# Chapter 8
# Urban Drainage Infrastructures Toward a Sustainable Future

**Ahmad Ferdowsi and Kourosh Behzadian**

## 8.1 Introduction

Urban drainage infrastructures (UDIs) have had major impact on human and environmental health, urban life quality, and development of cities [1, 2]. UDIs have a long history in urban areas from the time when the traditional open gutters were in place until now that most UDIs' components are underground, and those open gutters/channels have mainly been replaced with closed conduits and piped systems. In fact, the history of using stormwater collection systems coincides with the appearance of human civilization, i.e., thousands of years ago. Although the main goal of drainage systems is to collect surface runoff and flood flows, combined sewer systems in some countries are used to collect and convey both surface runoff and sanitary sewage in the same conduits. As cities grew, the need for larger drainage systems increased, which resulted in more investments in UDIs [3]. However, the performance of combined sewer systems has been found unsatisfactory due to unwanted discharge of untreated wastewater into receiving water bodies that can be the main source of water supply in urban water metabolism [4]. Generally, flooding, erosion, water quality reduction, and environmental issues are probable hazards threatening the performance of UDIs [3].

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There is no doubt that efficient water infrastructure consisting of many structures and elements [5] can be vital to reach the United Nations' 2030 goals [6], which are known as sustainable development goals (SDGs) and were adopted based on a universal agreement [7]. However, water infrastructure is already under massive pressure from external drivers especially urbanization, population growth, and more importantly climate change.

Despite great importance of UDIs in achieving SDGs, external drivers such as climate change, population growth, and urbanization can undermine the satisfactory performance of UDIs. Although climate change is known as the continuous changes in some climatic variables such as precipitation and temperature [8], the change indicates a rapid rate over the last century [9] due to anthropogenic activities by greenhouse gas emissions from fossil fuels and land-use changes [10, 11]. Temperature, precipitation, relative humidity, and incident solar radiation are some affected parameters in a changing climate. In addition, an increase in world population has been predicted [12], and another projection showed a greater percentage of the world population will be living in urban areas [13]. These stressors can substantially impact natural and human-made structures. UDIs can both affect climate change (e.g., increasing greenhouse gas emissions, acidification, and eutrophication) and also be influenced by climate change (e.g., as a result of changes in urban flooding) [14]. Aging is another problem of current urban infrastructures [15, 16] including UDIs [17] that threatens their sustainability. As displayed in Fig. 8.1, UDIs must overcome a number of obstacles (i.e., aging of infrastructure, climate change, population growth, and urbanization) before reaching a sustainable future, through adaptation strategies. In Fig. 8.2, some problems that happened as a result of malfunctioning of UDIs in Tehran, Iran, are illustrated, which normally threaten the transportation system and public health.

Over the previous decade, various research works studied the impact of climate change [12, 18] and possible adaptation strategies [11, 19]. Reviewing these works demonstrates that the previous studies mainly neglect the role of achieving SDGs and the impact of urbanization; however, most of them emphasize the importance of climate change impacts on UDIs. It should be noted that the performance of current

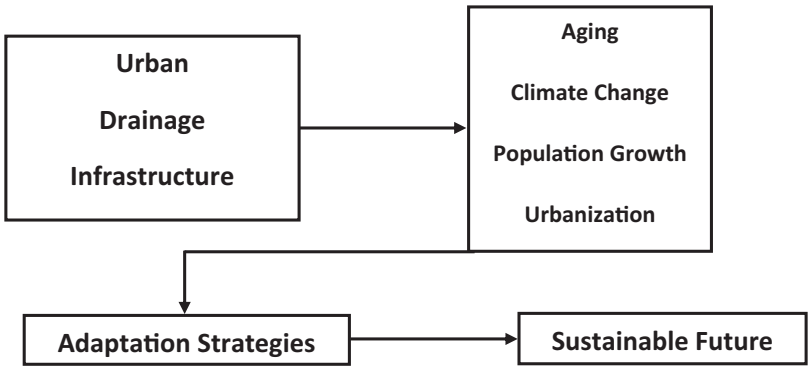


**Fig. 8.1** UDI: how to reach a sustainable future

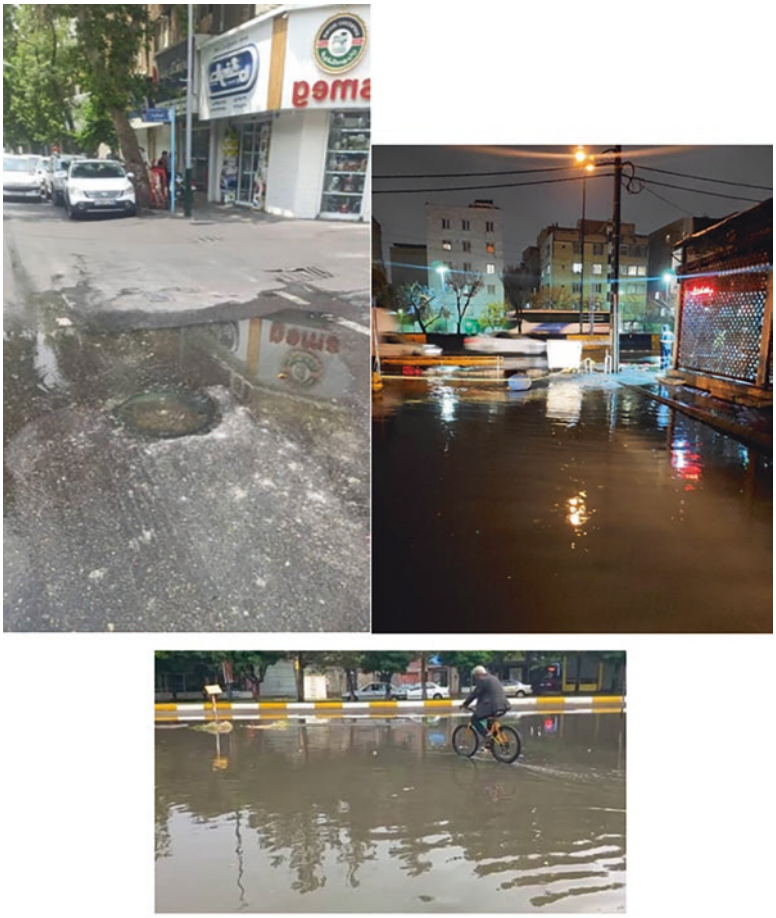

**Fig. 8.2** Examples of UDIs' failures in Tehran, Iran

UDIs is affected by climate change and urbanization [3], and applying sustainable drainage can be very challenging for real-world cases [20]. The main aim of the current chapter is to review the impacts of climate change and urbanization on UDIs and potential adaptation strategies to alleviate these negative impacts and help reach a sustainable future.

## 8.2 Climate Change, Population Growth, and Urbanization

Climate change is one of the most pressing world problems. It refers to the long-term persistent variations in the climate that happen either naturally or as a result of anthropogenic activities [21]. Carbon dioxide, methane, nitrous oxide, water vapor,

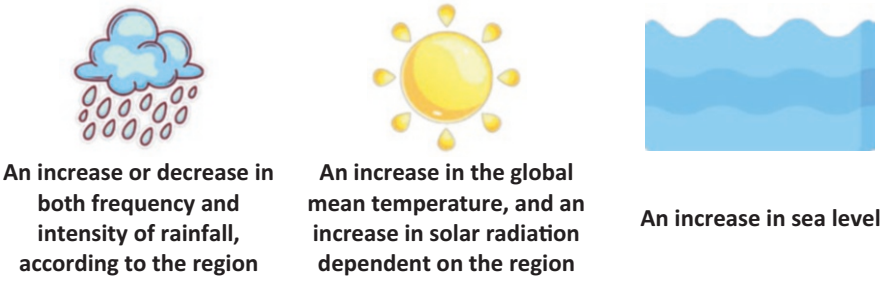


**Fig. 8.3** Projected changes of climate variables due to climate change

and fluorinated gases are the most important gasses that are responsible for the greenhouse effect [22]. Human activities are the main reason behind the global increase in greenhouse gases [23] – among all activities, using fossil fuels and land-use changes have had the greatest effect on global carbon dioxide increases [21]. Other impacts of climate change can include changes in migration [24], wildfires [25], extinction of plant and animal species [26], and social and political conflicts [27]. Figure 8.3 depicts some of the featured changes that can happen by climatic changes and affect urban infrastructures.

On the other hand, it has been predicted that the world's population will reach 9.8 billion by 2050 [28]. Another projection, for 2050, indicated that approximately 68% of the entire population of the world will reside in urban areas [13]. Hence, climate change, urbanization, and population growth can be considered the current important world stressors that can jeopardize the conditions of both natural and artificial systems like UDIs.

## 8.3 SDGs and UDIs

Global goals are an alternative name for SDGs that were set out by the United Nations General Assembly in 2015. Seventeen SDGs with 169 targets are included in the 2030 agenda for sustainable development, which started to be implemented from 1 January 2016. The framework of the goals was prepared in a way that can be acceptable scientifically, politically, and publicly. The final objective of SDGs is to provide sustainable health for all (from planet to local communities), by accounting for poverty, inequality, climate change, environmental degradation, peace, and justice [7, 28]. All 17 SDGs can be categorized into four sections related to people (goals 1–6), prosperity (goals 7–12), the planet (goals 13–15), and peace and partnerships (goals 16 and 17). It can be observed that many of these goals depend on each other, for example, zero hunger in a region affects the poverty of that region. Water is clearly mentioned in goal 6 (clean water and sanitation), which per se underpins many goals such as goals 1 (poverty), 2 (food), 3 (health), 4 (education), 7 (energy), 8 (economics), and 10 (equity) [7].

Since water is harvested, supplied, treated, and delivered through water infrastructure, the dependence of many goals and their associated targets to water infrastructure is undeniable. Flood control is another major task of water infrastructure [29] that is normally handled through drainage (stormwater) systems. UDIs can contribute to reaching goal 1 by reducing climate-related disasters on poor people, goal 3 as death rate and illnesses due to water pollution and contamination can be reduced or eradicated, goal 6 through affordable water production, pollution reduction, etc., goal 9 by making infrastructure and industries efficient, resilient, and eco-friendly, goal 11 by considering the environmental and financial problems associated with water in cities, goal 12 by controlling the release of wastes to water, and goal 13 by increasing public awareness related to climate change impacts and adaptation. Due to the role of UDIs in collecting and supplying water, mitigating flood, conveying water, and contributing in wastewater treatment, they play a significant part in providing safe and affordable water, preserving ecosystems, and other SDGs, which cover seven goals (1, 3, 6, 9, 11, 12, and 13) and their targets.

## 8.4 Climate Change and Urbanization Impacts on UDIs

In Table 8.1, the main probable impacts of climate change and urbanization on UDIs are reviewed. The capacity of the current UDIs and the quality of water are affected by these drivers. More specifically, floods can be generated because of sea-level rise and increased precipitation that both occur due to climate change. In addition, urbanization as a result of increased desire to live in cities, as mentioned in Table 8.1, increases the risk of flood formation and its associated consequences. Flooding endangers public health, threatens public transportation systems, increases financial losses and number of deaths, and results in untreated water, e.g., wastewater and sewage being released into receiving bodies (sea, lakes, etc.). Based on Table 8.1, the impact of climate change and urbanization can be categorized into four sections in which some problems arise themselves.

**Table 8.1** Probable impacts of climate change and urbanization on UDIs

| Climate change and urbanization features | Probable impact |
|---|---|
| A rise in sea level | Higher probability of urban runoff and flooding |
| Variations in temperature | Changing content of soil water that affects runoff formation |
| An increase in precipitation | Decreasing water quality; increasing overloading, costs, number of flooded nodes, and water spill from manholes, an increase in sedimentation |
| Urbanization and population growth | Making urban zones larger and denser, which increases their imperviousness and consequently the rate of floods; land-use changes through removing vegetated areas; a reduction in storage areas |

## 8.5 Performance Improvement of UDIs

Water infrastructure can be divided into three main sub-systems including water supply systems, stormwater systems, and wastewater systems. Needless to say, any new development or rehabilitation of any water infrastructures can be quite expensive, and their construction may take years. Clearly, their failures can result in loss of lives and property damage [30]. Another issue is that many of them were built many years ago which make them more vulnerable.

The impacts of climate change and urbanization on UDIs and their role in gaining SDGs were discussed in the previous sections. The probable impacts of these drivers may cause problems for the operation of UDIs and reaching SDGs. Hence, adapting UDIs to future changes is an urgent need. It was reported that UDIs cannot deal with the effects of climate change and urbanization [1, 12] that necessitate applying the adaptation measures. Design criteria that consider the impacts of urbanization, population growth, and climate change [12] should be added to the future design. Other flood control methods that are listed in Table 8.2 can mitigate flood impacts and reduce the excessive pressure on UDIs due to climate change and urbanization.

## 8.6 Conclusions

UDIs can contribute to achieving a future sustainable for all; however, it is under pressure from external drivers such as climate change, urbanization, and population growth. The impacts of these stressors not only prevent fulfilling the main functions of UDIs but also undermine reaching SDGs. This chapter investigated the requirements of SDGs in UDIs, the impacts of climate change and urbanization on UDIs, and the adaptation strategies that can be employed to tackle climate change and urbanization and making UDIs ready to achieve the universal goals of the United Nations. The role of UDIs seems to be major for achieving seven SDGs (goals 1, 3,

**Table 8.2** Adaptation strategies to counteract future problems in UDIs

| Impact | Adaptation strategy |
|---|---|
| Increased precipitation | Predicted precipitation should be considered for future UDIs; those parts of UDIs that are unable to bear excessive design discharge should be upgraded; changes in precipitation should be considered in simulation models [1] |
| Urbanization | Employing pervious concrete in urban areas to reduce flood water and to decrease pollution of water [31]; land-use and land-cover modification |
| Flood control | Using environmentally-friendly solutions (green roofs, vegetation cover, etc.) and source control of water (watershed management); developing prediction models and warning systems; increasing floodplain storage capacity; soil conservation |

6, 9, 11, 12, and 13) while climate change and urbanization can cause various problems for UDIs, and the different adaptation strategies were proposed in the literature to mitigate these problems and adapt UDIs to future changes.

## References


1. Arnbjerg-Nielsen, K., Willems, P., Olsson, J., et al. (2013). Impacts of climate change on rainfall extremes and urban drainage systems: A review. *Water Science and Technology, 68*(1), 16–28.
2. De Feo, G., Antoniou, G., Fardin, H. F., et al. (2014). The historical development of sewers worldwide. *Sustainability, 6*(6), 3936–3974.
3. Yazdanfar, Z., & Sharma, A. (2015). Urban drainage system planning and design–challenges with climate change and urbanization: A review. *Water Science and Technology, 72*(2), 165–179.
4. Landa-Cansigno, O., Behzadian, K., Davila-Cano, D. I., & Campos, L. C. (2020). Performance assessment of water reuse strategies using integrated framework of urban water metabolism and water-energy-pollution nexus. *Environmental Science and Pollution Research, 27*, 4582–4597.
5. Ferdowsi, A., Valikhan-Anaraki, M., Farzin, S., & Mousavi, S. F. (2022). A new combination approach for optimal design of sedimentation tanks based on hydrodynamic simulation model and machine learning algorithms. *Physics and Chemistry of the Earth, Parts A/B/C, 127*, 103201.
6. Grigg, N. S. (2019). Global water infrastructure: State of the art review. *International Journal of Water Resources Development, 35*(2), 181–205.
7. Morton, S., Pencheon, D., & Squires, N. (2017). Sustainable Development Goals (SDGs), and their implementationA national global framework for health, development and equity needs a systems approach at every level. *British Medical Bulletin, 124*, 1–10.
8. Raju, K. S., & Kumar, D. N. (2018). *Impact of climate change on water resources*. Springer.
9. Dagbegnon, C., Djebou, S., & Singh, V. P. (2016). Impact of climate change on the hydrologic cycle and implications for society. *Environment and Social Psychology, 1*(1). https://doi.org/10.18063/ESP.2016.01.002
10. Kondratev KI, Kondrat'ev KI, Kondratyev KY et al. (2003) Global carbon cycle and climate change. Springer Science & Business Media.
11. IPCC. (2014). Climate change 2014: Impacts, adaptation, and vulnerability. Part A: Global and sectoral aspects. In *Contribution of working group II to the fifth assessment report of the intergovernmental panel on climate change*. Cambridge University Press.
12. Kourtis, I. M., & Tsihrintzis, V. A. (2021). Adaptation of urban drainage networks to climate change: A review. *Science of The Total Environment, 771*, 145431.
13. UNDESAPD (United Nations, Department of Economic and Social Affairs, Population Division). (2019). *World urbanization prospects: The 2018 revision (ST/ESA/SER.A/420)*. United Nations.
14. Behzadian, K., & Kapelan, Z. (2015). Advantages of integrated and sustainability based assessment for metabolism based strategic planning of urban water systems. *Science of the Total Environment, 527*, 220–231.
15. Vahedifard, F., Robinson, J. D., & AghaKouchak, A. (2016). Can protracted drought undermine the structural integrity of California's earthen levees? *Journal of Geotechnical and Geoenvironmental Engineering, 142*(6), 02516001.
16. Roshani, E., & Filion, Y. R. (2015). Water distribution system rehabilitation under climate change mitigation scenarios in Canada. *Journal of Water Resources Planning and Management, 141*(4), 04014066.

17. Francisco, T. H., Menezes, O. V., Guedes, A. L., Maquera, G., Neto, D. C., Longo, O. C., et al. (2022). The Main challenges for improving urban drainage systems from the perspective of Brazilian professionals. *Infrastructures, 8*(1), 5.
18. Willems, P., Arnbjerg-Nielsen, K., Olsson, J., & Nguyen, V. T. V. (2012). Climate change impact assessment on urban rainfall extremes and urban drainage: Methods and shortcomings. *Atmospheric Research, 103*, 106–118.
19. Sørup, H. J. D., Fryd, O., Liu, L., Arnbjerg-Nielsen, K., & Jensen, M. B. (2019). An SDG-based framework for assessing urban stormwater management systems. *Blue-Green Systems, 1*(1), 102–118.
20. Zhou, Q. (2014). A review of sustainable urban drainage systems considering the climate change and urbanization impacts. *Water, 6*(4), 976–992.
21. IPCC. (2007). Climate change 2007: The physical science basis. In S. Solomon, D. Qin, M. Manning, Z. Chen, M. Marquis, K. B. Averyt, M. Tignor, & H. L. Miller (Eds.), *Contribution of working group I to the fourth assessment report of the intergovernmental panel on climate change*. Cambridge University Press.
22. Denchak M (2019) *Greenhouse effect 101*. Natural Resources Defense Council (NRDC). Visited on May 29, 2022. Access link: https://www.nrdc.org/stories/greenhouse-effect-101#:~:text=Earth's%20greenhouse%20gases%20trap%20heat,gases%20(which%20are%20synthetic
23. Lankester, P. (2013). *The impact of climate change on historic interiors*. Doctoral dissertation, University of East Anglia.
24. Feng, Q., Yang, L., Deo, R. C., et al. (2019). Domino effect of climate change over two millennia in ancient China's Hexi corridor. *Nature Sustainability, 2*(10), 957–961.
25. Pausas, J. G., & Keeley, J. E. (2021). Wildfires and global change. *Frontiers in Ecology and the Environment, 19*(7), 387–395.
26. Román-Palacios, C., & Wiens, J. J. (2020). Recent responses to climate change reveal the drivers of species extinction and survival. *Proceedings of the National Academy of Sciences, 117*(8), 4211–4217.
27. Kelley, C. P., Mohtadi, S., Cane, M. A., et al. (2015). Climate change in the Fertile Crescent and implications of the recent Syrian drought. *Proceedings of the National Academy of Sciences, 112*(11), 3241–3246.
28. United Nations. (visited on 5 December 2022). *Take action for the sustainable development goals*. Access link: https://www.un.org/sustainabledevelopment/sustainable-development-goals/
29. Ferdowsi, A., Zolghadr-Asli, B., Mousavi, S. F., & Behzadian, K. (2022). Flood risk management through multi-criteria decision-making: A review. In *Multi-criteria decision analysis* (pp. 43–54). CRC Press.
30. Ferdowsi, A., Nemati, M., & Farzin, S. (2021). Development of dam-break model considering real case studies with asymmetric reservoirs. *Computational Engineering and Physical Modeling, 4*(4), 39–63.
31. Azad, A., Mousavi, S. F., Karami, H., et al. (2020). Properties of metakaolin-based green pervious concrete cured in cold and normal weather conditions. *European Journal of Environmental and Civil Engineering, 26*(6), 2074–2087.

