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The Labor Market Implications of Restricted Mobility during the COVID-19 Pandemic in Kenya

Evidence from Nationally Representative Phone Surveys

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Abstract

The COVID-19 pandemic affected people's livelihoods in many ways, particularly in developing countries. This paper examines the degree to which recovering mobility levels impacted labor market outcomes in Kenya over the course of the pandemic, starting from May 2020 until June 2021. It uses an instrumental variable approach to identify the causal impacts of mobility reduction induced by policy changes on labor market outcomes. The findings show that a 10 percent recovery of mobility led to a 12 percentage points increase in labor force participation and a 9 percent points increase in household members being employed. At the same time, a 10 percent recovery of mobility caused an increase of 11 wage hours per week (formal and informal). Among the factors influencing self-reported mobility-reducing behavior, trust in the government's ability to deal with the pandemic correlates with less self-reported mobility reduction, while people who knew someone with an infection tend to reduce mobility less. Finally, countrywide policy stringency levels clearly reduce self-reported mobility. Given the demonstrated adverse impacts of reducing mobility on economic indicators, the government should explore options to limit the economic fall-out while protecting citizens from infections, for example, by using partial or geographically constrained lockdowns.

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The Labor Market Implications of Restricted Mobility during the COVID-19 Pandemic in Kenya: Evidence from Nationally Representative Phone Surveys

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Introduction

The pandemic of Coronavirus Disease-19 (Covid-19) has been an unprecedented situation for the world. To this date, estimates are that more than 230 million people have been infected and around 4.7 million people have died from the COVID-19 pandemic across the globe (WHO 2021, Johns Hopkins University 2021). At the same time, the pandemic has had significant labor market implications, with an estimated 225 million full-time jobs lost worldwide between the fourth quarter of 2019 and the first quarter of 2021 (ILO, 2021). These COVID-19 related labor market costs are driven by many factors, such as peoples' behavior in uncertain times as well as the policies and guidelines governments impose to curb the spread of the virus.

As a response to the pandemic many governments have imposed two types of measures. Firstly, measures aimed at restricting mobility and social interaction to reduce the speed of further infection as well as, secondly, measures to mitigate the economic consequences on businesses and households. The consequences from the pandemic 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 especially 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. As governments react and impose restrictions to save lives, people subsequently change their behavior (e.g. reduce mobility) and this in turn affects labor markets. Therefore, a better understanding of the causal relationships between human behavior 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.

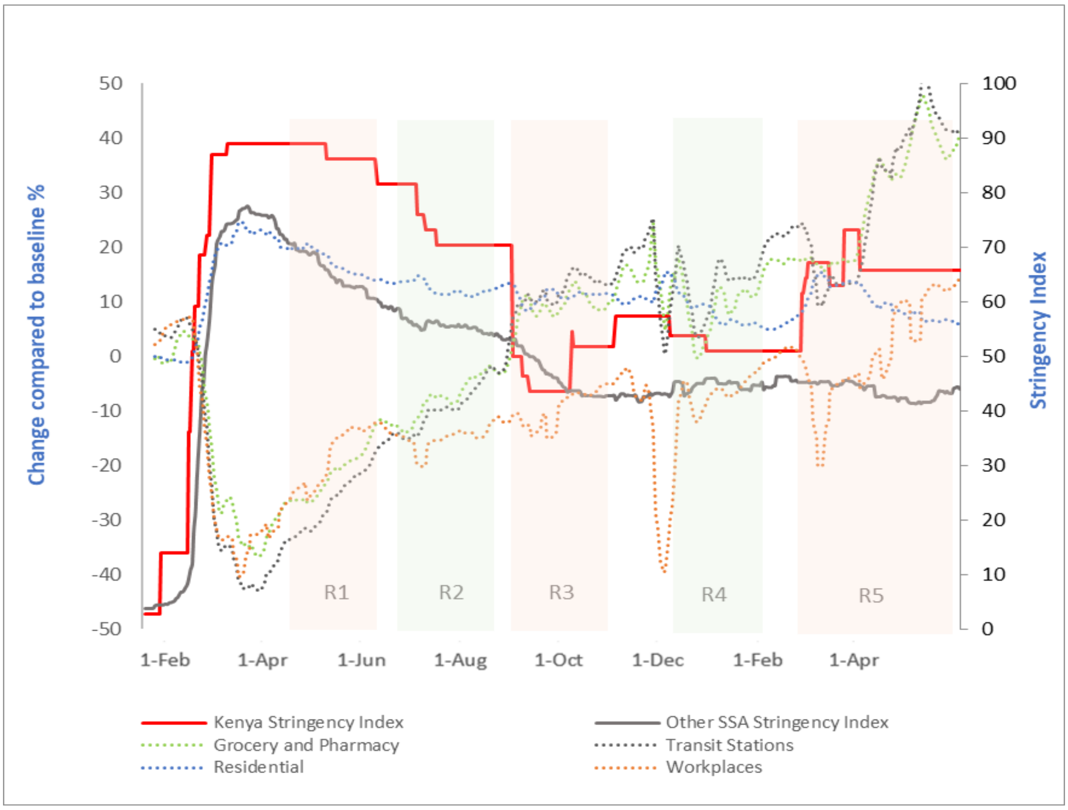
Kenya's first case of COVID-19 was recorded in March 2020. Since then, reported infections have considerably increased, peaking on October 31, 2020 with 1,395 new infections per day (Ritchie et al. 2020). Following Kenya's first case of confirmed COVID-19 in March 2020, the Government of Kenya quickly put in place multiple policies and measures to contain the spread of the virus. In March 2020 for instance, the Government of Kenya introduced a series of restrictions ranging from the closure of educational institutions to directing public and private sector workers to home-based work, except for essential workers (Bowmans 2020; Deloitte 2020; Nechifor et al. 2020). Entry into Kenya was limited to citizens and residents but required quarantine for 14 days while local air travel was suspended and resumed on July 15. These measures were followed by fast reductions in average mobility outside of residential areas but with an increase in residential movement (Graph 1).

