i)} + \vartheta_{it},$$

With m_{it} being self-reported mobility for household i in week t , x_{it} household characteristics, $C_{tc(i)}$ the change in

county case numbers for week t in county $c(i)$ of household i and ϑ_{it} the error term.

4. Results

Overall, there is a significant impact of changing mobility on the overall employment and labor force participation of household members with positive effects of increasing mobility on employment and unemployment and negative effects on not being in the labor force. Roughly 2/3 of people entering the labor force entered employment following increases in overall mobility, while a bit more than a third entered unemployment. A 10% increase in mobility caused a 11% if people to return to the workforce. We find that the mobility restrictions mainly affected peoples' participation in the labor force and thus affected extensive margins of employment. Given that our RRPS data commences in May at a time where mobility recovery was already underway, this can be interpreted as increased mobility signaling people that things are returning to being back to normal with causes them to look for jobs again. Surprisingly, these changes are consistent across urban and rural with minor yet statistically significant differences in employment, unemployment and not in labor force.

Looking at the intensive margins of employment, i.e. the indicators that provide context about an existing employment, we find that the most significant effects were for the hours worked by household members. Here, a 10% increase in mobility was associated with an increase of ~12 wage hours worked per week. Additionally, there seem to be more significant effects for wage professions (both formal and informal), even though the increase income from wage jobs is only significant at a 10% level. The agricultural labor market in Kenya seems to have been affected less by the pandemic. Hours worked in agriculture

is only statistically significant at 10% level and has a much lower coefficient than hours in wage jobs, while the effect on income earned in agriculture is not statistically significant. Self-employment hours seem to have been unaffected by the recovery of overall mobility.

Comparing urban vs. rural, we find that employment effects (from entering the labor force) and wage hours worked were larger in the rural setting, while agriculture employment in terms of hours worked and income generated was significantly affected in the urban setting. Looking at the other correlates that we included into our analyses we find that economic uncertainty is inversely related to people entering unemployment as well as the number of hours which are spent in self-employment. Additionally, age seems to be having a positive impact of (re-)entering employment rather than unemployment.

We also compare results for different stages of the pandemic (Table 5). Specifically, we split our sample into a “recovery” and “post-recovery sample”, the first reflecting waves 1 and 2, in which mobility returned to pre-pandemic levels and a post-recovery phase, in which mobility exceeded pre-pandemic levels. Our results show first that the effects on extrinsic margins of employment differed quite substantially between the two phases. Most of the re-entering the labor force in the beginning led to re-employment, while the re-entering into the labor market between wave 3-5 most notably led into unemployment. Looking at the split for urban and rural, we find that the initial employment recovery is mainly due to recovery in rural areas. Likewise, for the intrinsic margins of employment, most outcomes of hours worked, and income generated are significant in the immediate time of recovery, while not showing statistical significance in the time hereafter. In both regions, the effect of hours worked was significant in the recovery and post recovery phase

with larger effects on agriculture in urban settings and larger effects on wage work in rural settings. Interestingly in the rural post-recovery phase, more mobility caused less hours to be spent in agricultural jobs, hinting towards the possibility that as mobility increased, workers substituted agricultural jobs for reappearing wage work or self-employment opportunities.

Among the broad set of potential determinants of self-reporting any form of mobility reduction, we find that the trust in the government handling the pandemic well, employment status and the overall policy stringency level are statistically significant (Table 6). Interestingly, the trust in the government’s ability to handle the pandemic has a negative sign, implying that a good trust in the government’s ability to deal with the pandemic reduces the individual households perceived need to comply with recommended mobility restrictions. However, comparing coefficients, employment status may outweigh this effect, with people being employed (formally and informally) claiming to reduce their mobility more than people without employment which indicates higher opportunity costs of infection. Finally, the policy stringency index has a strong positive effect on self-reported mobility restricting behavior as well. Even though the coefficient is the smallest among the statistically significant coefficients, employment and trust in government are coded 0/1 while the policy stringency index regression coefficient relates to a one-point increase of the index. Therefore, a seven-point increase of the stringency index has a similar effect compared to being employed. It seems that one of the main drivers of self-reported mobility reduction is the overall severity of mobility restriction policy in Kenya. Interestingly, for this there seems to be no statistically significant differences between urban and rural respondents.