# The Impact of Digital Learning Technology on Higher Education Students' Mental Health

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## Introduction to chapter

Digital Learning Technology has transformed the landscape of higher education from myriad perspectives, students and practitioners to the institutions and management in which they all claim a stake. From the early days of computers being used for administrative purposes to the current era of virtual classrooms and online learning, digital technology has revolutionised the way students access and engage with education. However, the impact of digital technology on Higher Education (HE) student mental health and well-being has received relatively less attention, compared to engagement levels amongst learners (Bond et al. 2020). The aims of this chapter are to examine the origins of digital technology in higher education, its present state, and the impact of the COVID-19 pandemic on the use of digital technology in higher education with a focus on its impact on student mental health and wellbeing. Ultimately, it aims to provide recommendations on how higher educational institutions could utilise digital technology to mitigate the negative impacts on students' mental health and wellbeing.

## Conceptualising Mental Health

The term "mental health" has been widely debated. According to Cattan and Tilford (2006) mental health has been utilised as a euphemism for 'mental illness'. Dogra and Leighton (2009) argued that the two terms are inextricably interrelated as one will inevitably affect the other. Generally, other researchers linked mental health with Maslow's self-realisation, culture, and common sense (Jahoda, 1958; Murphy, 1978; Vaillant, 2012). The World Health Organisation (WHO) (2004) highlighted that mental, physical and social functioning are symbiotic. However, Rowling et al. (2002) indicated that mental health is when people and groups are able to interconnect with one another and the environment in ways that encourage individual wellbeing, optimum development and use of cognitive, emotional, and interpersonal abilities. Whilst Manwell et al. (2015) described it as "the absence of mental disease or a state of being that also includes the biological, psychological or social factors which contribute to an individual's mental state and ability to function within the environment". The World Health Organisation (2022) defined mental health as a "state of mental well-being that enables people to cope with the

stresses of life, realise their abilities, learn well and work well, and contribute to their community". Other researchers however argued that the definition provided by WHO is debatable as mental well-being is challenging to conciliate with various difficult life settings in which well-being may even be unhealthy (Galderisi et al., 2015). To thoroughly explore the impact of digital technology on higher education students' mental health, this chapter adopts WHO (2022)'s definition of mental health. However, to further explore the concept this chapter acknowledges that mental health is a "dynamic state of internal equilibrium which enables individuals to use their abilities in harmony with universal values of society" as emphasised by Galderisi et al. (2015). Hence, it is important to note that mental health should not only be conceptualised by positive influences as this may exclude other age groups, other ethnic groups and people who are in different life situations.

**Digital Learning Technology**

The development of digital technology within higher education can be traced back to the 1960s, when universities began to experiment with computer-based education. One of the first examples of this was the PLATO system developed at the University of Illinois, which provided students with interactive computer-based lessons (Selwyn, 2016). The development of the internet and the World Wide Web in the 1990s led to the widespread adoption of digital technology in higher education, with universities using web-based platforms to deliver online courses and to facilitate communication between students and teachers (Bates, 2019).

With the rapid growth of digital technology in higher education over the past decade, the number of students enrolled in online courses has increased significantly. According to a report by the Babson Survey Research Group (Allen & Seaman, 2017), the number of students enrolled in at least one online course has increased by over 5 million since 2012. This number is significant and therefore is apparent that a multitude of factors can be considered as to how this has become the case:

- **Accessibility**: Online courses have made higher education more accessible to people who may not have been able to attend traditional, on-campus courses due to geographical location, work commitments, or family responsibilities. This has allowed more people to pursue higher education and improve their career prospects.

- **Flexibility:** Online courses offer greater flexibility in terms of scheduling and pacing, which allows students to balance their studies with other commitments. This can be

particularly important for non-traditional students, such as working adults or those with family responsibilities.

- **Cost:** Online courses are often less expensive than traditional, on-campus courses, which can make higher education more affordable for students. This is especially important as the cost of higher education has risen significantly in recent years.

- **Innovation:** The growth of digital technology in higher education has led to new and innovative ways of teaching and learning. Online courses often incorporate multimedia elements such as videos, interactive simulations, and online discussions, which can enhance the learning experience for students.

Overall, the significant increase in the number of students enrolled in online courses represents a major shift in the way that higher education is delivered and accessed, with significant implications for accessibility, flexibility, cost, and innovation. (Allen & Seaman, 2017; Hodges et al., 2020; Seaman et al., 2018).

**Influences of mental health in higher education students**

*Factors impacting mental health.*

The understanding and interest of mental health has improved with policies supporting mental health being developed and implemented by various countries and territories. However, WHO (2022) contended that progress has been slow, and counties are still reluctant to tackle issues of mental health. The same report indicated that mental health systems and services remain ill-equipped to meet people's mental health needs. Therefore, it is imperative to recognise the factors that impact on one's mental health as this provides an opportunity to have a better understanding of the concept. This will also prompt effective support to be provided to individuals. Numerous factors can impact mental health and these factors vary from individual to individual. These factors can also adapt during one's lifetime for example childhood, teenage years, young or older adults.

The factors impacting on mental health can be categorised as psychological factors such as poor self-esteem; biological factors such as genetics; social factors such as poverty and unemployment; and childhood events such as emotional neglect (WHO, 2022). Some of the triggers include abuse, discrimination, and grief which can all lead to feelings of isolation, worthlessness, and hopelessness. The environment, experiences, family, and upbringing affect

mental health. Social and financial circumstances, negative childhood experiences, and underlying medical conditions can all shape a person's mental health (Behzadifar et al., 2015; National Institute of Mental Health, 2020). This indicates that mental health is a complex subject with numerous contributing risk factors.

Risks of experiencing mental health conditions can be evident at any stage of one's life, however, risks at childhood development stage are more damaging. These include abuse and bullying. Factors such as neglect and conflict have a negative impact on future social behaviour, educational results, and employment status (Marmot et al., 2012). Therefore, children who are subjected to neglect, direct physical and psychological abuse are more likely affected. Furthermore, changes between childhood and adolescence can be stressful due to the changes in the social environment. This has an impact on adolescence's mental health. Adolescence can be dependent on their peers' opinions to make decisions and have a heightened need to belong. Social isolation and loneliness can intensify mental health problems that can lead to a lack of motivation and engagement in academic activities. This aversion to social exclusion might lead students to make harmful decisions to avoid social rejection (Blakemore, 2018). The increased sensitivity to the threat of social rejection might lead to some mental health problems such as depression. This will eventually impact a student's ability to maintain social relationships, which is essential for emotional support and academic achievement. The age at which many mental disorders are evident is between 18 and 24, which directly overlaps with the average age of students in higher education (Kessler et al., 2005).

The number of students in higher education being treated with psychological disorders such as depression and anxiety is increasing in severity (Kruisselbrink Flatt, 2013). Stress and anxiety are regarded as part of student life because of various personal, family, and circumstantial expectations that affect students. Depression and anxiety can also affect students' ability to concentrate, retain information, and complete assignments. Consequently, this can result in lower grades, and academic probation. As much as stress is unavoidable among all students due to their academic workloads, adolescents are more susceptible to academic stress because of personal and social changes (Reddy et al., 2018). This makes it imperative to provide emotional support to students struggling with mental health issues.

Although the subject of mental health of university students has been well documented, the number of students withdrawing from university due to mental health issues has more than tripled (Bolton and Hubble, 2020; Universities UK, 2018). Factors such as lack of social support,

financial troubles, and learning environment influenced mental health problems among higher education students (Mutalib et al., 2021). However, Pereira (2020) established that anxiety and depression were generally the most diagnosed conditions in university. Some studies concluded that financial concerns in students from a poor background have contributed to mental health problems (Benson-Egglenton, 2019; Jessop et al., 2005). Fear of academic failure, education system and long lectures are some of the factors that have contributed to the increase in student stress levels. Consequently, these can impact on students' academic performance (Britton and Tesser, 1991). Grasping the factors that influence students' mental health provides higher education institutions with the potential to identify strategies that promote the students' abilities to cope with the challenges of higher education.

The COVID-19 pandemic is another factor which had a significant impact on mental health across society, with higher education students being extremely affected. The number of students who dropped out of university considerably increased across the world, and this had a negative impact on their education, in particular, their academic achievement. Although, prior to COVID 19 pandemic, the levels of mental health issues in students were on the upward trend, the pandemic intensified the stress, constructing an ideal environment for a mental health crisis. Mental health of more than half of UK students became worse than before the pandemic (National Union of Students (NUS), 2020).

**Covid-19 and Higher Education**

The impact of Covid-19 on higher education has been discussed extensively by media and other outlets globally, with universities forced to move their courses online in response to the pandemic, and with many institutions having to quickly transition from in-person to online learning. This has highlighted the importance of digital technology in higher education and has accelerated the adoption of online learning platforms (Croucher & Mather, 2020). According to a report by the Babson Survey Group, the proportion of US higher education institutions that offer online programs has increased from 52% in 2018 to 56% in 2020 (Allen & Seaman, 2020). Whilst a survey by Inside Higher Ed found that 91% of college and university students in the US were taking at least one online course during the pandemic. (Inside Higher Ed, 2020). This transition has highlighted the importance of digital technology in higher education and has led to increased investment in digital infrastructure and training for faculty and staff.

One major facilitator in the move to online has been the increased use of video conferencing platforms like Zoom and Microsoft Teams for remote teaching and learning. A survey of higher education institutions by Educause found that the use of video conferencing platforms increased from 46% in 2019 to 96% in 2020 (Educause, 2021). These platforms have allowed for synchronous online learning experiences and have enabled instructors to maintain a sense of community and connection with their students (Hewitt & Brett, 2020). Naturally, this has led to increased use of Learning Management Systems (LMS) and other digital tools for online course delivery, such as virtual labs and simulations, which have helped to create more engaging and interactive online learning experiences (Lieberman et al., 2021).

However, the rapid transition to remote learning has also highlighted issues of equity and access. Not all students have equal access to digital technology, and some may struggle with the technological demands of remote learning. The pandemic has highlighted the need for institutions to address these issues and provide support for students who may be experiencing digital inequalities (Jaschik, 2020). It is also worth noting that they may not fully capture the scope of the impact, as the situation is still evolving, and data collection may not be comprehensive. The pandemic has also highlighted the importance of supporting students' mental health and wellbeing in the context of online learning (Poulter, 2020).

**How digital technology impacts on mental health of students in higher education**

Millions of people across the world had different viewpoints and experiences on how they were impacted by the COVID-19 pandemic. These experiences varied from positive aspects with reference to spending time with the families to serious negative manifestations of isolation, sickness, and boredom, resulting in mental health issues. As such digital technology has been considered to come for the rescue of the students to somehow continue their engagement, retention, progression, and achievement during the pandemic and post-pandemic times through online and blended modes. There have been mixed reactions to this mode of content access and sharing through a digital device and its impacts upon mental health. Boden et al. (2021) are of the opinion that severe distress was caused by the difficulties of adjusting to remote education in a very short span of time, followed by anxiety and depression by the overinflated use of digital media and difficulties with online learning/working during the pandemic (Aboujaoude & Gega, 2020). Further, as the pandemic had shifted much of life online, some negative effects on mental health including suicidality are likely to have been mediated by technology-specific factors even though it is further to be explored as to how heavy online

coverage of pandemic-related suicides may have spurred further suicidal behaviour amongst the students. Also, the digital divide seems to have contributed to negative mental health issues because many of the high-risk digitally disadvantaged groups were less likely to benefit from the technology via remote work, recreation, social connection, and access to health services (Khilnani, Schulz, & Robinson, 2020)

With reference to the positive impact of digital technology upon mental health during the pandemic has been about getting an opportunity to engage in enjoyable, purposeful, and rewarding activities, and increasing social connectedness. Further, digital media has offered a sustainable solution to the chronic problem of limited access to mental health care, by helping services overcome geographical barriers and make the most out of the available workforce through remote consultations and supported self-management. But the disruption brought by the pandemic meant that many students and universities would have not considered using technology otherwise had an opportunity to try it, often with encouraging results, even if the benefit was not evenly distributed across social and socioeconomic groups due to differences in digital access and skills. One of the encouraging facts is that the trend continues even after the pandemic is over in the form of blended teaching and learning which is becoming an integral part of various HEIs across the sector to enhance student's overall experience.

**A Supportive Tool for Learners**

The disruption to in-person learning and social interaction has led to feelings of isolation and disconnection for many students, which can have negative impacts on mental health and wellbeing such as contributing to feelings of isolation, distraction, and technological overload (Kshetri & Voas, 2020) . However, Digital technology has played a role in mitigating some of these negative effects by providing opportunities for online social interaction and mental health support services (Lebiedowska & Olszewska-Guizzo, 2020).

A systematic review by the Journal of Medical Internet Research found that digital mental health interventions can be effective in improving mental health outcomes in college students. However, the authors note that more research is needed to determine the most effective types of interventions and how to best implement them (Fleming et al., 2019). A survey of college students by the National Alliance on Mental Illness found that 72% of respondents reported experiencing mental health symptoms that impacted their academic performance, and 80% felt that COVID-19 had negatively impacted their mental health. The survey also found that

technology-based resources, such as online counselling and mental health apps, were among the most helpful resources for students(National Alliance on Mental Illness, 2020). Additionally, the Journal of Medical Internet Research found that the use of a mindfulness meditation app was associated with reduced symptoms of anxiety and depression in college students. The authors suggest that digital technology can be a useful tool for promoting mental health and well-being in this population (Perez-Edgar et al., 2020).

There is clear data showing the efficacy of digital technology used by learners in promoting mental health and wellbeing among students in higher education (Kshetri & Voas, 2020). Access to mental health resources and support, an increased flexibility in scheduling and studying, and opportunities for social connection online and collaboration are part of this. The potential to support student wellbeing by providing access to resources, increasing communication and social support, and improving engagement and motivation should therefore be at the heart of all endeavours in this field. One example of how this can be achieved is to provide access to online mental health services. These services can provide students with access to mental health support and resources regardless of their location, which can be particularly important for students who may not have easy access to traditional mental health services (Poulter, 2020). Another example is online mindfulness and relaxation resources, which have been found to be effective in reducing stress and promoting wellbeing among students while studying online (Elliott & Drummond, 2017).

However, there is a fine balance to strike, and it is worth considering the negative effects of over exposure, or prolonged use and dependency of being online only, such as in the case of excessive use of social media or other digital platforms than can lead to feelings of anxiety, depression, and social isolation (O'Brien & Gierdowski, 2018). While there is still much to be learned about the impact of digital technology on student mental health in higher education, these studies suggest that the use of it can be both helpful and harmful, and that careful consideration is needed to ensure that it is used in a way that promotes positive outcomes. The effectiveness of such technologies depends upon the specific use and how it is implemented in such a setting.

**Support provided by higher education institutions with regards mental health**

As discussed earlier in the chapter, there are many contributing factors affecting student’s mental health in higher education institutions which have multiple implications over their learning

retention, progression, and achievements. However, unfortunately this area has not been much explored and remains poorly understood especially given the evidence of a high and increasing prevalence of mental health problems among youth which could be further supported by World Health Organisation statistics (2020) that globally, about 20% of adolescents suffer from mental health problems. Furthermore, the students in the higher education institutions have been identified as a high-risk population due to the stress associated with their educational transitions and HE studies (Barden et al., 2019). The existing documented research clearly outlines the adverse impacts of mental health problems on students' capability and motivation to learn (Bowman et al., 2020).

It goes without saying that a comprehensive policy framework that enables successful intervention through early identification and remediation of mental health problems among young people can go a long way to help ease out the situation if not totally eliminate it. Even though there is always a scope for further improvement, the higher educational institutions in the UK have clearly identified mental health as a serious issue and taken steps to resolve it. Some of them include campaigns aimed at raising awareness among the students, parents, and educators, and increasing the availability of on-demand mental health screening services for students moving to the university environment. As part of the comprehensive policy framework that enables successful intervention, the universities allow the students to take time off until they feel "ready, mental health wise" to successfully complete their qualification with a positive learning experience. Further, the students experiencing mental health issues are offered enhanced HE support in terms of free mental health counselling or dedicated tutoring sessions and provided viable alternatives to access extended periods of mental health leave or giving mental health problems greater consideration as extenuating circumstances for academic participation and performance. Moreover, the focus of various equity and diversity programmes in the sectors is to ensure student access and success (Bennett et al, 2015). Some of the professional groups supporting mental health and wellbeing in the UK HEIs are:

• British Association of Counselling and Psychotherapy

• Equality Challenge Unit

• Heads of University Counselling Services

• Higher Education Academy

• Mental Wellbeing in Higher Education Working Group

• National Association of Disability Practitioners

• National Union of Students

• Student Health Association

• University Mental Health Advisers Network

Source: https://www.m25lib.ac.uk/wp-content/uploads/2021/02/student-mental-wellbeing-in-he

Some student's led initiatives at UK HEI's are.

**Nightline**- which offers peer support and information for students out of hours at many institutions across the UK.

**Students Against Depression**- a web-based resource with student-contributed case studies, blogs, and clinically validated self-help information

**Student Minds**- an organisation that carries out research and advocacy for students nationally and supports a network of student–led societies at universities across the UK.

**Mental Wealth UK-** a non-profit organisation founded by students to promote positive wellbeing on campuses and beyond. It serves as a hub for campus 'mental wealth' initiatives that work in partnership with staff and wider stakeholders. In 2014, Mental Wealth UK merged with Student Minds.