Many studies in different contexts have shown that COVID-19-related containment measures aiming to reduce mobility and social contacts are a key tool in slowing the spread of the virus and as such, saving lives and buying vital time to develop vaccines and flatten the curve such that a country's health infrastructure is not overwhelmed (Yilmazkuday 2021, Jarvis et al. 2020). Additionally, studies have used Google Mobility Data to demonstrate these policies' successes in reducing mobility compared to pre-COVID-19 levels (Saha et al. 2020, Drake et al. 2020, Vinceti et al. 2020). However, as the disease is better understood, socioeconomic effects of the COVID-19 pandemic have started receiving increased attention. Multiple studies have looked into COVID-19 effects on different dimensions of household livelihoods both in the developed world (Bonaccorsi et al. 2020, Auriemma et al. 2020) as well as developing countries (Josephson et al. 2020, Khamis et al. 2021). Using data from high-frequency phone surveys, Khamis et al. (2021) for example estimated the early impact of COVID-19 on the labor markets of 39 countries. Their findings show that the pandemic has negatively affected labor market outcomes in these countries (job and income losses, lack of payment, job changes), with more pronounced impacts among workers in manufacturing (40%) and services (38%) than in agriculture (22%) as well as among self-employed (46%) compared to employees (39%).

While there is extensive literature on the aggregated socio-economic effects of the COVID-19 pandemic both in developed countries (Bonaccorsi et al. 2020, Auriemma et al. 2020) as well as developing countries (Khamis et al. 2021) including Kenya (Kansiime et al. 2021, Janssen et al. 2021, Pape et al. 2021) little research has been conducted looking into the specific mechanisms through which the pandemic affected labor market outcomes in developing countries. In particular, the channel of changing mobility has not been investigated extensively yet most likely due to both measurement difficulties and identification issues.

Mobility is an outcome of labor market activity as well as something that drives labor market activity, for example by providing jobs in the transportations sector. Likewise, the ability to move determines whether people have access to markets to sell their goods, as well as whether customers can attain the goods that they would like to have. Finally, supply chains as well as trade rely on frictionless mobility, which in turn may impact production and thus labor markets further downstream (Espitia et al. 2021). Given that mobility was severely impacted by policy to curb the spread of the virus in Kenya, it is an interesting shock-like mechanism driving labor market outcomes to look at. We intend to quantify the changes in labor market outcomes that were driven by changing mobility levels over the course of the pandemic in Kenya by applying IV analyses.

Graph 1 Development of Kenyan Policy Stringency and Mobility Types since February 2020



Source: Authors' calculations

Graph 1 shows how the policy stringency and different types of mobility changed over time. The graph highlights another important factor determining the actual observed mobility levels, i.e. the peoples' adherence to the implemented policies and the government's ability to enforce them. In the beginning, mobility changes followed the changes of policy stringency with opposite direction. However, by the time mobility levels recovered to pre-pandemic levels at the end of 2020, this relationship became much less clear. Therefore, to better understand mobility levels as mechanism that drives labor market outcomes, it is important to also better understand what drives policy adherence of citizens in the respective setting. Many studies have looked at determinants of mobility restriction and COVID-19 guidelines. However, most of them were either placed in developed countries (Al-Hasan et al 2020, Coroiu et al. 2020, Carlucci et al. 2020) or lacked a representative sample size (Ahmed et al. 2020, Usman et al. 2020). Given the importance of policy adherence to understand mobility levels, we complement our analysis by determining which factors were associated with respondents self-reported mobility reduction in Kenya over the course of the pandemic.

We aim to add to the literature by examining labor market effects driven by changing mobility levels that can be attributed both to the measures imposed by the Kenyan government as well as people's adherence to these policies, combining data on policy restrictions with insights from Google Mobility Reports and large-scale household surveys. As far as we are aware, this is the first paper to investigate the causal effects of changing mobility levels on labor market outcomes over the course of the pandemic in a developing country. This study would be the first to do this in a nationally representative setting in a developing country with panel data reaching into early 2021. By estimating these causal effects, our findings will inform both researchers aiming to establish direct links from mobility to labor market outcomes as well as policy makers looking to balance the trade-off between curbing the spread of the virus and containing the magnitude of socioeconomic costs. In line with this, our analysis of factors associated with adherence to mobility restrictions add important information on how to design, target and communicate mobility restrictions in Kenya more effectively in order to increase the restrictions' ability to slow the spread of the virus.