5. Discussion

Our study has a few salient findings. First, the recovery of mobility in Kenya following the initial declines in early 2020 have caused people to enter the labor force again, two thirds of them re-entering employment. Second, while increased mobility caused an increase in wage hours and agricultural hours, the effects are much lower for two-week incomes generated by these activities. Comparing urban vs rural, we do find statistically significant positive effects of mobility on agriculture in an urban setting, which may be due to the fact that the agricultural workplace in the rural setting is often directly linked to the place of living i.e., farms or plantations connected with villages. At the same time in rural settings, wage workers recovered more which may be explained by increased need to travel for wage work in rural settings or an increased elasticity of job availability in downturn times compared to urban areas. Overall, it seems that particularly the number of hours worked were significantly reduced in the beginning of the pandemic, with employed older people leaving the workforce. However, as mobility recovered, especially in the beginning of the recovery, these people returned into their previous jobs particularly in the rural setting (probably also due to less competition). Thinking about safety nets and mitigation measures, awareness of differential impacts across sectors in urban and rural areas carry important insights into target groups and economic costs of restriction measures in these specific areas.

Finally, we find that peoples' trust in the Kenyan Government's ability to deal with the pandemic, employment status and overall level of stringency significantly influence people's self-reported reductions of mobility. For rural households the level of stringency and employment status are of significance but in the urban setting additional factors are statistically relevant such as

education, knowing someone who was infected and being the household head. Comparing coefficients, a 10-point increase of policy stringency outweighs most of the other coefficients, underscoring the signaling effect of severe measures by the government of a serious pandemic situation. While we are aware that self-reported behavior data needs to be treated with caution (Jakubowski et al. 2021), we nevertheless believe that our large sample allows for important insights into determinants of self-restricting behavior during the time of a pandemic. Our insights underscore the importance of strong government measures to save lives. However, they also show that different messages and different channels need to be applied to convince citizens to self-reduce mobility and social interaction. Integrating risks to employment in rural areas into the messaging may be much more effective than raising awareness about the government's inability to solve the pandemic by itself.

Finally, providing safety nets and working to save employment status in formal and informal wage employment will continue to be important measures to shield people from the most severe consequences of the pandemic but based on self-reported behavior can also be beneficial especially to people's adherence in rural areas to officially recommended mobility reductions.

To determine causal effects of mobility not just during a recovery phase but for overall economic and labor market activity, future research will rely on researchers' ability to attain high-frequency data covering not only the course of a pandemic but also the time prior to the outbreak.