**The Alliance for Student-Led Wellbeing**- an umbrella group for student-led organisations that aims to raise awareness, reduce the stigma of mental ill health, and provide practical help and emotional support to university and college students

**Source:https://www.m25lib.ac.uk/wp-content/uploads/2021/02/student-mental-wellbeing-in-he**

Additionally, the University of Central Lancashire initiatives in the last two decades towards 'healthy settings' has stimulated similar developments and interest in other institutions across the sector in UK. They advocated promoting health and wellbeing through the pioneering research and implementation of various interrelated factors ( social, academic, economic and environmental) which can affect mental health and recommended strategies to improve the mental wellbeing of everyone in the universities' environment.

**Higher Education's Practical Role and Engagement**

Colleges and universities can use digital technologies to increase access to mental health resources for students, such as online counselling services, mental health apps, and virtual support groups. This can help students to receive the care they need while also reducing the stigma associated with seeking help in person (National Institute of Mental Health, 2021).

There are some practicable steps suggested:

- **Encourage healthy social media use:** Social media can have a negative impact on mental health, but it can also be used in positive ways to connect with others and provide social support. Colleges and universities can educate students on healthy social media use and provide resources for positive online interactions (Woods & Scott, 2016).
- **Promote digital mindfulness practices:** Digital mindfulness practices, such as using mindfulness meditation apps, have been found to be effective in reducing symptoms of anxiety and depression in college students. Colleges and universities can promote the use of these practices among students and provide resources for learning and practising mindfulness. (Perez-Edgar et al., 2020)
- **Use technology to increase flexibility:** Digital technologies can provide increased flexibility in scheduling and studying, which can reduce stress and support better mental health outcomes. Colleges and universities can use technologies such as online learning platforms and video conferencing to provide students with greater flexibility in their coursework (Schaffhauser, 2020).

The focal point of any HE establishment is increasing and improving student engagement with the learning content. Learning technologies that strike a chord within learners is where digital technology can improve student engagement by providing interactive and personalised learning experiences that promote active learning and collaboration. Some examples of digital technology that have been found to improve student engagement include:

- **Learning Management Systems (LMS):** LMS platforms like Blackboard, Canvas, and Moodle provide students with access to course materials, discussions, and assignments in one centralised location. LMS platforms also offer tools for online quizzes, tests, and surveys that can provide instant feedback to students and instructors.
- **Gamification:** Gamification involves incorporating game-like elements into learning activities to motivate and engage students. Gamification techniques can include points systems, leaderboards, and badges, and have been found to improve student engagement and motivation (Hamari et al., 2014).
- **Video-based learning:** Video-based learning platforms like YouTube and TED Talks provide students with access to a wide range of educational content. These platforms can be used to supplement traditional lectures and offer a more engaging and interactive learning experience.
- **Increasing interaction:** Digital tools can facilitate communication between students, teachers, and peers, increasing interaction and collaboration. This can include discussion forums, videoconferencing, and collaborative projects.
- **Promoting active learning:** Digital tools can create active learning environments that engage students with interactive content such as simulations, quizzes, and games.
- **Providing personalised learning experiences:** Digital technology can tailor learning to individual students' needs and interests, increasing motivation and engagement. This can include adaptive learning systems and personalised feedback.

(Bower, M., 2017; Dunlosky et al., 2013; Hsu et., 2015)

## Conclusion

The topic of mental health has been widely debated with various academics and researchers exploring its impact on higher education students. Nonetheless, the number of students struggling with mental health problems continues to increase. The COVID-19 pandemic further exacerbated the mental health crisis because higher education institutions had to quickly transition from in-person to online learning. More focus was placed on delivering learning than on the issue of mental health. Thus, the number of students withdrawing from university due to mental health issues has more than tripled and more than half of UK students became worse than before the pandemic. The disruption to in-person learning and social interaction led to feelings of disconnection for many students. However, digital technology has played a role in mitigating some of these negative effects by providing opportunities for online social interaction and mental health support services. This chapter therefore provided some suggestions on how higher education institutions can utilise digital technology to improve student engagement through interactive and personalised learning experiences that promote active learning and collaboration. It also concludes that it is fundamental for educators to choose the appropriate technology and use it effectively to enhance the learning experience.

**References:**


Aboujaoude E, Gega L.(2020) From digital mental health interventions to digital “Addiction”: where the two fields converge. Front Psychiatry. doi: 10.3389/fpsyt.2019.01017

Allen, I. E., & Seaman, J. (2017). Digital Learning Compass: Distance Education Enrollment Report 2017. Babson Survey Research Group.

Allen, I. E., & Seaman, J. (2020). Online report card: Tracking online education in the United States. Babson Survey Group.

Bates, T. (2019). Teaching in a Digital Age: Guidelines for designing teaching and learning for a digital age. Tony Bates Associates Ltd.

Behzadifar, M., Behzadifar, M., Sayehmiri, A., Behzadifar M., Sarokhani, M. & Sayehmiri, K. (2015) Economic factors influencing mental health using multiple regression model in Ilam province of Iran*. Medical Journal of The Islamic Republic of Iran (MJIRI),* 15 (29), 292.

Benson-Egglenton J. (2019) The financial circumstances associated with high and low wellbeing in undergraduate students: a case study of an English Russell Group institution, *Journal of Further Higher Education,* 43(7):901-13.

Blakemore, S-J. (2018). Avoiding social risk in adolescence. *Current Directions in Psychological Science.* 27(2), 116-122.

Boden M, Zimmerman L, Azevedo KJ, Ruzek JI, gala S, Abdel magid HS, et al.(2021) Addressing the mental health impact of COVID-19 through population health. Clin Psychol Rev. doi: 10.1016/j.cpr.2021.102006

Barden, N., & Caleb, R. (Eds.). (2019). Student mental health and wellbeing in higher education: A practical guide. Sage.

Bennett, A., Naylor, R., Mellor, K., Brett, M., Gore, J., Harvey, A., Munn, B., James, R., Smith, M., & Whitty, G. (2015). The critical interventions framework part 2: Equity initiatives in Australian higher education: A review of evidence of impact.

Bond, M., Buntins, K., Bedenlier, S. et al. (2020) Mapping research in student engagement and educational technology in higher education: a systematic evidence map. Int J Educ Technol High Educ 17, 2 .

Bower, M. (2017). Technology-mediated learning theory. In M. J. Spector, B. B. Lockee, & M. D. Childress (Eds.), Learning, Design, and Technology: An International Compendium of Theory, Research, Practice, and Policy (pp. 1-27). Springer International Publishing.

Bowman, S., McKinstry, C., Howie, L., & McGorry, P. (2020). Expanding the search for emerging mental ill health to safeguard student potential and vocational success in high school: A narrative review. Early Intervention in Psychiatry, 14(6), 655–676**.**

Britton, B. K., & Tesser, A. (1991).Effects of time-management practices on college grades. *Journal of Educational Psychology*, 83(3),405

Cattan, M. and Tilford, S. (2006) *Mental health promotion: a lifespan approach.* New York, NY: McGraw-Hill International.

Croucher, S. M., & Mather, R. (2020). Coronavirus (COVID-19): implications for telepsychology and mental health. *Journal of Telemedicine and Telecare,* 26(5), 263-266.

Dalgarno, B., & Lee, M. J. (2010). What are the learning affordances of 3-D virtual environments? *British Journal of Educational Technology,* 41(1), 10-32.

Dogra, N. & Leighton, S. (Eds) (2009) *Nursing in Child and Adolescent Mental Health.* Open University Press.

Dunlosky, J., Rawson, K. A., Marsh, E. J., Nathan, M. J., & Willingham, D. T. (2013). Improving students' learning with effective learning techniques: Promising directions from cognitive and educational psychology. Psychological Science in the Public Interest, 14(1), 4-58. doi:10.1177/1529100612453266

Educause. (2021). The 2021 Educause Horizon report: Teaching and learning edition.

Elliott, R., & Drummond, C. (2017). The impact of mindfulness on the wellbeing and performance of educators: A systematic review of the empirical literature. Teaching and Teacher Education, 61, 132-141.

Federal Reserve Bank of New York. (2019). Is College Still Worth It? Grads, Debt, and Unemployment.

Fleming, T. M., et al. (2019). EHealth interventions for anxiety and depression in children and adolescents with long-term physical conditions. *Journal of Medical Internet Research,* 21(5), e10847.

Galderisi, S., Heinz, A., Kastrup, M., Beezhold, J. and Sartorius, N. (2015) Toward a new definition of mental health. *World Psychiatry,*14(2):231-3

Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? A literature review of empirical studies on gamification. Proceedings of the 47th Hawaii International Conference on System Sciences.

Hewitt, J., & Brett, C. (2020). Video conferencing in the age of COVID-19. Journal of Chemical Education, 97(9), 3351-3355.

Hodges, C. B., Moore, S., Lockee, B. B., Trust, T., & Bond, A. (2020). The Difference Between Emergency Remote Teaching and Online Learning. EDUCAUSE Review.

Holon IQ. (2021). The global learning landscape 2021.

Hsu, T.-C., & Ching, Y.-H. (2015). Mobile microblogging: Using Twitter and mobile devices in an online course to promote learning in authentic contexts. The International Review of Research in Open and Distributed Learning, 16(2), 232-249. doi:10.19173/irrodl.v16i2.2102

Inside Higher Ed. (2020). Inside higher ed's fall 2020 student survey.

Jaschik, S. (2020). Remote learning and the digital divide. Inside Higher Ed.

Jessop, D.C., Herberts, C., & Solomon, L. (2005) The impact of financial circumstances on student health. *British Journal of Health Psychology,*10(3):421–39.

Khilnani A, Schulz J, Robinson L (2020)The COVID-19 pandemic: new concerns and connections between e-Health and digital inequalities J Inform Commun Ethics Soc. 393–403. doi: 10.1108/JICES-04-2020-0052

Kruisselbrink-Flatt, A. (2013) A Suffering Generation: Six factors contributing to the mental health crisis in North American higher education, *College Quarterly,* 16(1).

Kshetri, N., & Voas, J. (2020). Impacts of emerging digital technologies on mental health and wellbeing in the workforce and in the general population. Telemedicine and e-Health, 26(9), 1032-1039.

Lebiedowska, M. K., & Olszewska-Guizzo, A. (2020). Online support for student mental health during the COVID-19 pandemic. *Journal of Medical Internet Research*, 22(9), e22815.

Lieberman, M. A., Alper, J., & Hoffman, K. (2021). Technology use in higher education during COVID-19: A systematic review of academic articles. *International Journal of Technology in Education and Science*, 5(1), 81-92.

Marmot, M. Allen, J. Bell, R. Bloomer, E. and Goldblatt, P. (2012) WHO European review of social determinants of health and the health divide. *The Lancet,* 380 (9846):1011-29.

Murphy, H.B.M. (1978) The meaning of symptom check-list scores in mental health surveys: a testing of multiple hypotheses. *Social Science and Medicine.* 12, 67–75.

Mutalib, S., Nor, S. M.S., & Shuzlina, A.R. (2021) Mental Health Prediction Models Using Machine Learning in Higher Education Institution,*Turkish Journal of Computer and Mathematics Education*,12 (5) pp.1782-1792

National Alliance on Mental Illness. (2020). College students speak: A survey report on mental health.

National Center for Education Statistics. (2021). Enrollment in Distance Education Courses, by State: Fall 2018. U.S. Department of Education.

National Institute of Mental Health, (2020) *Looking at My Genes: What Can They Tell Me About My Mental Health?*, [online], available at: https://www.nimh.nih.gov/health/publications/looking-at-my-genes, Accessed 20 March 2023

National Institute of Mental Health. (2021). Technology and the future of mental health treatment.

O'Brien, N., & Gierdowski, D.C. (2018). Digital wellness: Theoretical and practical considerations. The Routledge Handbook of Philosophy of Information, 455-465.

Perez-Edgar, T., et al. (2020). Mindfulness meditation for college students: The impact of a smartphone app on well-being and depression symptoms. *Journal of Medical Internet Research,* 22(8), e20779.

Poulter, D.R. (2020). COVID-19 and the rise of digital mental health services. *Journal of Medical Systems,* 44(7), 1-8.

Reddy, K.J., Menon, K.R., & Thattil, A. (2018).Academic stress and its sources among University students. *Biomedical and Pharmacology Journal,* 11(1), 531–537.

Rowling, L., Martin, G. & Walker, L. (eds) (2002) *Mental Health Promotion and Young People:* Concepts and Practice. Roseville, NSW: McGraw-Hill Australia.

Schaffhauser, D. (2020). *5 ways colleges can leverage technology for student mental health*. Campus Technology.

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). Grade increase: Tracking distance education in the United States. Babson Survey Research Group.

Selwyn, N. (2016). Education and technology: key issues and debates. Bloomsbury Publishing.

Vaillant GE. (2012), Positive mental health: is there a cross-cultural definition? *World Psychiatry,*11:93–9.

World Health Organization. (2022) *Mental Health,* [online], available at: Mental health (who.int) accessed 28 March 2023

World Health Organization. (2020). *Adolescent mental health* [online]. World Health Organization. Available at: https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health accessed 12 April 2023.

World Health Organization. (2004) *Promoting Mental Health: Concepts, Emerging Evidence,* Practice: Summary Report. Geneva: WHO.

Woods, H. C., & Scott, H. (2016). #Sleepyteens: Social media use in adolescence is associated with poor sleep quality, anxiety, depression and low self-esteem. *Journal of Adolescent Health,* 59(1), 93-99.

# The Impact of Covid-19 on Household Welfare in Comoros

**Vibhuti Mendiratta, Olive Umuhire Nsababera and Hannah Sam**[1]

**Abstract:** In this paper, we investigate the causal impact of a stringent Covid-19 lockdown policy on Comoros's household welfare, poverty, and labor market outcomes. Our identification strategy uses the national government lockdown policy implemented to curtail the unexpected outbreak of Covid-19. The lockdown policy coincided with the 2020 Harmonised Survey on Living Conditions of Households (EHCVM) data collection. It lends itself to a quasi-natural experiment in which households interviewed before the lockdown policy fall into the control while those interviewed after the lockdown fall into the treated group. We explore the impact of the Covid-19 using descriptive regression analysis and matching techniques and find a reduction in household expenditure, increased poverty, and a reduction in the likelihood of employment. The reduced welfare outcomes linger three months after the lockdown policy, and households resorted to selling expensive assets as a coping mechanism. In the absence of safety nets and government interventions, stringent lockdown policies increase the vulnerability to poverty for a developing country.

**Key Words:** Covid-19, lockdown, welfare, poverty, employment, Comoros

**JEL Classifications:** I18, I30, I39, J21, O55

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## Introduction

The Covid-19 pandemic took the world by surprise and has claimed over 4.5 million lives (as of September 2021). Since the Covid-19 pandemic was first identified in December 2019, more than 100 countries worldwide have resorted to either full or partial economic and social lockdowns. These interventions are detrimental to socio-economic activities at the macro level and at the micro-level (Dunford et al., 2020). The political economy evaluation of the best-possible curtailment measures or responses at country and global level has attracted controversial and ongoing debates (Van, 2021). The controversy around curtailment measures revolves around the trade-off between saving lives and prioritising the economy. An emerging consensus is that the level of preparedness to deal with the health emergency that came from Covid-19 was below standard (Sathyamala, 2021).

The pandemic is expected to have had profound socio-economic impacts. The lack of a cure for the virus, the different variant or mutation episodes and the nature of its contagion necessitated the use of non-medical interventions. Policymakers resorted to national lockdowns and international travel restrictions, resulting in the worst economic downturns experienced in decades (Dunford et al., 2020). The colossal uncertainty directly from the Covid-19 virus coupled with the distortion in market and socio-economic activities has had ripple effects on the labor market. The macro-level effects will have implications at the household and individual levels. The cost of suppressing the spread of the pandemic and the intricacies of the economic shutdown adds to the challenges of policy responses in unprecedented times.

Although African countries had relatively lower infection rates at the outset, the socio-economic impacts on the continent are expected to be high. They resorted to similar curtailment measures (national lockdown, social distancing, and international travel restrictions) observed

in developed economies. In addition, many African countries are already vulnerable to inadequate health systems. Within Africa, Comoros provides a particularly insightful case study in evaluating national lockdown measures on socio-economic outcomes for several reasons. Firstly, by April 18, 2020, a month after the World Health Organization declared the Covid-19 a global pandemic, Comoros and Lesotho were the two countries in Africa that were still virus-free (Lone and Ahmad, 2020). Comoros' proactive measures led to the restriction of social activities following the President's address on March 16, 2020. Furthermore, the national government enacted a complete national lockdown on March 23, 2020, over a month before the first confirmed case of Covid-19 on May 1, 2020. Thus, Comoros is a typical example of a developing country in Africa which resorted to strict lockdown measures with low confirmed cases of Covid-19.

Secondly, households and individuals in developing countries are susceptible to shocks that have an adverse impact on their livelihood. Changes in commodity prices, climate-related shocks (drought and floods) as well as idiosyncratic shocks (illness and death) have a negative impact on their economic status, especially for the poor (Dercon 2002, 2004). Comoros is one of the poorest countries in Africa (World Population Review, 2021)[2]. Its geographical location increases its vulnerability to climate change shocks. In addition, the nation was still recovering from the Cyclone Kenneth experienced in April 2019, when the Covid-19 pandemic hit and consequently led to lockdown measures (World Bank, 2020). The tourism sector is one of the country's major contributors to economic activities and income generation, thus exposing the country to a decline in economic growth as a result of lockdown measures. Therefore, the analysis can guide future responses to similar economic shocks and crises that necessitate lockdown measures, especially for African countries.

[2] The evaluation was based on Gross Domestic Product as an economic measure and indicated Comoros to be among Africa's ten poorest countries.

Finally, it has been previously found that research on the African continent tends to be skewed to a few countries. The evidence base for local policymakers in neglected countries or "research deserts" is relatively small. Porteous (2020) documents statistics on economic research in Africa and shows that 87% of all published economics journal articles account for one-third of African countries and are highly skewed towards five countries[3]. The distribution is uneven and accounted for only 16% of the continent's population. It is evident that Comoros falls within the forgotten 21 countries that have an average number of publications of 0.2 per country (Porteous, 2020). Heterogenous characteristics (socio-economic and political) and policy adaptions can limit external validation across countries, especially in Africa. Even before the pandemic, as highlighted above, Comoros had one of the highest poverty rates in the world. It is also vulnerable to natural disasters and climatic shocks. It is thus important to understand how the pandemic has affected a small island state like Comoros, which is already facing several development challenges but with a narrow evidence base. Our unique data consisting of pre- and post-pandemic observations provides an opportunity to make a meaningful contribution. To our knowledge, our research will be the first to evaluate the welfare consequences of the Covid-19 lockdown in Comoros in a robust manner.