2. Data Sources and Variables Used

2.1 Rapid Response Household Surveys

To conduct our analyses of the mobility-related labor market effects of the COVID-19 containment measures, we leverage multiple sources of data. Central to our analyses, we use the Kenya COVID-19 Rapid Response Phone Household Surveys (RRPS) to 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. Five rounds of the survey were completed between May 2020 and February 2021 (Supplement Table 1). 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. The household head or a knowledgeable person within the household was interviewed via Computer Assisted Personal Interviews (CAPI) and were asked to provide telephone numbers. Given that this sampling frame was five years old at the time of the first RRPS wave, an additional group was added by applying Random Digit Dialing (RDD). This method contacted households from a list of mobile phone numbers that was created using a random number generator from the 2020 Numbering Frame produced by the Kenya Communications Authority. The initial sampling frame consisted of 92,999,970 randomly ordered phone numbers assigned to three networks: Safaricom, Airtel, and Telkom. There was no stratification, and individuals, regardless of their household head status, that were reached through the selected phone numbers were asked about the households they live in. Household reached via RDD make up between 18.7% and 20.4% of our sample in the five survey waves (Supplement Table 1).

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. Our analysis focuses on working adults between 14 and 65 years old. We attain nationally representative RRPS data from 24,340 respondents. Out of these, 22,708 respondents gave complete information on employment status, 11,045/ 11,860 respondents on agricultural hours/income, 4,486/3,197 respondents on wage hours/income and 1,681 respondents on self-employment hours as well as the other covariates we consider. Sample characteristics are consistent across survey waves (Supplement Table 1). For the analyses of determinants of self-reported mobility reduction, we attain complete data from a total of 12,563 respondents.

2.2 Mobility Development

To determine mobility trends during the time of the pandemic, we use Google Community mobility reports (Google LLC 2021). These mobility reports provide insights into how mobility changes during the pandemic and into policies' effectiveness aimed at reducing mobility. Google mobility reports tracks aggregated, anonymized sets of GPS data for changes in mobility from users who opted-in/ did not opt out of location history for their Google Account. The data shows how visits to (or time spent in) categorized places change compared to a baseline. The baseline is the median value for the specific weekday from the 5-week period Jan 3 – Feb 6, 2020. Data is recorded for a total of six different location types, residential, grocery and pharma, transit, workplaces, retail and recreation and parks and leisure and collected on a county level (admin 1) as is our RRPS data. We consider five of them, excluding parks and leisure as we want to focus on dimensions of social and economic life (Chen et al. 2020) to construct the average mobility change. The average mobility change is computed by taking weekly overall average mobility change of the four location types (multiplying residential mobility change with minus one to attain a negative value for overall mobility reduction outside of home).

2.3 Policy Stringency

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 and collects systematic information on 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. Among the containment that are part of the index and that are assigned ordinal values are school closures, workplace closures, cancellation of public events, restrictions on gatherings, closure of public transport, stay at home requirements, as well as restrictions on national and international travel. The index is calculated using these ordinal containment and closure policy indicators, plus an indicator recording public information campaigns (Hale et al. 2021). Data for Kenya is aggregated on a national level for each day starting January 1, 2020, ranging from 0 to 88.89. For our analyses, we calculate weekly average policy stringency levels to match the granularity of data of mobility and labor market outcomes.

2.4 Confirmed COVID-19 Cases in Kenya

As part of our analyses, we also consider confirmed COVID-19 cases in Kenya, both national aggregates and county cases. National confirmed COVID-19 cases were obtained from both published government briefs as well as the data set on Policy Stringency, that also included national reported confirmed COVID-19 cases. For state specific confirmed cases, we used regular updates by the Kenyan Ministry of Health from the respective homepage and Twitter.

2.5 Labor Market Outcomes of Interest

Labor market outcomes from the RRPS can be allocated into three categories: A) employment status; B) hours worked in past 7 days; C) income earned in past 14 days per adult 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: 1) % employed, 2) % unemployed, 3) % not in the labor force, 4) hours worked in agriculture, 5) hours worked in wage employment, 6) hours worked in self-employment, 7) agricultural earnings and 8) wage earnings (Supplement Table 2). The wage indicators combined both formal and informal employment. 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. County specific weekly datapoints range from 1 to 51, with 75% of week averages comprising depending on the labor market outcomes between more than 2- 6 observations per county. For three of the eight variables, i.e 4) hours in agriculture, 5) hours in wage employment and 8) wage earnings, the RRPS survey also asks recall questions for levels prior to COVID-19 in February 2020, which we include into our analysis as additional week averages in the last week of February, giving us additional pre-pandemic datapoints.

3. Statistical Analyses and Estimation Strategy

3.1 Causal Impact of Mobility on Labor Market Outcomes

3.1.1 Regression Results

We start our analysis by running OLS and county fixed effects regression for the average weekly mobility change and average weekly labor market outcomes in a simple model and a model including additional covariates averages of economic uncertainty, fear of illness, knowing someone who had an infection, the change in national confirmed COVID-19 cases compared to the previous week in %. All models yield significant correlations between mobility levels for the extensive margins of employment as well as the number of hours worked both in formal and informal wage employment. Coefficients are similar for the extensive margins of employment with a correlation coefficient of ~0.004 for outcome employed, implying that a 1 percent increase of mobility is associated with an increase in employment of 0.4 percentage points (Table 1). Including the set of additional covariates yields significant results for both outcomes related to agriculture.