References

- Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys. *IZA , Institute of Labor Economics Discussion Papers*, 13183, 51.
- Ahmed, M. et al. (2020) "COVID-19 in Somalia: adherence to preventive measures and evolution of the disease burden." *Pathogens* 9.9: 735.
- Aloi, A.; Alonso, B.; Benavente, J.; Cordera, R.; Echániz, E.; González, et al., Effects of the COVID-19 Lockdown on Urban Mobility: Empirical Evidence from the City of Santander (Spain). *Sustainability* 2020, 12, 3870. <https://doi.org/10.3390/su12093870>
- Al-Hasan, A., Yim, D. and Khuntia, J. (2020). "Citizens' adherence to COVID-19 mitigation recommendations by the government: a 3-country comparative evaluation using web-based cross-sectional survey data." *Journal of medical Internet research* 22.8: e20634.
- Auriemma, V., Iannaccone, C. (2020) COVID-19 pandemic: socio-economic consequences of social distancing measures in Italy. *Front. Sociol* 5
- Bargain, O. and Ulugbek, A. (2021) "Poverty and COVID-19 in Africa and Latin America." *World Development* 142: 105422
- Béland, L. P., Brodeur, A., Mikola, D., & Wright, T. (2020). The Short-Term Economic Consequences of Covid-19: Occupation Tasks and Mental Health in Canada. *IZA Discussion Paper* No 13254., 13254, 101.
- Bonaccorsi, G., Pierri, F., Cinelli, M., Flori, A., Galeazzi, A. (2020) Economic and social consequences of human mobility restrictions under COVID-19, *PNAS* 117 (27); <https://doi.org/10.1073/pnas.2007658117>
- Bowmans. (2020). COVID-19: Tracking Government Response in Kenya. <https://www.bowmanslaw.com/wp-content/uploads/2020/12/Bowmans-Kenya-Government-Response-Tracker.pdf>, Last accessed 09.08.2021
- Brodeur, A., Gray, D., Islam, A., & Bhuiyan, S. J. (2020). A Literature Review of the Economics of COVID-19. *IZA Discussion Paper* No. 13411, 63.
- Carlucci, L, D'ambrosio, I and Balsamo, M (2020). "Demographic and attitudinal factors of adherence to quarantine guidelines during COVID-19: the Italian model." *Frontiers in psychology* 11: 2702.
- Coroiu, A. et al.(2020) "Barriers and facilitators of adherence to social distancing recommendations during COVID-19 among a large international sample of adults." *PloS one* 15.10: e0239795.
- Chen, S., Igan, D. O., Pierri, N., Presbitero, A. F., Soledad, M., & Peria, M. (2020). Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States, *IMF Working Papers*, 2020(125), A001.
- Chetty, R., Friedman, J. N., Hendren, N., Stepner, M., & the_Opportunity_Insights_Team. (2020). How Did COVID-19 and Stabilization Policies Affect Spending and Employment? A New Real-Time Economic Tracker Based on Private Sector Data. *National Bureau of Economic Research Working Paper* 27431.
- Dabalén, A., Etang, A., Hoogeveen, J., Mushi, E., Schipper, Y., & Engelhardt, J. v. (2016). Mobile Phone Panel Surveys in Developing Countries: A Practical Guide for Microdata Collection. Retrieved from International Bank for Reconstruction and Development / The World Bank, Washington, DC: <http://dx.doi.org/10.1596/978-1-4648-0904-0>
- Drake, T., Docherty, A., Weiser, T., Yule, S., Sheikh, A., Harrison, E (2020) The effects of physical distancing on population mobility during the COVID-19 pandemic in the UK, *The Lancet Digital Health*, Volume 2, Issue 8, 2020, Pages e385-e387, [https://doi.org/10.1016/S2589-7500\(20\)30134-5](https://doi.org/10.1016/S2589-7500(20)30134-5).
- Egger, E.-M., Jones, S., Justino, P., Manhique, I., & Santos, R. (2020). Africa's lockdown dilemma: High poverty and low trust. *WIDER Working Paper* 2020/76, 20.
- FAO. (2020). Impact of COVID-19 on informal workers. Retrieved from <https://doi.org/10.4060/ca8560en>
- Gupta et al. (2020). Effects of social distancing policy on labor market outcomes, *National Bureau of Economic Research Working Paper* 27431
- Gupta, J et al. (2021) "COVID-19, poverty and inclusive development." *World Development* 145: 105527.
- Google LLC (2021) "Google COVID-19 Community Mobility Reports". <https://www.google.com/covid19/mobility/> Last accessed 15.07.2021
- Hale, T. et al. (2021). "A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker)." *Nature Human Behaviour*. <https://doi.org/10.1038/s41562-021-01079-8>
- Haug, N., Geyrhofer, L., Londei, A. et al. Ranking the effectiveness of worldwide COVID-19 government interventions. *Nat Hum Behav* 4, 1303–1312 (2020). <https://doi.org/10.1038/s41562-020-01009-0>
- Hill, R., & Narayan, A. (2020). Covid-19 and inequality: a review of the evidence on likely impact and policy options. *Centre for Disaster Protection Working paper* 3 , London.
- Himelein, K. (2014). Weight Calculations for Panel Surveys with Subsampling and Split-off Tracking. *Statistics and Public Policy*, 1(1), 5.
- ILO. (2021). ILO Monitor: COVID-19 and the world of work. Seventh edition, Updated estimates and analysis.
- Islamaj, E., Kim, Y. E., & Le, D. T. (2021). The Spread of COVID-19 and Policy Responses. *Research and Policy Brief* No. 40. World Bank, Washington, DC. © World Bank.
- Jakubowski, A. et al. (2021). Self-Reported Mask Wearing Greatly Exceeds Directly Observed Use: Urgent Need for Policy Intervention in Kenya. *medRxiv* 2021.01.27.21250487; doi: <https://doi.org/10.1101/2021.01.27.21250487>
- Janssens, W., Pradhan, M., Groot, R. d., Sidze, E., Donfouet, H. P. P., & Abajobir, A. (2021). The short-term economic effects of COVID-19 on low-income households in rural Kenya: An analysis using weekly financial household data. *World Development*, 138(105280), 8.
- Jarvis, C.I., Van Zandvoort, K., Gimma, A. et al. (2020). "Quantifying the impact of physical distance measures on the transmission of COVID-19 in the UK." *BMC Med* 18, 124. <https://doi.org/10.1186/s12916-020-01597-8>