Our research therefore aims to quantify the implication of direct lockdown measures on household welfare in developing countries and specifically in understudied developing countries. Comoros was one of few developing countries that implemented the Covid-19 national lockdown almost two (2) months before recording its first confirmed Covid-19 case.[4] First, this paper presents descriptive statistics, followed by ordinary least square and probit

[3] These five frequently researched countries are South Africa, Kenya, Ghana, Uganda and Malawi.
[4] The government announced a national lockdown on March 23, 2020 whiles the first confirmed case was recorded months later on May 1, 2020.

regression analysis to control for key correlates of household welfare. It then aims at obtaining causal estimates using the propensity score matching technique by exploiting the timing of the 2020 Harmonized Survey on Living Conditions of Households (EHCVM). The unexpected outbreak of Covid-19 coincided with data collection for the survey, lending itself to a quasi-natural experiment in which households interviewed prior to the lockdown could be considered as the control group and those interviewed after the lockdown as the treated group. Finally, we used detailed information on household and individual welfare indicators pre and post the Covid-19 lockdown to ascertain the changes in expenditure, poverty and the distributional impact on household expenditure. We also examine the channels through which Covid-19 impacts household welfare such as asset ownership and labor market outcomes. Furthermore, we extend our analysis to assess the evolution of our indicators as the period after the lockdown elapses. This analysis informs on the immediate impact and the dynamism in the recovering trend of household welfare indicators post Covid-19 lockdown.

The paper finds a negative impact of Covid-19 induced national lockdown on household expenditure, thereby leading to an increase in poverty. The negative effect is prominent within the first three months after the lockdown, with a somewhat sluggish recovery. The result appears to be driven by a loss of employment as evidenced by a decline in the share of working household members. Nevertheless, there was no significant impact on monthly salary for those that remain employed. Exploring the effect of the Covid-19 lockdown on coping mechanisms, we find that households had reduced asset value. Our evaluation reveals the sale of assets as a welfare mitigating strategy for Comorian households during the lockdown.

The remainder of this paper is structured as follows: the following sections outline the relevant literature, context and data description detailing the household welfare impact of the pandemic.

The subsequent sections discuss the empirical methodology and results while the final section highlights the policy implications and conclusion.

**Literature Review**

The emerging empirical literature on the economic impact of the Covid-19 pandemic curtailment measures (national lockdown) has relied heavily on aggregated macro-level models and data. Atkeson (2020) evaluates the use of the SIR model to determine the lockdown measures associated with a less severe economic downturn and low contagion of the virus. The author's application of the model to the US predicts social distancing of 12-18 months (in the absence of vaccine) as the best measure, compared to a strict national lockdown. Summer, Hoy and Ortiz- Juarez (2020) evaluate the potential short-term impact of the Covid-19 on global poverty incidence. They report a substantial increase in global poverty that might mitigate the sustainable development goal of ending poverty by 2030. The relevant research to understand the impact of the Covid-19 on income, consumption patterns, and the labor market has been at the macro level and focused on the United States and the United Kingdom. The emphasis has been on the effectiveness of mitigation policies on household and labor market structure (see Piyapromdee and Spittal, 2020; Brewer and Gardiner, 2021). The heterogeneous impact of the Covid-19 on employment patterns and welfare outcomes depicts severe consequences for workers in low-income jobs, social and flexible work in Japan (Kikuchi, Kitao and Mikoshiba 2020). In the developing country context, Schotte et al. (2021) estimated a reduction in employment with an adverse impact on informal sector for Ghana as a result of stringent lockdown measures.

The intensity of the spread of the Covid-19 infection has been more severe for developed countries than developing countries. However, the same curtailment measures as national

lockdowns, social distancing and curfew implemented in developed countries have also been implemented in developing countries. Furthermore, the macro level evidence has predicted age-specific and school closure policies in developing countries as the best in curtailing the contagion of the virus from young to old and providing a modest economic downturn (see Alon et al., 2020).

Our first contribution to the literature is to provide an empirical analysis of the impact of Covid-19 beyond aggregated economic indicators. It presents a robust causal empirical analysis of the Covid-19 lockdown measures on household welfare in a developing country based on micro data on household expenditure and labor market outcomes. It further informs on the economic cost of lockdowns for households, which can be used as a yardstick in measuring the impact of macro-level policies against micro-level welfare consequences.

An evaluation of past pandemics like HIV predicts negative economic growth and labor market outcomes (see Dixon, 2002 and Arndt and Lewis, 2001). The emerging literature has begun to investigate the Covid-19 pandemic on the economic livelihoods of households in developing countries. The research has heavily evaluated the economic lives of the poor using phone surveys on retrospective household welfare indicators (see Ceballos et al., 2020, Egger et al., 2021 and Schotte et al., 2021, among others). In extension, the empirical estimation has focused on the poor, agricultural or rural areas to understand the impact of the Covid-19 lockdown on the economic livelihoods and global food system (see Gupta et al., 2021; Janssen et al., 2021; Rönkkö, Rutherford and Sen 2021; Swinnen and Vos 2021). Gupta et al. (2021) evaluate the impact of the Covid-19 pandemic on economic outcomes of the poor and vulnerable households living in rural areas in India. They used a micro-level survey on weekly financial data for households in the high remittance regions and found a negative impact on household

income. The adverse effect was exacerbated by the increasing interest rate on cash loans and reduction in remittances.

In addendum, households and individuals in developing countries are faced with a variety of shocks that can affect household livelihoods. Changes in commodity prices, climate-related shocks (drought and floods) as well as idiosyncratic shocks (illness and death) have an adverse impact on their economic status, especially for the poor (Dercon 2002, 2004). However, rarely have economic activities been distorted through strict lockdown policies such as those used in the curtailment of the Covid-19 outbreak. National lockdowns restrain households and individuals from engaging in their daily socio-economic activities and distort or cause a complete cessation of both market and non-market activities. National lockdown measures that prevent physical contact with others outside a household will distort the usual coping mechanisms observed in developing countries in mitigating welfare consequences or render them useless or impractical. Household welfare coping mechanisms like borrowing from family members and other informal risk-sharing strategies (local money lenders) and microfinance is limited or not accessible during a national lockdown (Townsend, 1994). Rönkkö et al. (2021) analysis of the impact of the Covid-19 on the poor in Bangladesh using daily dairies on socio-economic activities showed variable but significant adverse effects on the poor. The evidence highlighted the use of cash reserves and reduction in non-food expenditure as coping mechanisms during the pandemic.

The second contribution of this paper is to go beyond assessing the pandemic on the economic lives of the poor and captures a broader impact on household welfare status and labor market outcomes of households vulnerable to falling into poverty and those holding precarious employment. Moreover, accounting for the impact of the pandemic on household welfare,

which is not solely limited to the already poor, will provide policymakers evidence on the types of pro-poor policies that will not only elevate households from poverty but prevent susceptibility to poverty or reduced welfare. It is thus necessary to evaluate how the pandemic impacts household livelihoods in developing countries and the coping mechanisms employed, regardless of their economic status.

Finally, to the best of our knowledge, this paper is the first in empirically analyzing the Covid-19 lockdown measures on micro-level individual and household welfare, poverty status and labor market outcomes for Comoros. It will inform on the thin micro literature on pandemic shocks on household welfare in a developing country context. The analysis will provide an understanding of the pandemic on Comoros, which falls in the "forgotten countries" category in terms of economic research (Porteous, 2020). This paper will go beyond a descriptive assessment of Covid-19 on the socio-economic status of households. The research aims to causally estimate the lockdown impact using a detailed door-to-door household survey conducted in two phases before and after the lockdown implementation in Comoros. An understanding of the mechanisms through which the lockdown can affect the welfare coping strategies of households is important. As such, this paper examines the impact of the pandemic on the expenditure, poverty status, asset and livestock ownership and labor market outcomes of individuals and households in Comoros.

**Contextualization and Data Description**

The Covid-19 virus was reported in Comoros in May 2020 as the world battled with the outbreak, which was declared a pandemic by the World Health Organization on 11 March 2020. Comoros was still recovering from the devastating cyclone Kenneth that had hit the country in April 2019 when the first Covid-19 case was recorded in May 2020. Comoros is a

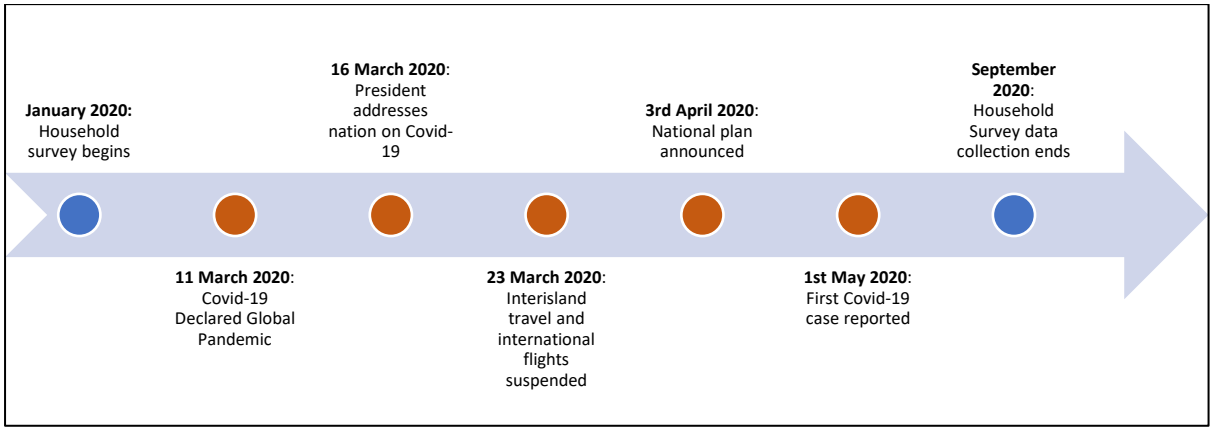
densely populated country with approximately 465 inhabitants per $Km^2$ (World Bank, 2020) and is susceptible to higher contagion given the nature of the virus. The measures enacted by the government encompassed sensitization from the president on 16 March, closure of schools and universities on 20 March, and restrictions to international and interisland movements on March 23, 2020. These measures were implemented before the first confirmed case on May 1, 2020 and aimed to reduce the potential spread of the virus.[5] The proactiveness of the government saw a national "state of preparedness" curtailment plan drawn and announced to the public on April 3, 2020. As of August 26, 2021, there were 4,055 confirmed cases with 147 related Covid-19 deaths in Comoros. Majority of the reported deaths took place between December 2020 and March 2021. The low confirmed cases suggest the national lockdown measures may have slowed the rate of contagion.

Nevertheless, the geography and location of Comoros encourage tourism and interisland trade, which are major aspects of the country's economy. Hence the national lockdown had a high potential to increase vulnerability and worsen the economic status of households. According to the World Bank data, in 2017, Comoros's estimated annual GDP growth rate was 3.82 per cent, and the growth trajectory has been declining and stood at 1.97 per cent in 2019. As such, the country's per capita rate of growth was low and average 1 percent between 2016-19, with consequences for household welfare. The pandemic led to a contraction of GDP growth of 0.1 percent in 2020. Early imposed lockdowns and social-distancing measures slowed the spread of the virus but weakened economic activity due to mobility restrictions and the suspension of international travel, resulting in a drop of tourism receipts. Demand and supply effects related

[5] Before the first confirmed cases, the president addressed the nation on March 16, 2020 on the threat of the Covid-19 pandemic and the implications for social activities and the health sector. A week later, the government of Comoros implemented prevention measures through suspension of international flights and interisland travel.

to external trade hit Comoros' main earning sectors, particularly trade-related services such as restaurants, hotels, and transport.

**Figure 1: Timeline of the EHCVM Survey and Covid-19 response**




The empirical analysis of the Covid-19 outbreak's impact on household welfare was undertaken using the 2020 Harmonized Survey on Living Conditions of Households (EHCVM) for Comoros. The survey was conducted by the National Institute of Statistics and Economic and Demographic Studies and The World Bank and was collected between January and September 2020.[6] Figure 1 above provides the timeline of the survey and the relevant Covid-19 intervention policies in Comoros. Due to its timing, the survey provides informative data pre-and post-Covid-19 lockdown on household socio-economic status and characteristics. The survey was conducted across the four islands that make up the Union of Comoros and was therefore representative of the four (4) regional locations (Moroni, rest of Ngazidja, Ndzuwani and Mwali). We use the lockdown announcement date as a natural treatment or cut-off date for identifying households surveyed pre- and post-Covid-19 lockdown measure. The sample distribution of interviews covered before and after the Covid-19 lockdown in Comoros is provided in Table A1 in the appendix. A total of 11,712 individuals belonging to 2,150 households were interviewed before the national lockdown. The samples for the main regions in Comoros, Ngazidja and Ndzuwani, accounted for 39% and 42%, respectively. The post-

[6] The survey included a few households interviewed in November 2018 and January 2019 and were excluded from this analysis.

covid-19 interview sample was 17,480 individuals belonging to 3,414 households but presented a similar regional distribution as the pre-Covid-19 sample.

Our identification strategy to assess the impact of national lockdown measure on household welfare explores the proactive measure of the Comoros government lockdown policy that came into effect on 23 March 2020 (see Figure 1 above). Our evaluation uses a treatment variable, a dummy that takes the value 1 if a household was surveyed after 23 March 2020 and 0 otherwise. In validating our treatment effect, it is worth noting that the Covid-19 effect could come from the direct contagion of the virus or through the curtailment measures implemented by the national government. First, on the effect of contagion, we do not know whether individuals suffered from Covid-19 cases directly from the survey, and thus this cannot be estimated in our analysis. Nevertheless, Comoros was one of the last countries with lowest records of infection from the virus.[7] According to the World Health Organization's recorded Covid-19 cases, Comoros accounted for 4,038 out of the 207 million worldwide cases of Covid-19 by 15th August 2021. The number of confirmed cases in Comoros was only 0.46% of the country's population. Second, curtailment measures are expected to have restricted and distorted socio-economic activities and markets. Hence, our treatment indicator using the dummy variable of national lockdown is a good approximation of the Covid-19 impact on household welfare. It is acknowledged that the knowledge of Covid-19 was already in circulation after the President of Comoros addressed the nation on 16 March 2020. Therefore, we may have reason to believe there may be anticipatory effects as people changed their behavior in response to the news. As such, we test the sensitivity of our analysis using the date the president addressed the nation as an alternative treatment cut off.

[7] Comoros and Lesotho were the two countries in Africa that were still virus-free (Lone and Ahmad, 2020) by April 2020 a month after the WHO announced the virus a pandemic.

The household survey data used for analysis (EHCVM 2020) contains information on household aggregated consumption expenditures in nominal terms and the monetary value of household assets. It provides extensive household and individual welfare indicators used in estimating objective and subjective poverty measurements and labor market outcomes. The aim of this paper is to empirically estimate the impact of the Covid-19 pandemic on household expenditure, asset value and ownership, poverty status, and labor market outcomes in Comoros. To achieve the above, the paper analyzes the impact of the virus curtailment measures at both the household and individual levels. The household-level analysis explores total per capita household expenditure, asset accumulation, and poverty. We construct the log of household per capita consumption expenditures from the estimated consumption expenditure for a given household. We extend our analysis by constructing monetary and non-monetary outcome measures for household asset accumulation. The monetary measure captures the log value of total assets owned by the household. The non-monetary household welfare metric includes the total count of assets owned by a household, the different types of assets, and the total count of livestock ownership. Our last household measure considers poverty status using both objective and subjective measures. The objective poverty status is a binary variable that takes the value 1 if a household is below the national poverty line and 0 otherwise.[8] The subjective poverty measures are three separate binary variables taking the value 1 if a household self-reports as "living averagely well", "living in difficulty", or "living rich" according to their socio-economic standards, respectively, and 0 otherwise. The binary subjective measures come from a categorical subjective measure of poverty. The motivation for creating binary subjective poverty measures is to ensure comparable estimation techniques and interpretations to the objective poverty measure.

[8] The estimated poverty line used in this analysis is the 2020 national poverty line of 497,957 Comorian francs per person per annum.

Panel A of Table 1 presents summary statistics for our selected household outcome variables. The pre-and post-Covid-19 conditions are different across the welfare outcomes, which could be the impact of Covid-19 itself or the difference in samples interviewed before and after the Covid-19 restriction. The log of per capita household expenditure shows a decline after the Covid-19 restrictions came into effect. Similarly, the different number of assets and number of livestock ownership show a decline after the lockdown. Not surprisingly then, household objective and subjective poverty measures are higher in the post Covid lockdown period.

In addition, we explore continuous and binary measures of labor market outcomes at the household and individual levels. The continuous outcomes include the share of working individuals in the household, the number of daily working hours, and the log of total monthly salary. The binary labor market outcomes include individuals in any employment and formal sector employment. Panel B of Table 1 represents the summary statistics regarding household and individual labor outcomes. The Covid-19 lockdown measure shows a negative correlation with labor market outcomes. The increase in the proportion of workers in formal employment and employment in the agricultural sector is noteworthy. By contrast, the proportion in the trade and service sector show a reduction. Table A2 in the appendix provides a detailed breakdown of employment across sectors. The employment sectoral distribution shows a high proportion of the employed in agriculture and the service sector. The service sector includes tourist related activities (hotel, restaurants, recreational and cultural activities).