Table 1: OLS and FE estimates results for labor market outcomes of interest using changing mobility levels as explaining variable

	OLS (1)	OLS incl. covariates (2)	FE (3)	FE incl. covariates (4)
Employment (% of Hh members)				
Employed	**0.004***** (0.00)	**0.003***** (0.00)	**0.004***** (0.00)	**0.003***** (0.00)
n	*1649*	*1555*	*1649*	*1555*
Unemployed	**-0.001**** (0.00)	**-0.002***** (0.00)	**-0.001**** (0.00)	**-0.001*** (0.00)
n	*1649*	*1555*	*1649*	*1555*
Not in labor force	**-0.002***** (0.00)	**-0.002***** (0.00)	**-0.003***** (0.00)	**-0.003***** (0.00)
n	*1649*	*1555*	*1649*	*1555*
Hours Worked in past 7 days				
Agriculture	-0.003 (0.02)	0.004 (0.02)	0.014 (0.02)	0.002 (0.03)
n	*1441*	*1440*	*1441*	*1440*
Wage Job (formal and informal)	**0.064**** (0.03)	0.040 (0.03)	**0.166***** (0.03)	**0.142***** (0.03)
n	*1161*	*1161*	*1161*	*1161*
Self-Employment	0.038 (0.04)	0.043 (0.04)	0.050 (0.05)	-0.001 (0.08)
n	*780*	*779*	*780*	*779*

Income in past 14 days in KSH				
Agriculture	10.635 (5.90)	0.659 (7.84)	11.895 (6.3)	10.866 (10.67)
n	*1495*	*1493*	*1495*	*1493*
Wage Job (formal and informal)	14.742 (11.70)	4.492 (2.32)	13.149 (12.38)	22.108 (19.76)
n	*1018*	*1018*	*1018*	*1018*

Note: Aggregated on weekly levels, *** is significant at the 1% level, ** is significant at the 5% level and *is significant at the 10% level

However, plain OLS regression results (including fixed effects regression) can hardly be interpreted as causal. At first, it is easy to find third variables that have explanatory power for both, such as overall levels of fear of economic and health consequences. Our surveys ask specifically for these sentiments of uncertainty and fears of health and economic consequences. However, even if we control for these sentiments, the main problem of reverse causality remains, i.e. the fact that mobility does not only explain changes in labor market outcomes but that labor market outcomes and overall economic activity themselves have impacts on observed mobility. Therefore, the regression results in Table 1 cannot be considered causal in any direction.

3.1.2 Identification Strategy

To address these issues and given that mobility levels are highly interlinked with economic activity, we leverage policy stringency as exogenous shock in an IV estimation framework to overcome the issue of reverse causality and determine the causal impact of varying mobility levels on labor market outcomes in Kenya. As such, we use the overall policy stringency levels as instrument for observed mobility levels. We apply the following first stage regression controlling for the percentual change of confirmed national cases:

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

M_{tc} refers to the average mobility change on a county-level, PSI_t to the Policy Stringency Index on national level, and C_{tc} to the % change in confirmed cases in week t compared to week t-1 on the national level. We also considered county-level case changes, however these did not prove useful, given the low figures and large uncertainty between reported vs. actual numbers. We incorporate the % change in confirmed cases compared to the prior already in the first stage, to filter out “fear” effects that were not driven by public policy changes.

The second stage of our analysis is a county fixed effects regression at the county-week level. We include responses on concerns about the disease in terms of concerns about the illness itself, as well as fear of economic consequences. Households were asked if the pandemic was cause for concern, and if so, they were asked to provide the specific source of concern. Furthermore, we control for age and education (ranging from no formal education to postgraduate university degree). For respondents that provided us with recall-baselines, we assumed the education as well as the age to be the same at the time of the baseline, given that recall values were from February and survey data was available as of June of the same year. To control for the overall development of the pandemic, we include changes in Kenya's weekly reported COVID-19 cases as well as answers to the questions, whether a household knew of someone who had been infected with COVID-19. This latter control was added, because reported cases can be expected to be much lower than actual cases and therefore nationally representative surveys asking about known cases may serve as important addition to representing the overall course of a pandemic. A full overview of the covariates can be found in Supplement Table 2. This yields our second stage regression:

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

With Y_{ct} being our labor market outcomes of interest, δ_c denoting the county fixed effect and X_{tc} capturing the county/week specific averages of economic uncertainty, fear of illness, age and education levels of respondents and the overall progress of the pandemic.