- Josephson, A., Kilic, T., & Michler, J. D. (2020). Socioeconomic Impacts of COVID-19 in Four African Countries. *World Bank Policy Research Working Paper* 9466, 60.
- Kansiime, M. K., Tambo, J. A., Mugambi, I., Bundi, M., Kara, A., & Owuor, C. (2021). COVID-19 implications on household income and food security in Kenya and Uganda: Findings from a rapid assessment. *World Development*, 137(105199), 10.
- Kenyan Ministry of Health: Covid-19 Website, <https://www.health.go.ke/>
- Khamis, M., Prinz, D., Newhouse, D., Palacios-Lopez, A., Pape, U., & Weber, M. (2021). The Early Labor Market Impacts of COVID-19 in Developing Countries: Evidence from High-Frequency Phone Surveys. *World Bank Policy Research Working Paper* 9510, 54.
- KNBS. (2018). Basic Report: Based on 2015/16 Kenya Integrated Household Budget Survey (KIHBS).
- Kokas, D., Lopez-Acevedo, G., Lahga, A. R. E., & Mendiratta, V. (2020). Impacts of COVID-19 on Household Welfare in Tunisia. *World Bank Policy Research Working Paper* 9503, 21.
- Nechifor, V., Ferrari, E., Kihui, E., Laichena, J., Omanyo, D., Musamali, R., & Kiriga, B. (2020). COVID-19 impacts and short-term economic recovery in Kenya. Retrieved from Joint Research Centre (JRC), the European Commission's science and knowledge service, Luxembourg:
- Omemo P, Wasonga J (2020) Determinants of Adherence to the Recommended COVID-19 Prevention and Control Guidelines by Small Scale Retail Shop Operators in Rural Parts of Siaya County, Kenya. *J Epidemiol Public Health Rev* 5(3): [dx.doi.org/10.16966/2471-8211.198](https://doi.org/10.16966/2471-8211.198)
- Pape,U.J.; Baraibar Molina,J.; Delius,A.; Gitau,C.; Rios Rivera,L.(2021). Socioeconomic Impacts of COVID-19 in Kenya on Households : Rapid Response Phone Survey Round One. Washington, D.C.: World Bank Group.
- Pape,U.J.; Delius,A.; Khandelwal,R. Gupta,R.(2020). Socio-Economic Impacts of COVID-19 in Kenya: Results Update. Washington, D.C.: World Bank Group.
- Ritchie, H. et al. (2020) - "Coronavirus Pandemic (COVID-19)". Published online at OurWorldInData.org. Retrieved from: <https://ourworldindata.org/coronavirus/country/kenya>, last accessed 09.08.
- Saha,J., Barman, B., Chouhan, P. (2020) Lockdown for COVID-19 and its impact on community mobility in India: An analysis of the COVID-19 Community Mobility Reports, 2020, *Children and Youth Services Review*, Volume 116
- Usman, I. et al. (2020). "Community drivers affecting adherence to WHO guidelines against covid-19 amongst rural Ugandan market vendors." *Frontiers in public health* 8: 340.
- Vinceti, M., Filippini, T., Rothman, K., Ferrari, F., Goffi, A., Maffei, G., et al. (2020) Lockdown timing and efficacy in controlling COVID-19 using mobile phone tracking, *EClinicalMedicine*, Volume 25, 2020, <https://doi.org/10.1016/j.eclinm.2020.100457>.
- World Bank: Economic and social impact of coronavirus in Sub-Saharan Africa, press release of January 25, 2020; <https://www.wsws.org/en/articles/2021/01/25/afri-j25.html>
- World Health Organization (2021): Covid-19 Dashboard, <https://covid19.who.int/>
- Yilmazkuday,H. (2021) Stay-at-home works to fight against COVID-19: International evidence from Google mobility data, *Journal of Human Behavior in the Social Environment*, DOI: 10.1080/10911359.2020.1845903