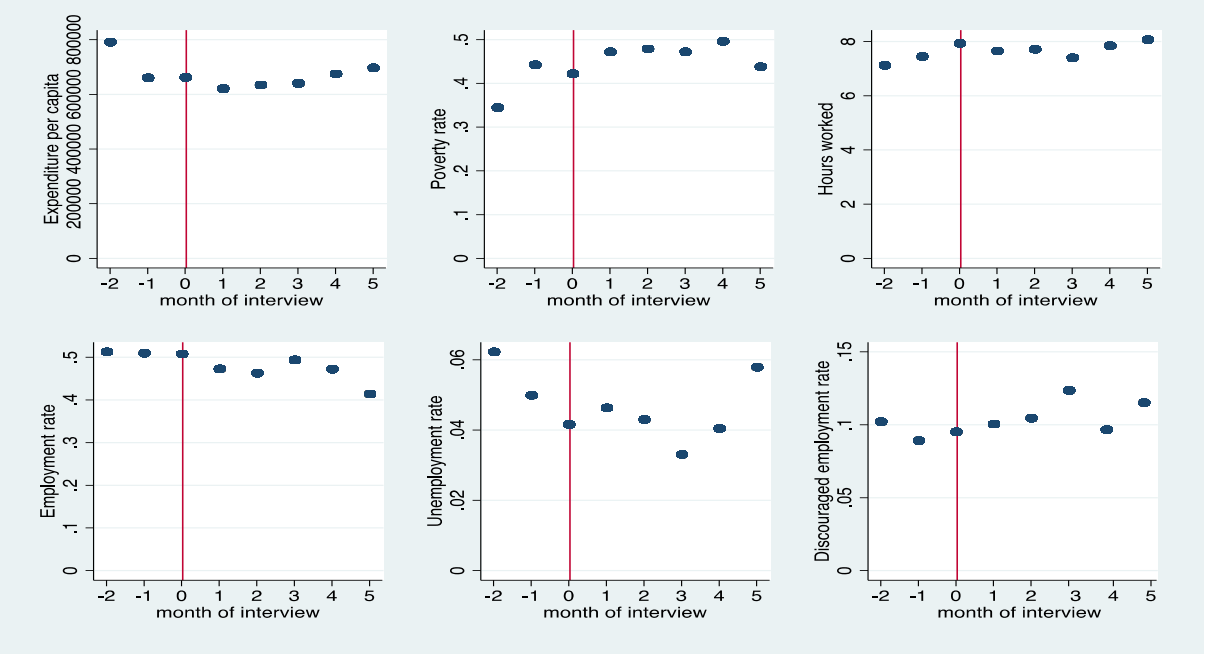
**Table 1: Summary Statistics for Household- and Individual-Level Outcome Variables by Covid-19 Status**

| | Full | Control | Treatment | Difference | Standard error | P-value |
|---|---|---|---|---|---|---|
| **Panel A Household Welfare Outcomes:** | | | | | | |
| log expenditure per capita | 13.23 | 13.26 | 13.21 | -0.05*** | 0.01 | 0.00 |
| **Asset Type** | | | | | | |
| Phone | 0.88 | 0.91 | 0.86 | -0.05*** | 0.00 | 0.00 |
| TV | 0.58 | 0.59 | 0.57 | -0.01* | 0.01 | 0.09 |
| Motorcycle | 0.02 | 0.03 | 0.02 | 0.00** | 0.00 | 0.05 |
| Car and/or truck | 0.05 | 0.06 | 0.05 | -0.02*** | 0.00 | 0.00 |
| Bicycle | 0.01 | 0.01 | 0.01 | -0.01*** | 0.00 | 0.00 |
| Radio | 0.20 | 0.22 | 0.18 | -0.04*** | 0.01 | 0.00 |
| Furniture | 0.95 | 0.96 | 0.94 | -0.02*** | 0.00 | 0.00 |
| Small appliances | 0.36 | 0.41 | 0.32 | -0.08*** | 0.01 | 0.00 |
| Large appliances | 0.36 | 0.37 | 0.35 | -0.02*** | 0.01 | 0.00 |
| Total number of different assets owned | 6.76 | 7.04 | 6.54 | -0.50*** | 0.05 | 0.00 |
| Total number of assets owned (count) | 11.79 | 12.26 | 11.44 | -0.83*** | 0.09 | 0.00 |
| Current value of all assets owned | 469160 | 546326 | 416422 | -129904*** | 11160.84 | 0.00 |
| Log of value of assets | 12.18 | 12.29 | 12.09 | -0.20*** | 0.02 | 0.00 |
| **Livestock Ownership** | | | | | | |
| has livestock | 0.28 | 0.31 | 0.27 | -0.04*** | 0.01 | 0.00 |
| total number of different livestock | 0.39 | 0.43 | 0.36 | -0.06*** | 0.01 | 0.00 |
| total number of livestock in herd owned by household | 1.80 | 1.72 | 1.88 | 0.16 | 0.17 | 0.35 |
| **Household Poverty Status** | | | | | | |
| Objective Poverty: Poor | 0.45 | 0.42 | 0.47 | 0.05*** | 0.01 | 0.00 |
| Objective Poverty: Multidimensional poverty index | 0.39 | 0.38 | 0.39 | 0.01*** | 0.00 | 0.00 |
| Subjective Poverty: I live well | 0.24 | 0.27 | 0.23 | -0.04*** | 0.01 | 0.00 |
| Subjective Poverty: I live poorly | 0.31 | 0.30 | 0.32 | 0.02*** | 0.01 | 0.00 |
| Subjective Poverty: Rich social rank | 0.32 | 0.34 | 0.31 | -0.03*** | 0.01 | 0.00 |
| **Panel B: Labor Market Outcomes** | | | | | | |
| **Household Outcome:** | | | | | | |
| Share of working individuals in household | 0.30 | 0.31 | 0.29 | -0.02*** | 0.00 | 0.00 |
| **Individual Outcomes:** | | | | | | |
| Daily hours worked | 7.66 | 7.56 | 7.72 | 0.16** | 0.08 | 0.03 |
| Employed | 0.49 | 0.51 | 0.47 | -0.04*** | 0.01 | 0.00 |
| Unemployed | 0.05 | 0.05 | 0.04 | -0.01 | 0.00 | 0.18 |
| Discouraged worker | 0.10 | 0.09 | 0.11 | 0.01** | 0.01 | 0.04 |
| Formally employed | 0.22 | 0.21 | 0.23 | 0.02** | 0.01 | 0.02 |
| Works in agriculture sector | 0.34 | 0.31 | 0.37 | 0.06*** | 0.01 | 0.00 |
| Works in industry sector | 0.13 | 0.13 | 0.12 | -0.01 | 0.01 | 0.33 |
| Works in trade sector | 0.05 | 0.06 | 0.05 | -0.02*** | 0.01 | 0.00 |
| Works in services sector | 0.48 | 0.49 | 0.46 | -0.03*** | 0.01 | 0.01 |
| Log salary | 11.08 | 11.06 | 11.09 | 0.03 | 0.04 | 0.43 |
| **Sample size** | **29,192** | **17,480** | **11,712** | | | |

Note: "Difference" captures the raw difference between the post-Covid sample (treatment) and the pre-Covid sample (control).
Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.1

Figure 2 below shows the mean distribution of selected outcomes pre- and post-Covid-19 lockdown month. Per capita expenditure shows an immediate reduction in April which is a month after the Covid-19 lockdown, with a slight recovery in the second month (May) but still below the January 2020 average (two months pre-Covid-19 lockdown).

**Figure 2: Distribution of Household welfare indicators and labor market outcomes across the month of interview**




**Note:** The zero (0) reference line denotes the Covid-19 lockdown month (March 2020) in Comoros. We positioned the x-axis to reflect the time trend of the interviews before and after the treatment variable (covid lockdown month). Hence, the scale reads from left of the reference line as January 2020 (-2), February (-1) and to the right as April (+1) to August/September (+5). The observations for August and September 2020 interviews were pooled together given their small sample sizes, hence the absence of (+6) that would have corresponded to September 2020.

The poverty rate exhibits an increase after the Covid-19 lockdown and only starts falling in August/September 2020. The total hours worked per day also indicate a decreasing trend after the Covid-19 lockdown, increasing after three months but still below the pre-Covid-19 hours. Hours worked are observed to decline, but some evidence of recovery in July. Similarly, the employment rate is observed to recover in July before declining again. The unemployment trend shows variation but generally increases after the implementation of the Covid-19 restrictions, albeit with some recovery in July[9]. The level of discouragement post-Covid increases until the fourth/fifth month. The differences observed across outcome variables among households interviewed before and after the Covid-19 restriction are only descriptive in nature, and these two groups of households are not necessarily comparable. As such, it is

[9] The descriptive analysis predicts some recovery in household welfare by July. The national government lifted the total lockdown measure in the first week of July. The lockdown lifting was accompanied by a curfew from 23:00 to 04:00, use of mask in public areas, reduced number in public transport and opening of some educational institutions.

important to check household and individual characteristics across these two groups of households.

**Table 2: Summary Statistics of Household Demographics and Individual Characteristics by Covid-19 Status**

| | Full Sample | Control | Treatment (Covid) | Difference (T-C) | Standard Error | P-value |
|---|---|---|---|---|---|---|
| **Individual Characteristics** | | | | | | |
| Male | 0.48 | 0.48 | 0.48 | 0.00 | 0.01 | 0.87 |
| Age | 25.19 | 25.09 | 25.24 | 0.15 | 0.25 | 0.56 |
| Literate | 0.64 | 0.66 | 0.63 | -0.03 | 0.01 | 0.00 |
| **Location and Settlement Type** | | | | | | |
| Moroni | 0.11 | 0.12 | 0.10 | -0.02 | 0.01 | 0.00 |
| Rest of Ngazidja | 0.40 | 0.39 | 0.40 | 0.00 | 0.01 | 0.72 |
| Ndzuwani | 0.43 | 0.40 | 0.45 | 0.05 | 0.01 | 0.00 |
| Mwali | 0.07 | 0.09 | 0.05 | -0.03 | 0.00 | 0.00 |
| Urban | 0.32 | 0.35 | 0.29 | -0.07 | 0.01 | 0.00 |
| **Household Characteristics** | | | | | | |
| **Amenities** | | | | | | |
| Water Access | 0.86 | 0.83 | 0.88 | 0.05 | 0.00 | 0.00 |
| Sanitation Access | 0.59 | 0.58 | 0.60 | 0.02 | 0.01 | 0.00 |
| Electricity Access | 0.84 | 0.85 | 0.83 | -0.02 | 0.00 | 0.00 |
| **Dwelling Features** | | | | | | |
| Improved Roof | 0.99 | 0.99 | 0.99 | 0.01 | 0.00 | 0.00 |
| Improved Wall | 0.48 | 0.48 | 0.48 | 0.00 | 0.01 | 0.85 |
| Improved Floor | 0.81 | 0.81 | 0.81 | -0.01 | 0.01 | 0.14 |
| **Other characteristics** | | | | | | |
| Female- Headed | 0.34 | 0.31 | 0.35 | 0.04 | 0.01 | 0.00 |
| Dependency Ratio | 1.12 | 1.14 | 1.10 | -0.03 | 0.01 | 0.01 |
| Polygamous | 0.07 | 0.06 | 0.07 | 0.00 | 0.00 | 0.30 |
| Single- Headed | 0.10 | 0.10 | 0.11 | 0.00 | 0.00 | 0.24 |
| People per Room | 2.37 | 2.48 | 2.30 | -0.19 | 0.02 | 0.00 |
| **Head's characteristics** | | | | | | |
| Age | 45.76 | 45.92 | 45.66 | -0.26 | 0.17 | 0.13 |
| Literate | 0.75 | 0.78 | 0.73 | -0.06 | 0.01 | 0.00 |
| No Education | 0.59 | 0.58 | 0.59 | 0.01 | 0.01 | 0.08 |
| Primary Educ. | 0.12 | 0.13 | 0.12 | -0.01 | 0.00 | 0.01 |
| lower secondary | 0.10 | 0.10 | 0.11 | 0.00 | 0.00 | 0.31 |
| upper secondary | 0.06 | 0.07 | 0.06 | -0.01 | 0.00 | 0.03 |
| Tertiary | 0.13 | 0.12 | 0.13 | 0.00 | 0.00 | 0.52 |
| **Samples** | **29,192** | **17,480** | **11,712** | | | |

**Note**: "Difference" captures the raw difference between the post-Covid-19 sample (treatment) and the pre-Covid-19 sample (control).
Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.1

The survey data provides important individual and household characteristics like age, gender, marital status, location of settlement, educational attainment, access to basic amenities, and other household demographics. Table 2 presents summary statistics of these characteristics by Covid-19 status. The regional distribution shows no difference between the pre- and post-Covid-19 samples for the rest of Ngazidja, the main island, which accounts for 40% of the total sample. About 43% of the sample is resident in Ndzuwani Island, the second largest in Comoros, with observed differences between the treatment and control group. The individual demographics are similar for pre- and post-Covid-19 except for the literacy rate, which is higher for the control group. There are some differences in household access to basic amenities

and dwelling features between the pre- and post-Covid-19 samples. Additionally, there is evidence of a higher dependency ratio in the pre-Covid-19 sample and a higher percentage of female household heads in the post-Covid-19 sample. The characteristics of household heads are similar across the two groups except for literacy rate.

The analysis of the summary statistics indicates a negative association of Covid-19 with household- and individual-level welfare indicators. However, a comparison of observable characteristics between treatment and control groups suggests that these may be driving the observed differences. Therefore, the objective of this paper is to go beyond association in a bid to evaluate the causal impact of Covid-19 on household welfare in Comoros. The empirical strategy discussed in the next section will use household and individual characteristics as control variables to identify the causal impact of Covid-19 on welfare and labor market outcomes.

## Empirical Methodology

### Descriptive Regression Estimations

We first explore descriptive econometric analysis examining the impact of the Covid-19 lockdown measure on household and individual welfare indicators and labor market outcomes. We specify three models of the correlates of continuous indicators of household welfare. The first captures the Covid-19 treatment related to the exact month the national lockdown came into effect, and the last two evaluate the time-elapsed variation in interview month relative to the start of the national lockdown.

$$welfare_i = \beta_0 + \beta_1 (Post) + X_i + \theta_j + e_i \quad (1)$$

$$welfare_i = \beta_0 + +\beta_1 (Post * monthselapsed) + X_i + \theta_j + e_i \quad (2)$$

$$welfare_i = \beta_0 + \beta_1 (Post) + \beta_2 (Post * (1to3monthselapsed) + \beta_3 (Post * (morethan3monthselapsed) + X_i + \theta_j + e_i \quad (3)$$

Where: $welfare_i$, is a continuous variable that represents a variety of indicators of welfare measures (i.e., log of per capita household expenditure, related asset ownership indicators, and livestock ownership) for household $i$ or individual $i$; $Post$ is a dummy variable that indicates whether the interview occurred after the Covid-19 lockdown measure to curtail the outbreak of the pandemic; $monthselpased$ is a continuous variable capturing the total count of months that elapsed from the month of the national lockdown; the other important explanatory variables *1to3monthselapsed* and *morethan3monthselapsed* are dummy variables representing samples that were interview between 1 to 3 months and more than 3 months after the month of the national lockdown month, respectively; $X_i$ is a vector for the $ith$ household and individual that includes covariates relating to, among others, age, gender, marital status, and educational attainment, and is further comprised of household dependency ratio, access to basic amenities, dwelling features, and settlement type; $\theta_j$ represents location fixed effects; and $e_i$ represents a random idiosyncratic error term. The estimations from models 1, 2, and 3 are important for understanding the overall and monthly variation of the effect of Covid-19 on our selected welfare outcomes. The estimators of interest are $\beta_1$ , $\beta_2$ , and $\beta_3$ which provide the average impact of the Covid-19 lockdown measures and the variation of the effect over time elapsed from the lockdown month on our selected welfare indicators. Pandemic outbreaks have dynamic effects on socio-economic indicators, hence an understanding of the evolution of the effect after a curtailment measure is key for policy analysis. The above equations are estimated by ordinary least square regression analysis with robust standards errors.

In addition to the continuous measures of household welfare indicators, we also use binary (0/1) poverty measures for households. The estimation of the Covid-19 impact on household poverty (both objective and subjective) is obtained from the probit model specification as follows:

$$prob[poverty_i = 1] = \phi(\beta_0 + \beta_1 post + X_i) \quad (4)$$

Where $\phi(.)$ is the cumulative distribution function operator for the standard normal; $poverty_i$ is a binary variable that represents whether a household or individual is below the national poverty line or the three subjective poverty measures computed from self-assessed economic status as living in difficulty, living well, and living rich, respectively; and $post_i$ and $X_i$ are the variables for the Covid-19 lockdown measures and the related poverty determinants as defined in equation1 above. Our probit model estimation does not consider the month-elapsed variables from the national lockdown, as the interaction marginal effect interpretation from probability model estimation lacks theoretical justification and entails computational difficulties (Williams, 2012).

In addition to the analysis of welfare indicators, we explore the effect of Covid-19 on household and individual labor market outcomes. The labor market outcomes can be separated into continuous and binary measures. The continuous labor market outcomes of interest include the share of working members in the household, the total hours worked, and the log of total monthly salary. The first outcome is a household level variable, and the last two are individual level outcomes. The relevant estimation technique follows the forms specified for models 1, 2, and 3 above, with continuous measures of the labor outcomes replacing the welfare indicator on the left-hand side of the specifications. The estimation provides the average effect for post-Covid-19 and time-elapsing effect on the labor market outcomes for households in Comoros.

The estimation follows an Ordinary Least Square (OLS) regression analysis. In addition, our labor market binary outcomes (employed and formally employed) are estimated for model 1 only using Probit estimation analysis. The aim of this evaluation is to provide an understanding of the mechanisms through which the associated government lockdown measure during the pandemic affected the general welfare.

**Causal Impact Estimation: Propensity Score Matching**

The above analysis provides an initial descriptive empirical outlook of the estimation of the impact of Covid-19 on welfare, poverty, and labor market outcomes for Comoros. In order to predict a causal impact of Covid on our selected outcome variables, we expand our analysis using the Propensity Score Matching (PSM) technique. The PSM methodology allows for the estimation of the average treatment effect of Covid-19 on household and individual welfare, poverty status, and labor market outcomes. Given that the analysis uses observational data for one time period, the PSM approach is appropriate in an attempt to causally identify the key effects of interest.

The PSM approach simulates a random allocation of households and individuals into treatment and control groups based on their estimated propensity scores. The propensity score estimation in the PSM empirical approach begins with an estimation of a treatment assignment equation using a logistic regression model. The case of the Covid-19 government lockdown measure is unique as it provides a natural demarcation of households and individuals interviewed pre- and post-lockdown. The treatment assignment equations empirically predict the probability that a household or individual is in the post-Covid-19 sample (the treatment group). The logistic model includes sets of household and individual covariates that are not necessarily informed

by economic theory and may comprise polynomial and interaction terms. The motivation behind the logistic specification is the need to achieve strong predictions of treatment and control group allocation probabilities and effective covariate balancing in the matching procedure. The model estimates are used to compute the propensity scores on which the households and individuals from the two groups are subsequently matched. In specifying the logistic regression, the included explanatory variables should not be pre-determined by the treatment variable (Covid-19 lockdown measure) but should be correlated with the outcome variables (welfare indicators and labor market outcomes). The included covariates in the treatment equation are the same welfare determinants used in equations 1, 2, and 3. The above consideration limits potential concerns on the internal validity of the approach. The crucial identifying assumption is that, conditional on the input variables, the assignment to the treatment group (post-Covid-19 lockdown sample) and the control group (pre-Covid-19 lockdown sample) can be simulated as random and independent of the treatment. This is the Conditional Independence Assumption (CIA) (see Heckman, Ichimura and Todd, 1997; Smith and Todd, 2005; among others for details on the PSM technique). The assumption overcomes the problem of counterfactual simulation in natural experiments using observational data, and the matching quality can be assessed through the distribution of the included covariates after matching.

The estimation of the average treatment effect subjects the treatment and control groups to a common support which eliminates the possible bias from non-overlapped observations from the two groups. The kernel density matching technique is used for matching purposes. However, an extension to the use of other matching technique will be evaluated in the robustness section. After the implementation of the matching exercise, the uninfluenced explanatory variables for the treatment and control groups should exhibit a similar

distributional pattern. A satisfactory outcome is achieved only if the households assigned to the treatment and control groups provide identical observations in terms of the marginal distributions of the input variables. If this balancing property is satisfied, this implies that no measured confounder bias remains. The property is assessed using several different diagnostics. These include the standardized bias approach suggested by Rosenbaum and Rubin (1985), which measures the distance in the marginal (or unconditional) distributions of the input variables between the control and treatment groups prior to and after matching. In addition, t-statistics and variance ratios (i.e., F-tests) for each variable included in the treatment assignment equation are also used to determine if there are statistical differences between the means and variances (of the continuous input variables) after matching.