3.1.3 Threats to Identification Strategy

Our identification strategy relies on two assumptions. The first, our exclusion restriction is that the reduction of mobility is the only channel through which the government's policies aimed at curbing the spread of the virus effected labor market outcomes. Clearly this is only possible when we can control for any signaling effect and concerns that the imposed policies may have had on households. As part of the RRPS survey data, we have representative data on fear of the illness as well as self-perceived economic uncertainty, which allows us to control for these sentiments. Additionally, our estimation strategy relies on the assumption that the IV is exogenous, i.e. that there is no causal impact running from labor market outcomes to our instrument, the policy stringency index itself. There are a couple of observations that we believe justify this assumption. At first, the Kenyan government immediately implemented very strong measures including a national curfew at a time, where only a handful COVID-19 cases had been confirmed in the country. Secondly, the government quickly enacted several economic relief policies which can be taken as anecdotal evidence that the mobility policy's primary concern was to curb the spread of the virus (see Presidential Announcement from April 16th, 2020) and economic considerations were tried to be addressed otherwise. We investigate this idea by looking at survey responses for questions on whether households had received transfers from government or politicians including the amounts. The share of people self-reporting receiving transfers from government programs ranged from 1.3% in wave 4 to 4.1% in wave 5 yet with no clear patterns across the waves. However, looking at the magnitude of transfers compared to pre-pandemic levels, there is anecdotal evidence that of increases in all survey waves (n=381) compared to pre-pandemic levels with increases ranging from an additional 913 KSH on average in wave 2 to 2,120 KSH in wave 4. Additionally, we look at the development of people's trust in the government's ability to deal with the pandemic as proxy for public sentiment about the government's performance that could reflect increasing pressure on politicians to take economic consequences more into consideration. Indeed, average scores changed from 1.51 during wave 1 of the RRPS to 1.40 during wave 5. However, given that trust levels were on average high (distrust was coded as 0, neutral as 1 and trust as 2), we do not believe this change to have made much of a difference. Overall, it does not seem that more severe labor market conditions were associated with increased political pressure, enabling the Government of Kenya to form mobility policies that were solely aimed at saving lives and containing the spread of the virus.

3.2 Factors Associated with Self-Reported Mobility Restrictions

Our second set of analyses 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 avoided groups more often, stay at home more, traveled outside less, gone to work less, or returned home earlier at night (Supplement Table 3).

Looking at factors that are associated with any self-reported mobility restriction, we – as above – consider the number of confirmed COVID-19 cases and the overall policy stringency. In addition, we incorporate a set of 10 covariates recorded in the RRPS. The co-variates include respondents' answers on questions about their trust in the government in handling the pandemic, trust in their fellow citizens, characteristics such as sex, education level, age, employment status, location (urban vs rural) and household heads status and whether they know someone who was infected or whether they were worried about having enough food (Supplement Table 3). To determine factors that influence any self-reported mobility reducing behavior, we run a multilevel logit model at the household level, where week and county form our two levels of analysis:

$$m_{it} = x_{it} + PSI_t + C_t + \vartheta_{it},$$

With m_{it} being self-reported mobility for household i in week t, x_{it} household characteristics, C_t the % change in confirmed cases for week t compared to t-1 and ϑ_{it} the error term.

4. Results

Policy stringency on a national level and average mobility changes in the individual counties are significantly and negatively associated with one another. Table 2 shows the results of our first stage regression, which is significant not just for policy stringency but also negatively and statistically significantly related to the weekly change of national confirmed COVID-19 cases. We see that in terms of magnitude however, a one-point Policy Stringency Index increase is associated with a more than 8 times decrease of mobility compared to a percentage point increase in national weekly confirmed COVID-19 cases.

Table 2: First Stage Regression Results

Weekly Mobility Change Levels from Feb 2020-June 2021, n=2,617	Coefficient (S.E.)	95% Confidence Interval
Policy Stringency Index	**-0.252***** (0.014)	[-0.279;-0.223]
Weekly Change Confirmed COVID-19 cases (national)	**-0.029***** (0.003)	[-0.035;-0.023]

Note: Aggregated on weekly levels, *** is significant at the 1% level

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 three quarter 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 12 percentage points of people to return to the workforce. Hence, we see 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 which causes them to look for jobs again. Surprisingly, these changes are consistent across urban and rural areas with minor yet statistically significant differences in employment, unemployment and not in the labor force.

Table 3: IV estimation results for labor market outcomes of interest using changing mobility levels as explaining variable

	OLS- full sample	IV- full sample	IV- rural	IV-urban
	(1)	(2)	(3)	(4)
Employment (% of Hh members)				
Employed	**0.004*** ** (0.00)	**0.009*** ** (0.00)	**0.009*** ** (0.00)	**0.010*** ** (0.00)
n	*1649*	*1555*	*1470*	*1467*
Unemployed	**-0.001** ** (0.00)	0.002 (0.00)	**0.004*** ** (0.00)	**0.003** ** (0.00)
n	*1649*	*1555*	*1470*	*1467*
Not in labor force	**-0.002*** ** (0.00)	**-0.012*** ** (0.00)	**-0.014*** ** (0.00)	**-0.013*** ** (0.00)
n	*1649*	*1555*	*1470*	*1467*
Hours Worked in past 7 days				
Agriculture	-0.003 (0.02)	**0.127* ** (0.07)	-0.130 (0.08)	**0.399*** ** (0.08)
n	*1441*	*1440*	*1287*	*1233*
Wage Job (formal and informal)	**0.064** ** (0.03)	**1.143*** ** (0.38)	**1.772*** ** (0.50)	**0.958*** ** (0.20)
n	*1161*	*1161*	*721*	*910*
Self-Employment	0.038 (0.04)	**0.413** ** (0.16)	0.269 (0.24)	0.239 (0.15)
n	*780*	*779*	*400*	*567*