Supplement Table 2: Variables for causal effect of mobility on labor market outcomes analysis

Role in Analyses	Category	Variables	Coding	Pre-Covid Recall?
Outcome Variables	Employment Status	1. Household Members Employed (%)	Binary	
		2. Household Members Unemployed (%)	Binary	
		3. Household Members Not in Labor Force (%)	Binary	
	Hours worked	4. Working Hours in Agriculture per Working Household Member in past 7 days	Ordinal	Yes
		5. Working Hours in Wage Employment per Working Household Member in past 7 days	Ordinal	Yes
		6. Working Hours in Self Employment per Working Household Member in past 7 days	Ordinal	Yes
	Income earned	7. Agricultural Earnings (KSH past 14 days)	Ordinal	Yes
		8. Wage Earnings (KSH past 14 days)	Ordinal	Yes
Explaining Variables	Fear of Illness	Yes to the question “Are you feeling nervous or anxious due to the coronavirus outbreak?” and statement of one of the following reasons: <ul style="list-style-type: none"> - Fear of myself or family getting infected by coronavirus - Fear of myself or family dying due to coronavirus - Fear of me infecting others in the community - Fear of losing access to health facilities 	Binary (Yes/No)	N/A
	Economic Uncertainty	Yes to the question “Are you feeling nervous or anxious due to the coronavirus outbreak?” and statement of one of the following reasons: <ul style="list-style-type: none"> - Loss of employment / business - Fear of being unable to feed or provide for family - Effect on education system and school closures - Economic Crisis/Paralyzed Movement - Uncertainty of when lockdown will end / things will return to normal 	Binary (Yes/No)	N/A
	Know s/o Infected	Do you know anyone that has, or has had, COVID-19/coronavirus?	Binary (Yes/No)	N/A

Supplement Table 3: Variables for analysis of determinants of self-reported mobility reduction behavior

Role in Analyses	Category	Explanation	Coding
Outcome Variables	Self-reported behavior change	Any self-restricted mobility behavior (at least one answer with yes to the following questions): <ul style="list-style-type: none"> - Avoid groups more often? - Stay at home more? - Travel outside less? - Go to work less? - Return home earlier at night? 	Binary (Yes/No)
Explaining Variables	Trust in Government	The Government is trustworthy in the way it manages the Coronavirus crisis?	Binary (Yes/No)
	Trust in fellow citizens	Generally speaking, would you say that most people can be trusted?	Binary (Yes/No)
	Sex (Female)	Gender Dummy	Binary (Male)
	Education Level	No education=0, University postgraduate=8	Ordinary
	Household Head	Household Head Status Dummy	Binary (Yes, No)
	Age		Ordinary
	Urban/Rural	Urban Dummy	Binary
	Know s/o infected	Do you know anyone that has, or has had, COVID-19/coronavirus?	Binary
	Employed	Employment Dummy	Binary
	Worried about food	Household missing/cutting meals in past 7 days (%) (at least one yes answers to the following 2 questions): <ul style="list-style-type: none"> - In the past 7 DAYS, how many days have ADULTS in your household skipped meals or cut the number of meals? - In the past 7 DAYS, how many days have ADULTS in your household skipped meals or cut the number of meals? 	Binary

Table 3: IV estimates results for labor market outcomes of interest

	OLS- full sample (1)	IV- full sample (2)	IV- rural (3)	IV-urban (4)
Employment (% of Hh members)				
Employed	0.003*** (0.00)	0.007*** (0.00)	0.008*** (0.00)	0.007*** (0.00)
<i>n</i>	1557	1557	1477	1479
Unemployed	-0.001 (0.00)	0.004** (0.00)	0.004*** (0.00)	0.004*** (0.00)
<i>n</i>	1557	1557	1477	1479
Not in labor force	-0.003*** (0.00)	-0.011*** (0.00)	-0.012*** (0.00)	-0.011*** (0.00)
<i>n</i>	1557	1557	1477	1479
Hours Worked in past 7 days				
Agriculture	0.022 (0.02)	0.121* (0.06)	-0.078 (0.07)	0.322*** (0.07)
<i>n</i>	1447	1297	1447	1250
Wage Job (formal and informal)	0.211*** (0.04)	1.202*** (0.19)	1.397*** (0.27)	0.987*** (0.17)
<i>n</i>	1306	1306	895	1060
Self-Employment	0.086 (0.06)	0.018 (0.14)	-0.099 (0.22)	-0.069 (0.14)
<i>n</i>	725	725	404	525
Income in past 14 days in KSH				
Agriculture	3.542 (7.68)	68.965 (52.99)	15.838 (84.75)	129.127* * (50.70)
<i>n</i>	1492	1492	1344	1303
Wage Job (formal and informal)	-6.355 (16.50)	156.165* (84.40)	94.208 (133.80)	94.788 (106.84)
<i>n</i>	1127	1127	720	864