In investigating the balancing property, the logistic treatment assignment model is also re-estimated using the set of matched data. The expectation is that with good matching, the regression model's pseudo-R2 should be close to zero, and the corresponding Likelihood Ratio Test (LRT) for the overall statistical significance of the logistic regression model should yield a low value. We also use Rubin's B and R statistics (see Rubin, 2001), which provide a set of criteria for comparing the distribution of the propensity scores between the treatment and control groups. These latter two test statistics indicate whether the regression-based procedure adequately eliminates any measured confounder bias using an appropriate set of confidence intervals.

Once the balancing property is satisfied, we continue with the estimation of the treatment (post-Covid-19 sample) impact by computing the weighted average difference between the post-Covid-19 units and the average of the pre-Covid-19 counterfactual units in the control group.

The standardized weights are calculated on the magnitude of differences in the propensity scores between the individual treated units and the compared control units. The average treatment effect on the treated (ATT) is computed for our data to inform on the causal impact of Covid-19 on selected welfare indicators and labor market outcomes.

**Empirical Results**

The empirical results are presented and analyzed, starting with the descriptive regression results. The first sets of results encapsulate the impact of the three treatment variables capturing the Covid-19 lockdown on i) household welfare indicators using OLS estimations, ii) poverty indicators using the Probit estimation, and iii) labor market outcomes.

Table 3 below presents the results of the OLS estimates of the impact of the Covid lockdown on expenditure and asset ownership indicators, both overall average and time elapsed effect. Table 3 gives an overview of household wealth status using three different but complementary indicators. In the literature, household livestock and assets are viewed as stored wealth or savings accounts for households in developing countries (Andersson, Mekonneh and Stage, 2011). Therefore, it is important to understand the dynamic impact of economic shocks like the Covid-19 on household asset and livestock ownership for Comoros post-Covid-19 recovery policies. The first panel (A) in Table 3 represents the results for each of the three models for the log of household expenditure and livestock ownership. The second panel (B) of Table 3 represents the results for household asset status across three different measures.

## Table 3: Ordinary Least Square Results (Welfare Indicators)

| **PANEL A** | **Log of Household Expenditure** | | | **Household Livestock Ownership** | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | **Different Types Owned** | | | **Total Owned** | | |
| | **1** | **2** | **3** | **1** | **2** | **3** | **1** | **2** | **3** |
| Post-Covid | -0.068*** | | -0.150*** | -0.067*** | | -0.143*** | 0.223 | | 0.688* |
| | (0.006) | | (0.011) | (0.008) | | (0.018) | (0.178) | | (0.412) |
| Post-Covid*months elapsed (continuous) | | -0.030*** | | | -0.029*** | | | 0.129* | |
| | | (0.002) | | | (0.002) | | | (0.078) | |
| Post-Covid*months elapsed (1-3) | | | 0.026*** | | | 0.022 | | | -0.094 |
| | | | (0.009) | | | (0.015) | | | (0.135) |
| Post-Covid*months elapsed (>3) | | | 0.114*** | | | 0.109*** | | | -0.719* |
| | | | (0.008) | | | (0.013) | | | (0.387) |
| **R-squared** | 0.415 | 0.420 | 0.420 | 0.078 | 0.080 | 0.080 | 0.005 | 0.006 | 0.006 |
| **Observations** | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 |
| **PANEL B** | **Household Asset Ownership** | | | | | | | | |
| | **Number of Different Assets Owned** | | | **Number of Assets Owned** | | | **Log Value of Assets Owned** | | |
| | **1** | **2** | **3** | **1** | **2** | **3** | **1** | **2** | **3** |
| Post-Covid | -0.395*** | | -0.542*** | -0.521*** | | -1.146*** | -0.167*** | | -0.335*** |
| | (0.042) | | (0.086) | (0.076) | | (0.157) | (0.017) | | (0.035) |
| Post-Covid*months elapsed (continuous) | | -0.144*** | | | -0.206*** | | | -0.069*** | |
| | | (0.013) | | | (0.023) | | | (0.005) | |
| Post-Covid*months elapsed (1-3) | | | -0.136** | | | 0.164 | | | 0.040 |
| | | | (0.068) | | | (0.123) | | | (0.028) |
| Post-Covid*months elapsed (>3) | | | 0.443*** | | | 0.919*** | | | 0.252*** |
| | | | (0.064) | | | (0.120) | | | (0.027) |
| **R-squared** | 0.297 | 0.298 | 0.299 | 0.286 | 0.287 | 0.288 | 0.242 | 0.244 | 0.245 |
| **Observations** | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 | 28,902 |

**Note:** Robust standard errors in parentheses
Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.1
The controls include head of household and individual member age, education, and marital status; polygamous household; female-headed household; dependency ratio; number of working-age individuals in household; access to water, sanitation and electricity; improved floor and roof; location (region and urban settlement)

In Panel A of Table 3, the impact of the Covid-19 lockdown shows an average reduction in household expenditure of 6.8%, with a 3% reduction for each month that elapsed after the lockdown month, *ceteris paribus.* The interaction of our post-Covid-19 sample and the number of months that elapsed shows the effect lingered strongly during the first three months after the lockdown. There is some evidence of recovery, with the magnitude of the negative impact slowly reducing within the first 3 months. The rate of recovery improves post three months of the national lockdown.

The last six columns of Panel A in Table 3 present the estimation for the household livestock ownership across two measures (different types and total livestock owned) for the three models. The impact of the Covid-19 lockdown was a small decrease in the different types of livestock owned by a household, on average. Nevertheless, there was no significant impact on the total number of livestock owned after the lockdown. The results on the impact of the Covid-19

lockdown on the three household asset ownership measures are presented in Panel B. The number of different asset types owned by households decreased slightly by 0.4 asset counts, on average, after the Covid-19 lockdown policy. The unit decrease is approximately a 5.7% reduction in the number of different assets owned using the average number of different assets before the Covid-19 lockdown (average from the control group). The negative impact lingers but becomes weaker for the months that elapsed after the Covid-19 lockdown policy. In a similar line, the total number of assets owned by a household also declined slightly, with the loss being equivalent to a decline in number by 0.5. Thus, the loss in asset ownership accounted for approximately a 4.1% reduction as a result of the Covid-19 lockdown. The impact on the number of assets lingers within the first three months, with no substantial evidence of recovery after three months. The last three columns of Panel B, in Table 3, represent the Covid-19 impact on the monetary value of total assets for a household, and there was a 16.7% reduction on average, *ceteris paribus.* In addition, for each month after the Covid-19 lockdown, there was a 6.9% reduction in the value of total assets, which translates to a loss of approximately 37,696.5 Comorian francs using the pre-Covid-19 sample mean value. There is no evidence of recovery as the months elapsed after the Covid-19 lockdown policy implementation for the monetary value of asset ownership.

**Table 4: Probit Regression Analysis Results (Poverty Status) (Marginal Effects)**

| | | Subjective Poverty Outcomes | | |
|---|---|---|---|---|
| | **Objective Poverty** | **I live well** | **I live in difficulty** | **I am rich** |
| **Post-Covid** | 0.081*** | -0.047*** | 0.017*** | -0.048*** |
| | (0.007) | (0.006) | (0.006) | (0.009) |
| **Observations** | 28,902 | 28,005 | 28,005 | 27,131 |

**Note:** Robust standard errors in parentheses
Estimation by Probit. Marginal effect at means reported
Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.1

Table 4 represents the result of the Probit regression of household poverty status for both objective and subjective measures. An evaluation of the objective poverty indicator, measured by households below the poverty line, revealed an 8.1 percentage point increase, on average, post-Covid-19 lockdown. Regarding the subjective poverty measures, the results revealed a 4.7

and 4.8 percentage points reduction for households that self-assessed as living well and as socio-economically rich, respectively. In addition, the estimation showed an increase of 1.7 percentage points for households that self-assessed as living in difficulties. The overall impact of the Covid-19 lockdown measures was an increase in poverty status across the objective and subjective measures.

**Table 5: OLS Regression and Probit Analysis Results (Labor Market Outcomes)**

| | Continuous Outcomes | | | | | | | | | Binary Outcomes | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Share of working members | | | Total hours worked per day | | | Log salary | | | Employed (Model 1) | |
| | 1 | 2 | 3 | 1 | 2 | 3 | 1 | 2 | 3 | Total | Formal |
| **Post-Covid** | -0.028*** | | -0.038*** | 0.173** | | -0.113 | 0.008 | | 0.078 | -0.060*** | 0.022** |
| | (0.002) | | (0.005) | (0.075) | | (0.153) | (0.035) | | (0.077) | (0.009) | (0.011) |
| **Post-Covid*months elapsed (continuous)** | | -0.008*** | | | 0.021 | | | 0.001 | | N/A | N/A |
| | | (0.001) | | | (0.022) | | | (0.011) | | | |
| **Post-Covid*months elapsed (1-3)** | | | 0.002 | | | 0.198 | | | -0.096 | N/A | N/A |
| | | | (0.004) | | | (0.126) | | | (0.061) | N/A | N/A |
| **Post-Covid*months elapsed (>3)** | | | 0.016*** | | | 0.264** | | | -0.007 | | |
| | | | (0.003) | | | (0.111) | | | (0.057) | | |
| **R-squared** | **0.186** | **0.186** | **0.187** | **0.062** | **0.061** | **0.062** | **0.176** | **0.176** | **0.176** | | |
| **Observation** | **28902** | **28902** | **28902** | **8,697** | **8,697** | **8,697** | **1670** | **1670** | **1670** | **8,697** | **8,697** |

**Note:** Robust standard errors in parentheses
Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.1
**Share of working members estimation:** the controls include head of household and individual age, education, and marital status; polygamous household; female-headed household; dependency ratio; number of working-age individuals in household; access to water, sanitation and electricity; improved floor and roof; location (region and urban)
**Other Estimations:** the controls include individual age, education, and marital status; polygamous household; female-headed household; dependency ratio; number of working-age individuals in household; access to water, sanitation, and electricity; improved floor and roof; location (region and urban)

Table 5 presents the results of the descriptive OLS and Probit analysis on the impact of Covid-19 on labor market outcomes. The outcomes of interest include the share of working individuals in the household and the log of salary for an individual, across the three models using OLS. In addition, the results (marginal effects) of binary outcomes of being employed and being formally employed are highlighted for model 1, estimated by Probit estimation method. The share of working household members decreased by an average of 2.8% after the Covid-19 lockdown, with no significant recovery as the months elapsed and a 0.8% reduction in the share of working members for an additional month after the Covid lockdown measure, *ceteris paribus*. The total individual hours worked reduced slightly by 0.2 hours per day but no significant impact was found as the months elapsed. Similarly, the estimated effect of Covid-19 on individual monthly salary shows no significance across the three models. However, the

estimated impact on employment status was a significant 6 percentage points reduction in the likelihood of being employed, while probability of formal employment increased by 2.2 percentage points, on average, *ceteris paribus*.[10]

The descriptive regression analysis above shows that some of the negative impacts observed in the raw differences in Table 1 are still statistically significant even after controlling for characteristics that may be driving them. Specifically, Covid-19 is found to be associated with lower household expenditure, total asset value and ownership, the share of employed household members and individual level employment. In addition, both objective and subjective poverty measures are found to be worse.

We now discuss the PSM results of the estimation of the average treatment effect on the treated (ATT) of Covid-19 lockdown on selected household welfare indicators. Table A3 in the appendix presents the logit estimates for the treatment assignment model used to compute the propensity scores for the post-Covid-19 treatment variable. As discussed in the empirical methodology section, the specification of the logistic treatment assignment equation is not motivated by any economic theory, and the estimates do not need an economic interpretation. The aim of the treatment assignment equation is to provide a good predictive outcome of the propensity scores for the matching exercise. However, certain conditions need to be satisfied to ensure the ATT is valid and captures the causal impact of Covid-19 on household welfare. Firstly, the estimations were done within the common support, and only seven observations failed to satisfy the common support condition and were excluded from the empirical analysis (see Figure A1 in the appendix for the propensity score distribution for the treatment and control groups).

[10] However, after matching the impact on formal employment is found not to be statistically significant (Table 6).

The matching procedure yielded good balancing quality for the covariates across the different diagnostic checks. The mean and the median standardized bias estimates are below the required threshold, and none of the individual covariates yields a standardized bias outside of the ± 5% interval. The variance ratios for the continuous variables for the two groups (treatment and control) lie within the specified 95% confidence intervals. In addition, the pseudo-$R^2$ values for the logistic regression model re-estimation using the matched data are negligible, and the Likelihood Ratio Test (LRT) values for the overall significance of the regression are statistically insignificant. The estimated Rubin criteria for good balancing on the propensity score are all satisfied and reinforce a good balancing achievement. The full array of statistics and diagnostics for the balancing property is contained in Tables A4 and A5 of the appendix.

Table 6 below represents the average treatment effect of the Covid-19 lockdown measure on household welfare indicators, poverty, and labor market outcomes separately. In Panel A of Table 6, the average causal impact on the post-Covid-19 lockdown sample is a 4.2% (i.e., $[e^{-0.041}-1] \times 100$) reduction in household per capita expenditure, *ceteris paribus*. The estimated ATTs also predict a negative impact on household asset status. The number of different assets owned by a household decreased by 0.5, and the total number of assets owned decreased by 0.7 asset counts. A significant negative impact is also observed for the total monetary value of assets within a household, with a 16% (i.e., $[e^{-0.174}-1] \times 100$) reduction as a result of Covid-19 lockdown. The number of different types of livestock owned by a household also decreased slightly by 0.1, but there was no significant impact on the total livestock counts.

**Table 6: Average Treatment Effect (ATT) of Covid-19 on Household Welfare and Labor Market Outcomes**

| **Panel A: Household Indicators** | **Impact** |
|---|---|
| Log expenditure per capita | -0.041*** |
| | (0.008) |

| | |
|---|---|
| Number of different types of asset owned | -0.492*** |
| | (0.059) |
| Total number of assets owned (count) | -0.686*** |
| | (0.108) |
| Log value of assets | -0.174*** |
| | (0.023) |
| Number of different types of livestock owned | -0.106*** |
| | (0.010) |
| Number of livestock owned | -0.026 |
| | (0.208) |
| **Panel B: Household Poverty Status** | |
| Objective Poverty: Poor | 0.042*** |
| | (0.007) |
| Subjective Poverty: I live well | -0.041*** |
| | (0.006) |
| Subjective Poverty: I live in difficult | 0.006 |
| | (0.007) |
| Subjective Poverty: I am rich | -0.064*** |
| | (0.007) |
| **Panel C: Labor Market Outcomes** | |
| **Household Outcome:** | |
| Share of working household members | -0.025*** |
| | (0.003) |
| **Individual outcomes:** | |
| Employed | -0.051*** |
| | (0.008) |
| Formal employment | 0.008 |
| | (0.009) |
| Total hours worked per day | 0.192*** |
| | (0.072) |
| Log salary | 0.002 |
| | (0.039) |
| **Sectoral Employment** | |
| Agriculture | 0.048*** |
| | (0.011) |
| Industry | -0.001 |
| | (0.007) |
| Trade | -0.017*** |
| | (0.005) |
| Service | -0.029** |
| | (0.111) |

Note: The observations across the treatment and control groups for each outcome vary in the estimation in accordance with the available data.
Robust standard errors in parentheses
* p < 0.01, ** p < 0.05, * p < 0.1

Panel B of Table 6 presents the estimated ATT of Covid-19 on the poverty status of a household. The overall impact is an increase in objective poverty by 4.2 percentage points for the post-Covid-19 sample. Subjective poverty analysis supports a general reduction in the proportion of households that self-reported as living well or as rich by 4.1 and 6.4 percentage points, respectively. However, the subjective view of living in difficulty showed no significant impact from the Covid-19 lockdown. The results from Panel A and B of Table 6 represent a substantial loss in household welfare post-Covid-19. However, the casual impact showed no significant impact on the subjective measure of living in difficulty compared to the magnitude of 1.7 percentage points from the Probit estimates.

The last panel of Table 6 outlined the ATT for the household and individual labor market outcomes. The share of working individuals within a household decreased by 2.5%, with an overall 5.1 percentage points reduction in employment rate, on average. There was no significant impact on formal employment as opposed to the estimated 2.2 percentage points reduction from the Probit marginal effect. Similarly, there is no significant impact on individual monthly salary. However, the total number of working hours per day slightly increase by 0.2 hours per day (12 mins) post-Covid, on average, *ceteris paribus*. The evaluation on the employment sectoral impact of Covid-19 shows a significant 4.8 percentage point increase in the likelihood of employment in agriculture. By contrast, there was a significant reduction in the likelihood of employment in the Trade and Services sectors by 1.7 and 2.9 percentage points respectively.

**Robustness Checks**

The above empirical results provide an overview of the causal impact of Covid-19 on household welfare, individual and household labor market outcomes. To ensure the robustness of our findings, we first check for internal validity to our preferred estimation using other estimation techniques, namely inverse probability weighting and nearest neighbor matching.

**Table 7: ATT Estimates of Covid-19 Anticipation on Household Welfare and Labor Market Outcomes**

| | Inverse Probability Weighting | Nearest Neighbor Matching |
|---|---|---|
| **Panel A: Household Indicators** | | |
| Log expenditure per capita | -0.046*** | -0.052*** |
| | (0.006) | (0.008) |
| Number of different types of assets owned | -0.361*** | -0.401*** |
| | (0.044) | (0.058) |
| Total number of assets owned (count) | -0.540*** | -0.539*** |
| | (0.080) | (0.104) |
| Log value of assets | -0.159*** | -0.175*** |
| | (0.018) | (0.022) |
| Number of different types of livestock owned | -0.082*** | -0.085*** |
| | (0.009) | (0.011) |
| Number of livestock owned | 0.004 | 0.027 |
| | (0.157) | (0.199) |
| **Panel B: Household Poverty Status** | | |
| Objective Poverty: Poor | 0.043*** | 0.048*** |
| | (0.006) | (0.006) |
| Subjective Poverty: I live well | - 0.041*** | -0.041*** |
| | (0.006) | (0.007) |
| Subjective Poverty: I live in difficulty | 0.008 | 0.005 |
| | (0.006) | (0.007) |

| | | |
|---|---|---|
| Subjective Poverty: I am rich | -0.059*** | -0.069*** |
| | (0.006) | (0.007) |
| **Panel C: Labor Market Outcomes** | | |
| **Household Outcome**: Share of working household members | -0.023*** | -0.027*** |
| | (0.003) | (0.003) |
| **Individual Outcomes:** Employed | -0.056*** | -0.050*** |
| | (0.008) | (0.007) |
| Formal employment | 0.021** | 0.000 |
| | (0.008) | (0.008) |
| Total hours worked per day | 0.259* | 0.232* |
| | (0.159) | (0.161) |
| Log salary | 0.017 | -0.009 |
| | (0.039) | (0.039) |
| **Employment Sector** | | |
| Agriculture | 0.044*** | 0.043*** |
| | (0.010) | (0.011) |
| Industry | -0.002 | -0.003 |
| | (0.007) | (0.007) |
| Trade | -0.017*** | -0.018*** |
| | (0.005) | (0.005) |
| Service | -0.024** | -0.021** |
| | (0.011) | (0.011) |

**Note:** The observations across regression analysis for each outcome vary in the estimation according to the available data.
Robust standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

Table 7 above shows negative impacts of Covid-19 on welfare indicators and labor market outcomes as observed in our main estimates. The magnitudes are slightly on the lower bound for the inverse probability weighting estimation. The nearest neighbor estimates are on the upper bound. Nevertheless, the internal validity process affirms the Covid-19 lockdown impact on our selected outcomes, and the magnitudes are broadly consistent with our main findings.