Income in past 14 days in KSH				
Agriculture	10.635 (5.90)	66.154 (52.78)	16.141 (85.31)	**113.101**** (50.78)
n	*1495*	*1493*	*1342*	*1299*
Wage Job (formal and informal)	14.742 (11.70)	134.636 (86.72)	62.042 (205.26)	131.075 (112.40)
n	*1018*	*1018*	*591*	*761*

Note: Aggregated on weekly levels, *** is significant at the 1% level, ** is significant at the 5% level and *is significant at the 10% level

Looking at the intensive margins of employment, i.e. the indicators that provide context about 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 11 wage hours per week (formal and informal). Overall, there seem to be more significant effects for wage professions (both formal and informal). The coefficient of hours worked in agriculture is only statistically significant at the 10% level and has a much lower coefficient than hours in wage jobs. Self-employment hours seem to have been positively affected by the recovery of overall mobility as well. For income generated from wage work and agriculture, we find no statistically significant effects of recovering 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 agricultural employment in terms of hours worked and income generated was significantly affected in the urban setting. Finally, the estimated coefficients using our IV approach yield much higher results and higher statistical significance for amount if hours worked compared to our previous OLS estimates that were subject to reverse causality.

Looking at the other correlates that we included into our analyses (Table 4), we find that economic uncertainty is inversely related to people working in self-employment. Additionally, age and education seem are positively associated with (re-)entering employment, indicating that the overall labor market recovery was more pronounced for older, more experienced and educated workers.

Table 4: IV estimation results for whole set of covariates used in regression model

	Employed	Unemployed	Not in Labor Force	Agri Hours (7days)	Wage Hours (7days)	Self-employment Hours (7days)	Agri Income (14days)	Wage Income (14days)
IV Mobility	**0.009*** **	0.002	**-0.012** **	**0.127***	**1.143*** **	**0.413** **	66.154	134.636
Economic Uncertainty	0.037	-0.040	0.003	0.993	-1.118	**-6.826** **	956.343	189.959
Fear of Illness	-0.001	0.020	-0.035	2.272	**8.024** **	**9.628*** **	-263.304	2304.881
Know s/o Infected	0.041	**-0.162** **	0.152	-0.385	**-22.184** **	-3.000	-1659.48	-4327.56
Age	**0.010*** **	-0.001	-0.000	-0.037	-0.091	-0.043	0.182	**66.676** **
Education	**0.033*** **	**0.011** **	**0.017** **	**-0.612** **	**-1.230** **	0.112	136.823	**2255.364*** **

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

It is possible that our results are driven by different mechanisms that played a role at varying stages of the pandemic. For this reason, we also compare results for different stages of the pandemic. 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 (Table 5). 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 between wave 3-5 the most pronounced employment effects came from people leaving unemployment. Likewise, for the intrinsic margins of employment, most significant outcomes of hours worked, and income generated are significant in the past-recovery phase. Looking at the split for urban and rural, we find that the initial employment recovery is mainly due to recovery in rural areas. At the same time, recovery of hours worked both in agriculture as well as wage professions seems as well as agricultural income generated seems to be driven by urban areas.

Table 5: IV estimation 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	0.009 (0.00)	**0.017***** (0.01)	**0.016***** (0.01)	**0.012***** (0.00)	0.003 (0.01)	**0.016***** (0.00)
n	*492*	*1061*	*460*	*1002*	*456*	*1005*
Unemployed	0.001 (0.000)	**-0.011***** (0.00)	-0.001 (0.00)	**-0.009***** (0.00)	0.006 (0.00)	**-0.012***** (0.00)
n	*492*	*1061*	*460*	*1002*	*456*	*1209*
Not in labor force	**-0.010**** (0.00)	**-0.007***** (0.00)	**-0.016***** (0.01)	**-0.006**** (0.00)	-0.008 (0.01)	-0.003 (0.00)
n	*492*	*1061*	*460*	*1002*	*456*	*1005*
Hours Worked in past 7 days						
Agriculture	**0.473**** (0.19)	**0.243**** (0.09)	0.222 (0.23)	**0.248**** (0.11)	**0.644***** (0.21)	**0.280**** (0.11)
n	*452*	*986*	*398*	*884*	*380*	*849*
Wage Job (formal and informal)	0.653 (0.43)	-0.348 (0.22)	1.000 (0.71)	-0.373 (0.25)	**0.864*** (0.44)	-0.374 (0.26)
n	*302*	*858*	*147*	*574*	*215*	*693*
Self-Employment	0.808 (0.45)	-0.228 (0.22)	0.394 (0.96)	-0.208 (0.32)	0.369 (0.51)	-0.095 (0.35)
n	*240*	*539*	*120*	*280*	*178*	*389*
Income in past 14 days in KSH						
Agriculture	97.558 (152.36)	**-153.623**** (71.66)	263.063 (384.59)	-68.036 (42.38)	-14.600 (144.97)	**213.656**** (98.31)
n	*458*	*1033*	*404*	*932*	*393*	*901*
Wage Job (formal and informal)	116.376 (171.69)	-69.228 (114.33)	-301.697 (228.41)	-94.535 (131.30)	170.208 (260.21)	-64.162 (121.68)
n	*244*	*773*	*111*	*480*	*157*	*602*