Note: *** is significant at the 1% level, ** is significant at the 5% level and * is significant at the 10% level

Table 5: Estimates results for our outcomes of interest for different stages of the pandemic

	Wave 1-2 (initial recovery) Wave 3-5 (post-recovery)	National Wave 1-2 (1)	National Wave 3-5 (2)	Rural Wave 1-2 (3)	Rural Wave 3-5 (4)	Urban Wave 1-2 (5)	Urban Wave 3-5 (6)
Employment (% of Hh members)							
Employed		0.008* (0.00)	0.003 (0.01)	0.015*** (0.01)	0.009* (0.00)	0.007 (0.01)	0.003 (0.00)
<i>n</i>		321	1236	243	1234	242	1237
Unemployed		0.000 (0.000)	0.014** (0.00)	-0.002 (0.00)	0.009** (0.00)	0.005 (0.00)	0.007** (0.00)
<i>n</i>		321	1236	243	1234	242	1237
Not in labor force		-0.008** (0.00)	-0.017** (0.00)	-0.013** (0.01)	- 0.018*** (0.00)	-0.012** (0.00)	- 0.010*** (0.00)
<i>n</i>		321	1236	243	1234	242	1237
Hours Worked in past 7 days							
Agriculture		0.441*** (0.16)	-0.363 (0.23)	0.467** (0.23)	-0.343** (0.17)	0.798*** (0.25)	0.341** (0.41)
<i>n</i>		308	1139	226	1071	211	1039
Wage Job (formal and informal)		1.351*** (0.43)	3.764 (2.38)	1.668** (0.68)	2.483*** (0.89)	1.144*** (0.38)	1.761*** (0.48)
<i>n</i>		283	1023	156	739	198	862
Self-Employment		1.174*** (0.43)	-0.300 (0.44)	4.264 (3.15)	-0.721 (0.46)	0.651 (0.45)	-0.160 (0.28)
<i>n</i>		198	527	85	319	125	400
Income in past 14 days in KSH							
Agriculture		215.808*** (68.56)	67.211 (161.28)	188.867** (89.18)	-44.778 (152.16)	159.529 (213.87)	129.654* (70.81)
<i>n</i>		346	1146	263	1081	252	1051
Wage Job (formal and informal)		205.963 (175.75)	-4648.541 (11660.09)	-56.925 (190.15)	2652.110 (5390.52)	178.687 (231.72)	655.840 (490.40)
<i>n</i>		231	896	117	603	147	721

Note: * is significant on 10% level, ** significant on 5% level, ***significant on 1% level

Table 6: Determinants of self-reported mobility restricting behavior

Self-reported mobility restriction	National n=12,563	Rural n=5,864	Urban n=6,699
Trust in Government	-0.38***	-0.31	-0.42**
Trust in fellow citizens	0.22	0.40	-0.05
Sex (Female)	-0.26	-1.76	-0.29
Education Level	-0.07	0.08	-0.33**
Household Head	0.07	-0.08	0.73**
Age	0.00	-0.00	0.01
Urban/Rural	-0.12	N/A	N/A
Know someone who is/was infected	0.66	0.08	1.87***
Employed	0.41*	1.01***	-0.39
Worried about food	-0.09	-0.10	-0.12
Policy Stringency Index	0.06***	0.07***	0.08***
Weekly Change Covid-19 cases (%)	0.00	-0.01	-0.00

Note: *** is significant at the 1% level, ** is significant at the 5% level, * is significant at the 10% level