Secondly, we address the concern that anticipatory information regarding the Covid-19 lockdown was already in circulation after the President of the country made an official address to the nation on 16 March 2020. Specifically, we estimate the anticipation effect of Covid-19 on selected outcome variables. The preferred estimates are the average treatment effects from the propensity score matching method. However, we extend the analysis and implement the two other matching techniques to validate our estimates internally. We provide estimates using a binary treatment assignment, which takes the value one if a household was interviewed before the presidential address held on 16 March 2020 and zero otherwise. Table 8 below represents the average treatment effect of Covid-19 anticipation on our outcome variables across the three estimation methods.

In Panel A of Table 8, the first column highlights the results from the propensity score matching technique. The estimated impact of the Covid-19 anticipation measure is a significant reduction in household expenditure by 5% (i.e., $[e^{-0.0513}-1] \times 100$), on average, ceteris paribus. In addition, the effect on household asset counts negatively changed by a magnitude of 0.4 units, translating to a 5.7% reduction, on average. However, the anticipation of Covid-19 lockdown is linked with a 16% (i.e., $[e^{-0.171}-1] \times 100$) reduction in the monetary value of assets. There is evidence of a reduced number of types of livestock owned, but the magnitude of change is low, and the number of livestock owned shows no significant change. The anticipation of Covid-19 accounted for an increase in household objective poverty by 4.9 percentage points, on average. Similarly, subjective poverty measures also estimate a reduction in welfare as the proportion of households self-reported to be living well and subjectively rich reduced by a significant 4.4 and 6.9 percentage points, respectively.

**Table 8: ATT Estimates of Covid Anticipation on Household Welfare and Labor Market Outcomes**

| | Propensity Score Matching | Inverse Probability Weighting | Nearest Neighbor Matching |
|---|---|---|---|
| **Panel A: Household Indicators** | | | |
| Log expenditure per capita | -0.0513*** | -0.046*** | -0.052*** |
| | (0.008) | (0.006) | (0.008) |
| Number of different types of assets owned | -0.438*** | -0.361*** | -0.401*** |
| | (0.061) | (0.044) | (0.058) |
| Total number of assets owned (count) | -0.6130*** | -0.540*** | -0.539*** |
| | (0.113) | (0.080) | (0.104) |
| Log value of assets | -0.171*** | -0.159*** | -0.175*** |
| | (0.023) | (0.018) | (0.022) |
| Number of different types of livestock owned | -0.089*** | -0.082*** | -0.085*** |
| | (0.010) | (0.009) | (0.011) |
| Number of livestock owned | -0.0136 | 0.004 | 0.027 |
| | (0.197) | (0.157) | (0.199) |
| **Panel B: Household Poverty Status** | | | |
| Objective Poverty: Poor | 0.049*** | 0.043*** | 0.048*** |
| | (0.007) | (0.006) | (0.006) |
| Subjective Poverty.: I live well | -0.044*** | - 0.041*** | -0.041*** |
| | (0.007) | (0.006) | (0.007) |
| Subjective Poverty.: I live difficulty | 0.011 | 0.008 | 0.005 |
| | (0.007) | (0.006) | (0.007) |
| Subjective Poverty.: I am rich | -0.069*** | -0.059*** | -0.069*** |
| | (0.007) | (0.006) | (0.007) |
| **Panel C: Labor Market Outcomes** | | | |
| **Household Outcome:** | | | |
| Share of working household members | -0.028*** | -0.023*** | -0.027*** |
| | (0.003) | (0.003) | (0.003) |
| **Individual Outcomes:** | | | |
| Employed | -0.055*** | -0.056*** | -0.050*** |
| | (0.008) | (0.008) | (0.007) |
| Formal employment | 0.004 | 0.021** | 0.000 |
| | (0.009) | (0.008) | (0.008) |
| Total hours worked per day | 0.276*** | 0.259* | 0.232* |

| | | | |
|---|---|---|---|
| | (0.074) | (0.159) | (0.161) |
| Log salary | -0.009 | 0.017 | -0.009 |
| | (0.039) | (0.039) | (0.039) |
| **Individual Employment Sector** | | | |
| Agriculture | 0.045*** | 0.044*** | 0.039*** |
| | (0.011) | (0.010) | (0.011) |
| Industry | 0.008 | -0.006 | -0.007 |
| | (0.008) | (0.008) | (0.008) |
| Trade | -0.018*** | -0.019*** | -0.017*** |
| | (0.005) | (0.005) | (0.005) |
| Service | -0.034** | -0.031** | -0.029** |
| | (0.011) | (0.011) | (0.011) |

**Note:** The observations across regression analysis for each outcome vary in the estimation in accordance with the available data.
Robust standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

Panel C of Table 8 shows the Covid-19 anticipation effect on household and individual labor market outcomes. The results depict a reduction in the share of working-age individuals within a household by 2.8%, on average. In addition, the probability of employment reduced by 5.5 percentage points, with a slight increase in working hours per day of 0.28 hours for the employed, on average. In addition, the likelihood of employment in agriculture increased by 4.5 percentage points in anticipation of the Covid-19 lockdown while likelihood of employment in Trade and Service sector reduced by 1.8 and 3.4 percentage points, respectively.

The overall impact of the Covid-19 presidential address was a reduction in household welfare, an increase in poverty and worsening labor market outcomes with evidence of increased participation in agricultural activities. Analysis on assets shows that the total asset value declined significantly, but the average number of assets lost was less than one. This suggests that households were likely selling their expensive assets. The other two estimation techniques give internal validity to our analysis as the results are consistent across the different measures.

It is worth noting that our evaluation of the impact of Covid-19 on household welfare and labor market outcomes did not account for the direct contagion of the virus. Due to data unavailability, we were unable to capture the impact of direct case contagion of the Covid-19 pandemic on socio-economic status. Nevertheless, the proactiveness of the Comoros government in enacting a lockdown before the first recorded case alleviated the potential risk

of the virus contagion on household welfare. As noted previously, the recorded number of Covid-19 cases in Comoros is among the lowest in the world. Thus, impacts from the containment measures as analyzed in this paper are likely to outweigh direct impacts.

Finally, our estimates include the possible mitigating effect from support received during the Covid-19 lockdown in Comoros. The United Nations Development Programme (UNDP) contributed a total of US$10 million to Comoros Covid-19 pandemic preparedness and response strategy. This has a potential downward bias to our estimated impact. However, an evaluation from United Nations Development Program (UNDP) reveals that delivery of support to Comoros during the pandemic was limited due to the absence of other international humanitarian agencies to support the three United Nations agencies (UNDP Comoros, 2020).[11] Therefore, the limitations in aid delivery reduce the potential bias stemming from mitigating economic policies at the aggregate level on our empirical estimates. Nevertheless, we acknowledge that our estimates capture the broader effect of the Covid-19 lockdown without separating it from the mitigating impact of economic support.

**Extension: The Distributional Impact of Covid-19 in Comoros**

To better understand the welfare consequences of the pandemic and how to mitigate its negative impact, an evaluation of distributional implications is necessary. Our above analysis estimates the average welfare consequences of the Covid-19 lockdown, showing a reduction in household expenditure and increased poverty. Post-pandemic policy formulation aimed at promoting development and reducing poverty can benefit from an assessment of the impacts at different levels of welfare. Table A6 in the appendix presents the raw differences across

[11] The three United Nation resident agencies were World Health Organisation (WHO), United Nations Children's Fund (UNICEF) and United Nations Development Programme (UNDP).

household expenditure quantiles for the pre-and post-Covid-19 samples. The table shows a negative correlation across the distribution. We therefore investigate the impact of Covid-19 lockdown and its anticipation on the distribution of household expenditure at different quantiles using the Quantile Treatment Effect (QTT) estimation technique proposed by Firpo (2007). A brief description of the QTT approach in the context of our analysis is provided below.

The QTT represents the differences in the marginal distributions of the potential treatment (post-Covid-19) and control (pre-Covid-19) outcomes between quantiles. Firpo (2007) invoked the above definition to estimate the QTT with an additional strong assumption of homogeneity of the treatment conditional on selected covariates. The relevant restriction imposed in the estimation by Firpo (2007) is the assumption that selection into the treatment is based on observable characteristics. The assumption is simply a re-statement of the exogeneity assumption based on the conditional independence assumption, which implies that the assignment of individuals to either the treatment or control group given a set of observables is random. The assumption is also known as the unconfoundedness assumption in the literature (Rubin, 1977) and is used to compute the conditional average treatment effects on the treated (ATT). A similar approach is applied in estimating the unconditional quantiles treatment on the treated (QTT) estimates.

We first estimate a model of the probability of a household being among the post-Covid-19 interviewed households based on the included set of observable variables relative to those in the pre-Covid-19 group. The observable characteristics included should be pre-determined and should not be affected by the Covid-19 lockdown measure but may be associated with household expenditure. The non-parametrically estimated propensity scores predict the probability of a household being in the post-Covid-19 interview samples. The included

covariates are similar to those used in the propensity score matching discussed in our principal methodology. Second, we consider the case of the QTT estimation in the context of the Comoros Covid-19 lockdown and its anticipation. Both treatment variables (Covid-19 lockdown impact and Covid-19 anticipation) are defined as a dummy taking the value 1 if a household is interviewed either post-Covid lockdown or after the president's address on Covid-19, and zero otherwise, respectively. Finally, we explore the impact of Covid-19 at different points of the household expenditure distribution. We focus on household expenditure as it provides an outcome that can be observed in understanding household welfare distribution[12].

**Table 9: Quantile Treatment Effects using Log Per Capita Household Expenditure**

| | 10th | 20th | 50th | 75th | 90th |
|---|---|---|---|---|---|
| **Covid-19 Impact** | -0.044*** | -0.057*** | -0.053*** | -0.055*** | -0.077*** |
| | (0.011) | (0.010) | (0.010) | (0.012) | (0.015) |
| ***Observations*** | 28902 | 28902 | 28902 | 28902 | 28902 |
| **Covid-19 Anticipation** | -0.042*** | -0.056*** | -0.064*** | -0.065*** | -0.089*** |
| | (0.011) | (0.010) | (0.010) | (0.012) | (0.015) |
| ***Observations*** | 28902 | 28902 | 28902 | 28902 | 28902 |

Note: Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.1

Controls in the treatment assignment equation: head of household age, education, and marital status; polygamous household; female-headed household; dependency ratio; the number of working-age individuals in the household; access to water, sanitation, and electricity; improved floor and roof; location (region and urban settlement)

Table 9 provides the estimated impacts. The first sets of results show a reduction in household expenditure across the different quantiles. Households in the bottom quantile had a 4.3% (i.e., $[e^{-0.044}-1] \times 100$) reduction in household expenditure due to the Covid-19 lockdown, with a similar pattern in the middle of the distribution. However, the negative impact observed is stronger for households in the upper distribution with a magnitude of 7.4% (i.e., $[e^{-0.077}-1] \times 100$) reduction. Thus, the effect of the Covid-19 lockdown is a reduction in household expenditure distribution with a more substantial impact at the top of the distribution. Similarly,

[12] A detailed guide and understanding of the estimation method of the QTT can be found in Firpo (2007). The approach is based on close work on semiparametric estimation of the ATE (see Hahn, 1998; Heckman, Ichimura, Smith, and Todd, 1998). The semiparametric efficiency bounds are estimated as an asymptotic variance of the QTT estimator (Newey, 1990; Bickel, Klaassen, Ritov, and Wellner, 1993).

the Covid-19 anticipation indicator also negatively impacts household expenditure across the distribution and the effect increases as we move up the household expenditure distribution, with an 8.5% (i.e., $[e^{-0.089}-1] \times 100$) reduction for the top quantile.

**Results Discussion and Policy Implications**

The ongoing research on Covid-19 has predominantly revolved around the macro-economic impact, labor market implications, and mitigating social aids or policies undertaken by developed countries. Yet, the pandemic and the associated lockdown measures were observed across developing and developed countries, regardless of the number of confirmed Covid-19 cases (Dunford et al., 2020). Although overall findings point to reduced economic growth at the macro level (see Alon et al., 2020), the lockdown policies have a potentially heterogeneous impact on countries' socio-economic and labor markets, providing dynamic outcomes from country to country. Our findings on the Covid-19 national lockdown in Comoros validate a negative impact on welfare at the micro-level. The evidence shows a decline in household expenditure. The effect translates to increased poverty from both objective measures and subjective assessments of the economic status of households. The overall impact of the lockdown in Comoros, a country that heavily depends on tourism and interisland travel, is a reduction in the economic welfare of households. It validates the argument that lockdown measures cause tremendous economic downturns.

Our estimation supports the argument that the mechanism of the Covid-19 lockdown's impact on household welfare is driven by the breakdown in socio-economic activity and market disruption. Therefore, there is a need to evaluate beyond expenditure or income levels to understand the implications of Covid-19 for households' living standards and poverty status,

as well as its distributional impact. The evidence of socio-economic disruption of daily living activities can be assessed through the labor market consequences and the different coping mechanisms households employed during the Covid-19 pandemic to mitigate the unexpected loss in welfare.

Firstly, the observed decline in household expenditure might not necessarily be accompanied by a decline in household resources. During the Covid-19 lockdown, there was a natural limitation on spending of household resources; the inability to spend on social functions or hospitality and non-food items was characteristic of the strict lockdown experienced in Comoros. . However, our evaluation suggests a decrease in household resources driven by a decline in the share of people employed in a household and individuals in employment leading to a temporal shock in income. Our findings are in close comport with Simone et al. (2021) as their evaluation provides evidence of a negative impact of the Covid-19 lockdown on employment in Ghana. There was no evidence of a change in working hours and total salary for those that remain employed. The implication of the lockdown measure in Comoros is a decline in employment opportunities mostly within the service and trade sectors and reduced income generation.

Secondly, the lack of income flow and inability to contact family or friends to smooth welfare consequences can make households resort to coping mechanisms that erode their savings. In our analysis, household asset ownership provides a dynamic coping strategy for households. The decline in expenditure and increase in poverty is found to be accompanied with households selling assets and evidence suggests that it is the most expensive assets that were sold. In developing studies, assets are the equivalents of savings. Our findings support the evidence of the Covid-19 pandemic leading households to resort to unconventinal coping mechanisms

since the nature of the pandemic rendered typical coping mechanisms such as borrowing from family and friends difficult (see Gupta et al., 2021; Rönkkö et al., 2021).

Finally, the implementation of lockdown measures has lingering effects. The cost-benefit approach to understanding the trade-off between pandemic curtailment and socio-economic consequences is vital for developing countries. The nature of the infrastructure of a developing country's health sector is a critical consideration in a virus outbreak. During the Covid-19 pandemic, developed and developing countries resorted to the same lockdown measures, regardless of the number of confirmed cases. However, the welfare policies enacted in developed countries like wage security and other income benefits for households are lacking in developing countries. Government safety nets directed at all households and not just a specific few are an essential tool in mitigating a lockdown's restrictive welfare consequences. Developing countries' agendas have revolved around increasing growth and reducing poverty and inequality. The observed outcome for Comoros is an increase in the overall poverty rate and reduced welfare across the welfare distribution. Therefore, while pro-poor policies remain important, mitigating the impacts for less poor households will also be important to prevent their falling into poverty.

## Conclusions

This paper has examined the impact of the Covid-19 pandemic on household expenditure, poverty status, asset ownership, and labor market outcomes for Comoros, a country that was already grappling with a recent climatic shock to its economy. We used a unique door-to-door household survey data collected during the Covid-19 outbreak in Comoros, covering the pre-lockdown and post-lockdown periods. The data provide detailed information on household expenditure, asset count and monetary value, livestock ownership, and relevant household and

individual labor market outcomes. In addition, the availability of other household and individual characteristics allowed us to address endogeneity concerns in the estimation of the effect of the national lockdown policy on the welfare of households in Comoros.

We first evaluated the impact of the national lockdown implemented on 23 March 2020 by the government of Comoros on our welfare indicators and labor market outcomes. Then, we extended our analysis to evaluate the distributional impact on household expenditure. Our empirical research benefitted from descriptive analysis and causal estimation methods. Our empirical study found a negative effect of the national lockdown on household expenditure, and an increase in the poverty rate. The impact is observed across the expenditure distribution with increasing magnitude at the top of the distribution. Households were also found to subjectively assess their living status as having experienced difficulties due to the pandemic. The negative impact on welfare appears to be driven by a decline in employment and the share of working individuals in a household.

Furthermore, the analysis also highlighted a pronounced negative impact within three months of the lockdown measure. There is some evidence of recovery post-three months, but welfare indicators remain below pre-lockdown levels. Our findings suggest that the pandemic's negative effect on Comoros's household welfare status goes far beyond the immediate lockdown period and may be long lasting. Furthermore, our results showed a substantial decline in the total monetary value of assets but small decline in the count of assets and livestock . The evidence thus indicates that households likely engaged in selling their expensive assets to cope during the pandemic due to the cessation of conventional coping strategies, like help from family and friends, and limits to income-generating activities. In addition, the anticipation of the national lockdown also had negative welfare consequences.

Our study contributes to the understanding of the micro-level impact of national lockdown policies during the Covid-19 pandemic on household welfare in a developing country context where direct impacts from Covid-19 cases may be low but the impacts from disruptions in economic activity may be large. Development is a holistic process, and an unprecedented shock from a disease outbreak can put pressure on developing countries economic status and goals. The trade-off between economic gains and managing the outbreak can exacerbate the vulnerability to poverty. However, repercussions for the health sector, deaths, and the potential destruction of trust in governance in a developing context are policy considerations regarding lockdown measures. Therefore, the pandemic not only stopped economic activities, but the overall outcome for Comoros was a reduction in welfare and an increase in poverty and households coping by using their cash reserves in the form of assets and livestock ownership. In the absence of other possible welfare coping mechanisms when a household is hit by a shock, like help from families and borrowing from banks or informal lending agents, government safety nets may have mitigated the impact. The non-availability of government safety nets and direct welfare-enhancing policies is likely to prolong the negative impact of the lockdown, with a slow recovery.