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

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 (driven by urban areas), knowing someone who had been infected (driven by rural areas) and the overall policy stringency level are statistically significant (Table 6). Interestingly, both the trust in the government's ability to handle the pandemic as well as knowing someone who had been infected has a negative sign, implying either that a good trust in the government's ability to deal with the pandemic reduces the individual households need to comply with recommended mobility restrictions or that having someone infected in immediate reach implied increased need of support which translates into mobility. However, overall seems that one of the main drivers of self-reported mobility reduction is the overall severity of mobility restriction policy in Kenya. Given that the policy stringency is a continuous variable running from 0-100, a seven-point increase of the stringency index has a similar effect compared to being employed.

Table 6: Determinants of self-reported mobility restricting behavior

Self-reported mobility restriction	National n=11,351	Rural n=5,318	Urban n=6,033
Trust in Government	**-0.31****	-0.24	**-0.46****
Trust in fellow citizens	0.49	**0.73****	0.39
Sex (Female)	-0.26	-0.21	-0.27
Education Level	-0.06	0.12	**-0.37****
Household Head	-0.11	-0.12	0.10
Age	-0.00	-0.00	-0.01
Urban/Rural	0.04	N/A	N/A
Know someone who is/was infected	**-1.40****	**-2.30*****	-0.42
Employed	0.31	**0.78****	-0.22
Worried about food	0.21	**0.50****	-0.23
Policy Stringency Index	**0.06*****	**0.06*****	**0.06*****
Weekly Change COVID-19 cases (%)	0.00	0.00	-0.00

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

Comparing urban vs rural outcomes, we find that there seem to be different drivers of reducing mobility. While in rural areas, self-reported mobility reduction was associated with trust in fellow citizens, being employed and worrying about food, in urban areas education levels and the trust in the government's were associated with less self reported mobility restricting behavior.

5. Discussion

Our study has a few salient findings. First, recovering mobility levels in Kenya following the initial declines in early 2020 have caused people to enter the labor force again, three-quarters of them re-entering into employment. Second, while increased mobility caused an increase in hours worked for the different sectors, no effects can be found for generated incomes. Potential reasons for this observation may be that employers continued to support workers for a while up until their re-entry, or otherwise lowered payments at the beginning of the pandemic and did not increase payment as the number of hours worked went up again either due to financial distress or with the promise of later repayment. We allow ourselves a cautious interpretation by leveraging asset information for a total of seven assets (radio, mattress, charcoal jiko, refrigerator, television, landline telephone and computer/tablet/laptop) that became available during wave 4 and 5 of the RRPS surveys for a total of 10,785 households, which also incorporated baseline values from February 2020. Comparing wave averages to pre-pandemic levels show that overall asset ownership reduced over the course of the pandemic until wave 4 and wave 5 with a slight recovery between wave 4 and wave 5. These results are consistent when incorporating the full set and sub-sets of the seven assets. We interpret this as evidence that household had to sell assets to cope with income and job loss as well as health-related expenses, which makes the idea, that employers continued payments or that social safety nets were at play rather implausible. However, given that we lack precise income baseline data, understanding the exact dynamics over the full course of the pandemic will be a subject for future research.

Comparing urban vs rural, we do find additional statistically significant 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, the number of wage hours worked increased more which may be explained by an increased reliance on commuting to the workplace or an increased elasticity of job availability in downturn times compared to urban areas.

Looking at different stages of the pandemic, we find that particularly in rural settings people quickly re-entered employment already during the pre-recovery phase. During the post-recovery phase both in rural and urban areas people left unemployment more than re-entering the labor force. This implies that people that lost their jobs left the labor force and quicky re-entered into employment while people that could not afford to leave the labor force stayed unemployed for a longer period. Overall recovery in agriculture seems to be driven mainly by urban dynamics.

Thinking about safety nets and mitigation measures, awareness of differential impacts across sectors in urban and rural areas carries important insights into target groups and economic costs of restriction measures in these specific areas. 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. Furthermore, given that this is a country case, it will be interesting to see how estimates of the causal impact of mobility on economic recovery compare to findings from other countries or regions.

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. There are differences between urban and rural households. While for rural households the level of stringency and worry about food, knowing someone who was infected, employment and trust in fellow citizens were of significance, in the urban setting additional factors are statistically relevant such as education, and the trust in the government's ability to handle the pandemic. This may suggest that urban educated citizens generally perceive less risk for themselves and therefore are more receptive to the perception of the government doing the job. At the same time, the coefficient for employment in the rural setting is much larger than for urban households, pointing towards increased opportunity costs of illness. The significant negative impact of knowing someone who has been infected could point towards the need to support the person that falls ill which translates into additional mobility. This increased relevance of social ties is also backed by the relevance of peopl's trust in their fellow citizens in the rural setting. 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. Comparing coefficients, a 10-point increase of policy stringency outweighs most of the other coefficients, highlighting potential signaling or enforcement mechanisms that come with more severe government measures. These 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.

Our study has a few limitations that are mostly due to data availability. At first, given that the RRPS started in May, we lack baseline data for pre-pandemic levels. While for three of the five labor market outcomes, we do have retrospective recall values, this data is subject to the innate bias that recall data carries. While the lack of baseline data does not directly affect our message, the interpretation needs to be cautious as the causal effect of mobility recovery may differ from the causal effect of mobility on labor market outcomes in non-pandemic times. Another limitation is the fact that we do not have county-level stringency index data but had to rely on national aggregates to instrument for county-specific mobility changes. However, given that a) only very few policies were implemented on county-levels and b) the national index score is an average of stringency across the country, we believe that this is justifiable. In case that county-specific stringency index data for Kenya is released, it will be necessary to compare these results. Due to the nature of the RRPS survey waves and the fact, that due to COVID-19, interviews had to be conducted via phone, there is a potential bias due to the selection at baseline and the attrition of the selected population in the follow-up waves. Phone surveys can only reach respondents using a phone in an area with network coverage, therefore statistics are only representative for this part of the population, potentially excluding to some extent the poorest households who do not own phones or live-in areas with no network coverage. RRPS weights were adjusted by the World Bank in a two-step approach (Himelein 2014) to make sure the RRPS is as representative as possible for the entire population and adjusting for attrition. We therefore do not believe this bias to be significant. Finally, the instrumental variable approach hinges on the assumption that the policy stringency index has no direct causal relationship to the outcome measures, which are not mitigated through mobility changes or other measures that we control for as well as that the economic environment itself did not affect the policies put in place to reduce mobility. While we present anecdotal evidence that is in favor of this idea, we realize that it is indeed possible that decision makers worried about containing the spread of the virus did also factor in economic concerns, particularly at later stages of the pandemic as the virus was better understood.

As final sanity check we used weekly lags of explaining variables, given that low mobility levels may take a bit of time to translate into labor market outcomes. However, we do not find this to impact our results.

6. Conclusion

We examined the impact of increasing mobility on household labor market outcomes over the course of the pandemic following the initial steep declines in March and April 2020 and determined which factors influenced people's self-reported adherence to recommended mobility restricting behavior.

Over the course of the pandemic from May 2020 until June 2021, a 10 % of recovering mobility leads to a 12 percentage points recovery of labor force participation and an increase of 9 percentage points of household members being employed. At the same time, a 10% of recovering mobility causes an increase of 11 wage hours per week (formal and informal). Particularly the results for extrinsic margins of employment are consistent for urban and rural over the course of the past year, with differences regarding the timing of the recoveries. Looking at the intrinsic margins of employment, wage work was more affected in rural areas, while agricultural work was more affected in urban areas.

Among the factors influencing self-reported mobility and thus, nationwide mobility levels, the trust in the government's ability to deal with the pandemic leads to less self-restriction, while country wide policy stringency level leads to higher self-restriction, the overall policy stringency being of specific importance.

Knowing about the sectors affected most by mobility and at which stage of the pandemic this affect takes place is important knowledge for policy makers. Policy makers in future pandemics will need to carefully evaluate policies aimed at reducing mobility with the economic costs that are associated with them. We find that labor market recovery in terms of employment levels and hours worked comes quickly with increasing mobility, with strong effects on wage work across the country and agricultural work in urban areas. Income however does not seem to be causally influenced by recovering mobility. 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.

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Supplements

Supplement Table 1 Sociodemographic comparison of different RRPS waves

	Wave 1 (14/5/2020-8/7/2020)	Wave 2 (16/7/2020-18/9/2020)	Wave 3 (28/9/2020-30/11/2020)	Wave 4 (15/1/2021-25/3/2021)	Wave 5 (29/3/2021-25/6/2021)
Average Age of Respondent	35.03	35.19	34.71	36.1	36.22
Share of Female Respondents	50%	53%	51%	50%	49%
Average Education of Respondent*	3.29	3.31	3.39	3.25	3.31
Household size	4.13	4.15	3.4	3.65	3.26
Average Age of Household Head	39.53	40.08	37.42	37.7	37.67
Share of Female Household Heads	33%	36%	37%	41%	39%
Share Urban	35.9%	36.0%	37.0%	36.4%	40.0%
Sample Size	4,062	4,504	4,993	4,906	5,874
Share RDD	18.9%	18.7%	20.2%	17.2%	19.8%
Response Rate	36%	41%	45%	43%	51%

*An education level of 3 equals to completed post-primary, vocational, a score of 4 equals completed secondary education

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

Role in Analyses	Category	Variables	Coding	Pre-COVID-19 Recall Data?
Outcome Variables	Employment Status	1. Respondent Employed (%)	Binary (Yes/No)	
		2. Respondent Unemployed (%)	Binary (Yes/No)	
		3. Respondent Not in Labor Force (%)	Binary (Yes/No)	
	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: - 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: - 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): - 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 answer to the following 2 questions): - In the past 7 DAYS, how many days have ADULTS in your household skipped meals or cut the number of meals?	Binary