## Appendix

**Figure A1: The post-match distribution of propensity scores across treatment and control**

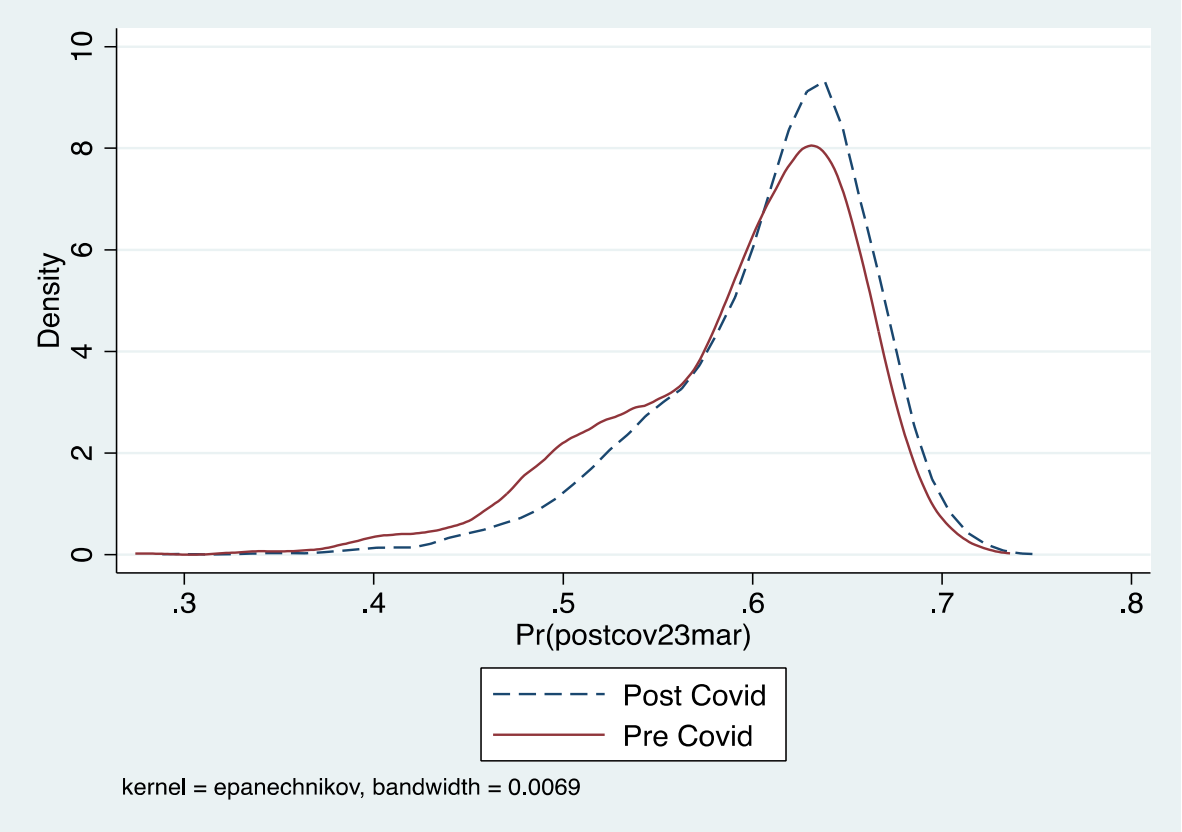



**Table A 1: Sample Distribution of individuals interviewed by Region and Lockdown Measure**

| | FREQUENCY | PERCENT |
|---|---|---|
| **Total Pre-covid sample** | **11,712** | |
| *Regional Composition:* | | |
| Moroni | 704 | 6.01 |
| Ngazidja | 5,715 | 48.8 |
| Ndzuwani | 4,476 | 38.22 |
| Mwali | 817 | 6.98 |
| **Total Post-covid sample** | **17,480** | |
| *Regional Composition:* | | |
| Moroni | 2,535 | 14.5 |
| Ngazidja | 6,851 | 39.19 |
| Ndzuwani | 7,277 | 41.63 |
| Mwali | 817 | 4.67 |

**Table A 2: Summary Statistics of Employment Distribution across the four main Sectors***

| Employment Type | *Freq.* | *Percent* | *Cum.* |
|---|---|---|---|
| Agriculture and forestry | 3,148 | 33.93 | 33.93 |
| extractive activities | 52 | 0.56 | 34.49 |
| Manufacturing activities | 429 | 4.62 | 39.11 |
| Water, Electricity and Gas | 84 | 0.91 | 40.02 |
| Construction | 606 | 6.53 | 46.55 |
| Wholesale, retail and repair | 483 | 5.21 | 51.75 |
| Hotel and catering | 121 | 1.3 | 53.06 |
| Transport, auxiliary activities | 402 | 4.33 | 57.39 |
| Financial activities | 176 | 1.9 | 59.28 |
| Real estate, rentals and services | 70 | 0.75 | 60.04 |
| Public administration activities | 742 | 8 | 68.04 |
| Education | 856 | 9.23 | 77.26 |
| Health and social action activities | 148 | 1.59 | 78.86 |
| Sanitation, roads and waste management | 11 | 0.12 | 78.97 |
| Community activities | 72 | 0.78 | 79.75 |
| Recreational,and cultural | 18 | 0.19 | 79.94 |
| Personal service activities | 1,349 | 14.54 | 94.48 |
| Household activities as an employee | 474 | 5.11 | 99.59 |
| Activities of extraterritorial organizations | 38 | 0.41 | 100 |

Note: *the main sectors are agriculture, Industry, Trade, and Service

**Table A3: Logit PSM Regression for Treatment Assignment**

| Variables | Post-Covid |
|---|---|
| Age of head of household | 0.016*** |
| | (0.006) |
| Squared age of head of household | -0.000*** |
| | (0.000) |
| Education of head of household (currently in school) | -0.695*** |
| | (0.149) |
| Education of head of household (primary) | -0.105** |
| | (0.050) |
| Education of head of household (lower secondary) | -0.035 |
| | (0.054) |
| Education of head of household (upper secondary) | -0.172*** |
| | (0.066) |
| Education of head of household (tertiary) | -0.041 |
| | (0.055) |
| Marital status head of household (married) | 0.335*** |
| | (0.077) |
| Marital status head of household (widowed) | 0.311*** |
| | (0.103) |
| Marital status head of household (divorced) | 0.337*** |
| | (0.096) |
| Polygamous household | -0.078 |
| | (0.057) |
| Dependency ratio | -0.129*** |
| | (0.018) |
| Number of working-age individuals in household | -0.083*** |
| | (0.009) |
| Access to water | 0.344*** |
| | (0.042) |
| Access to sanitation | 0.052* |
| | (0.030) |
| Access to electricity | -0.043 |
| | (0.043) |
| Improved floor | -0.032 |
| | (0.042) |
| Improved roof | 0.546*** |
| | (0.160) |

| | |
|---|---|
| Location (rest of Ngazidja) | 0.215*** |
| | (0.065) |
| Location (Ndzuwani) | 0.137** |
| | (0.068) |
| Location (Mwali) | -0.283*** |
| | (0.088) |
| Male | -0.006 |
| | (0.030) |
| Age | 0.010** |
| | (0.005) |
| Squared age | -0.000** |
| | (0.000) |
| Education attainment (primary) | 0.105** |
| | (0.053) |
| Education attainment (lower secondary) | 0.059 |
| | (0.051) |
| Education attainment (upper secondary) | 0.141** |
| | (0.057) |
| Education attainment (tertiary) | 0.063 |
| | (0.058) |
| Marital status (married) | -0.067 |
| | (0.054) |
| Marital status (widowed) | 0.032 |
| | (0.106) |
| Marital status (divorced) | -0.076 |
| | (0.097) |
| Constant | -0.912*** |
| | (0.242) |
| **Observations** | **21,141** |

Standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

## Table A4: Covariate Balancing Test Using Post-Covid Treatment Measure

| | Mean | | | | t-test | | |
|---|---|---|---|---|---|---|---|
| **Variable** | **Treated** | **Control** | **%bias** | **% reduction \|bias\|** | **T** | **p > \|t\|** | **Variance ratio** |
| Age of Head of Household | 47.78 | 47.79 | 0.00 | 99.50 | 0.01 | 0.99 | 1 |
| Squared Age of Head of Household | 2462.90 | 2463.50 | 0.00 | 98.40 | -0.04 | 0.97 | 0.98 |
| Educ. Head of HH (Currently in School) | 0.01 | 0.01 | 1.30 | 81.70 | 1.29 | 0.20 | . |
| Educ. Head of HH (Primary) | 0.12 | 0.12 | -0.90 | 56.50 | -0.75 | 0.45 | . |
| Educ. Head of HH (Lower Secondary) | 0.10 | 0.10 | -0.60 | -13.20 | -0.45 | 0.65 | . |
| Educ. Head of HH (Upper Secondary) | 0.06 | 0.06 | -0.60 | 72.50 | -0.50 | 0.62 | . |
| Educ. Head of HH (Tertiary) | 0.11 | 0.11 | 0.90 | 46.60 | 0.69 | 0.49 | . |
| Marital Status Head of HH (Married) | 0.84 | 0.85 | -2.40 | -71.00 | -1.99 | 0.05 | . |
| Marital Status Head of HH (Widowed) | 0.05 | 0.05 | 1.60 | -6.10 | 1.27 | 0.21 | . |
| Marital Status Head of HH (Divorced) | 0.07 | 0.06 | 1.50 | 3.00 | 1.20 | 0.23 | . |
| Polygamous Household | 0.07 | 0.07 | -1.60 | -85.20 | -1.27 | 0.20 | . |
| Dependency Ratio | 0.91 | 0.94 | -3.90 | 17.40 | -3.20 | 0.00 | 1.02 |
| Number of Working-Age People in HH | 3.65 | 3.68 | -1.80 | 78.10 | -1.54 | 0.12 | 1.03 |
| Water Access | 0.88 | 0.88 | -0.70 | 93.60 | -0.59 | 0.55 | . |
| Sanitation Access | 0.58 | 0.58 | 0.90 | 73.10 | 0.74 | 0.46 | . |
| Electricity Access | 0.85 | 0.85 | -0.50 | 78.90 | -0.36 | 0.72 | . |
| Improved Floor | 0.84 | 0.84 | -1.20 | -76.10 | -0.93 | 0.35 | . |
| Improved Roof | 0.99 | 1.00 | -1.00 | 82.40 | -1.03 | 0.30 | . |
| Location (Rest of Ngazidja) | 0.52 | 0.51 | 0.20 | 86.30 | 0.20 | 0.84 | . |
| Location (Ndzuwani) | 0.39 | 0.40 | -0.90 | 79.20 | -0.75 | 0.46 | . |
| Location (Mwali) | 0.04 | 0.04 | 0.50 | 94.60 | 0.44 | 0.66 | . |
| Individual is Male | 0.48 | 0.48 | -0.60 | -16.80 | -0.44 | 0.66 | . |
| Age of Individual | 33.36 | 33.23 | 0.70 | -48.30 | 0.53 | 0.59 | 0.98 |
| Squared Age of Individual | 1449.00 | 1445.90 | 0.20 | 66.70 | 0.16 | 0.87 | 0.99 |
| Educ. Att. of Individual (Primary) | 0.17 | 0.17 | -0.50 | -132.20 | -0.41 | 0.68 | . |
| Educ. Att. of Individual (Lower Secondary) | 0.20 | 0.20 | -1.40 | -47.00 | -1.15 | 0.25 | . |
| Educ. Att. of Individual (Upper Secondary) | 0.12 | 0.11 | 1.40 | 37.70 | 1.10 | 0.27 | . |
| Educ. Att. of Individual (Tertiary) | 0.12 | 0.11 | 1.30 | -245.50 | 1.07 | 0.28 | . |
| Marital Status of Individual (Married) | 0.46 | 0.46 | -0.20 | 89.30 | -0.13 | 0.90 | . |
| Marital Status of Individual (Widowed) | 0.04 | 0.03 | 1.10 | 23.20 | 0.88 | 0.38 | . |
| Marital Status of Individual (Divorced) | 0.04 | 0.04 | 0.50 | -51.00 | 0.40 | 0.69 | . |

Notes: * 'of concern', i.e. variance ratio in [0.5, 0.8) or (1.25, 2];
** 'bad', i.e. variance ratio < 0.5 or > 2

## Table A5: Rubin's Balancing Property Diagnostics

| Sample | Ps R2 | LR chi2 | p > chi2 | Mean Bias | Med Bias | B | R | % Var |
|---|---|---|---|---|---|---|---|---|
| **Unmatched** | 0.011 | 316.44 | 0 | 2.7 | 1.6 | 24.9 | 0.78 | 100 |
| **Matched** | 0.001 | 36.48 | 0.229 | 1 | 0.9 | 7.6 | 1.19 | 17 |

Note: * B > 25%, R outside [0.5; 2]

## Table A6: Raw Difference in the Log of Per Capita Household Expenditure between treatment and control by Quantiles

| Quantiles | Control | Treatment Covid-19 | Difference |
|---|---|---|---|
| $10^{th}$ | 12.577 | 12.540 | -0.037*** |
| | (0.008) | (0.006) | (0.010) |
| $20^{th}$ | 12.884 | 12.836 | -0.047*** |
| | (0.008) | (0.006) | (0.010) |
| $50^{th}$ | 13.233 | 13.197 | -0.036*** |
| | (0.007) | (0.006) | (0.009) |
| $75^{th}$ | 13.623 | 13.598 | -0.025** |
| | (0.008) | (0.007) | (0.011) |
| $90^{th}$ | 14.015 | 13.988 | -0.027 |
| | (0.009) | (0.010) | (0.013)** |

Note: Statistical significance: *** p < 0.01, ** p < 0.05, * p < 0.1
Difference" captures the raw difference between the post-Covid sample (treatment) and the pre-Covid sample (control).
Standard errors in parenthesis

**References**

Alon, T., Doepke, M., Olmstead-Rumsey, J. and Tertilt, M., 2020. *The impact of COVID-19 on gender equality* (No. w26947). National Bureau of economic research.

Andersson, C., Mekonnen, A. and Stage, J., 2011. Impacts of the Productive Safety Net Program in Ethiopia on livestock and tree holdings of rural households. *Journal of Development Economics*, *94*(1), pp.119-126.

Arndt, C. and Lewis, J.D., 2001. The HIV/AIDS pandemic in South Africa: Sectoral impacts and unemployment. *Journal of International Development: The Journal of the Development Studies Association*, *13*(4), pp.427-449.

Atkeson, A., 2020. On using SIR models to model disease scenarios for COVID-19. *Quarterly Review*, *41*(01), pp.1-35.

Brewer, M., and Gardiner, L., "The initial impact of COVID-19 and policy responses on household incomes." Oxford Review of Economic Policy, 36, S187-S199, 2020.

Ceballos, F., Kannan, S. and Kramer, B., 2020. Impacts of a national lockdown on smallholder farmers' income and food security: Empirical evidence from two states in India. *World Development*, *136*, p.105069.

Dercon, S., 2002. Income risk, coping strategies, and safety nets. *The World Bank Research Observer*, *17*(2), pp.141-166.

Dixon, S., McDonald, S. and Roberts, J., 2002. The impact of HIV and AIDS on Africa's economic development. *BMJ*, *324*(7331), pp.232-234.

Dunford D., Dale B., Stylianou N., Lowther E., Ahmed M., De la Torres Arenas I. 2020. Coronavirus: The World in Lockdown in Maps and Charts. Retrieved from https://www.bbc.com/news/world-52103747.

Egger, D., Miguel, E., Warren, S.S., Shenoy, A., Collins, E., Karlan, D., Parkerson, D., Mobarak, A.M., Fink, G., Udry, C. and Walker, M., 2021. Falling living standards during the COVID-19 crisis: Quantitative evidence from nine developing countries. *Science Advances*, *7*(6), p.0997.

Gupta, A., Zhu, H., Doan, M.K., Michuda, A. and Majumder, B., 2021. Economic Impacts of the COVID− 19 Lockdown in a Remittance-Dependent Region. *American Journal of Agricultural Economics*, *103*(2), pp.466-485.

Heckman, J.J., Ichimura, H. and Todd, P.E., 1997. Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, *64*(4), pp.605-654.

Janssen, M., Chang, B.P., Hristov, H., Pravst, I., Profeta, A. and Millard, J., 2021. Changes in food consumption during the COVID-19 pandemic: analysis of consumer survey data from the first lockdown period in Denmark, Germany, and Slovenia. *Frontiers in nutrition*, *8*, p.60.

Kikuchi, S., Kitao, S. and Mikoshiba, M., 2020. Heterogeneous vulnerability to the covid-19 crisis and implications for inequality in Japan. *Discussion papers*, *20039*.

Lone, S.A. and Ahmad, A., 2020. COVID-19 pandemic–an African perspective. *Emerging microbes & infections*, *9*(1), pp.1300-1308.

Piyapromdee, S. and Spittal, P., 2020. The income and consumption effects of covid-19 and the role of public policy. *Fiscal Studies*, *41*(4), pp.805-827.

Porteous, O., 2020. Economics research on Africa is unevenly distributed between countries. *Africa at LSE*.

Rönkkö, R., Rutherford, S. and Sen, K., 2021. *The impact of the COVID-19 pandemic on the poor: Insights from the Hrishipara diaries* (No. wp-2021-46). World Institute for Development Economic Research (UNU-WIDER).

Rosenbaum, P.R. and Rubin, D.B., 1985. Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, *39*(1), pp.33-38.

Rubin, D.B., 2001. Using propensity scores to help design observational studies: Application to the tobacco litigation. *Health Services and Outcomes Research Methodology*, *2*(3), pp.169-188.

Sathyamala, Christina, 2020, COVID-19: a biopolitical odyssey. ISS Working Paper No. 667, Erasmus University ISS: The Hague.

Schotte, S., Danquah, M., Osei, R.D. and Sen, K., 2021. *The labour market impact of COVID-19 lockdowns: Evidence from Ghana* (No. wp-2021-27). World Institute for Development Economic Research (UNU-WIDER).

Smith, J.A. and Todd, P.E., 2005. Does matching overcome LaLonde's critique of nonexperimental estimators? *Journal of Econometrics*, *125*(1-2), pp.305-353.

Sumner, Andy, Chris Hoy, and Eduardo Ortiz-Juarez. 2020. Estimates of the Impact of COVID-19 on Global Poverty. UNU-WIDER, April, 800-9. Available at: https://www.wider.unu.edu/sites/default/files/Publications/Working-paper/ PDF/wp2020-43.pdf

Swinnen, J. and Vos, R., 2021. COVID-19 and impacts on global food systems and household welfare: Introduction to a special issue. *Agricultural Economics*, *52*(3), pp.365-374.

Townsend, R.M., 1994. Risk and insurance in village India. *Econometrica: journal of the Econometric Society*, pp.539-591.

United Nations, 2020, Sustainable Development Goals, Comoros, 2020. http: Comoros voluntary national review 2020

van Bergeijk, P.A., 2021. The political economy of the next pandemic. *Available at SSRN 3831710*.

Williams, R., 2012. Using the margins command to estimate and interpret adjusted predictions and marginal effects. *The Stata Journal*, *12*(2), pp.308-331.

World Bank, 2010. *Comoros - Joint IDA-IMF staff advisory note and the poverty reduction and growth strategy paper (English).* Washington, D.C.: World Bank Group.

World Bank, 2020. *The World Bank in Comoros Overview*. Washington, D.C.: World Bank Group.

World Population Review, 2021. *Poorest Countries in the World 2021.* World Population Review. https://worldpopulationreview.com/country-rankings/poorest-countries-in-africa