Three Essays in Health and Labour Economics

by

Akbar Zamanzadeh

Ph.D. in Econometrics, the UMZ, Iran

M.A. in Theoretical Economics, the SBU, Iran

A thesis submitted for the degree of

Doctor of Philosophy in Applied Economics

UniSA Business



University of South Australia

December 2022

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Summary

This thesis covers three important topics in health and labour economics. The first two empirical chapters are connected to the recent health crisis, the coronavirus (COVID-19) pandemic. The third chapter investigates the association between labour market policy outcomes and crime rates.

The COVID-19 disease was named as a pandemic by the World Health Organization (WHO) and is causing death, spreading human suffering, and upending people's lives. It increases inequality, exclusion, discrimination and unemployment. However, because it is a new phenomenon, little is known about the social and economic environments that may be contributing to the spread of the virus. The first empirical chapter of this Ph.D. research project aims to show what factors explain differences in the infection rate of COVID-19 in 37 lower and middle-income countries. In this process, high dimensional regression methods are used to identify the specific factors among a large number of potential factors such as population density, adult educational level, smoking prevalence, income inequality, age structure, measures relating to international travel, health spending, health equipment, number of physicians, nurses and hospital beds and COVID-related government interventions. Findings show that school closure, contact tracing and stay-at-home restrictions significantly mitigate the infection rate in LMCs. In this regard, school closure and contact tracing have the highest effect compared to other interventions. However, no significant correlation between business closures and infection rates has been found. Further, the results confirm that the testing and infection rates are positively correlated with each other during the early stages of the pandemic. The findings revealed that the economic support package to households is negatively associated with the infection rate. The estimated coefficients also suggested that infections become higher in countries with greater income inequality, higher tourist inflows, poorly educated adults, and weak governance quality. The second empirical chapter provides robust statistical evidence based on individual level multi-country data to examine the impact of job loss on different measures of mental wellbeing loss, such as anxiety, boredom, insomnia, and loneliness. It also explores the association between several socioeconomic and demographic factors on mental wellbeing loss, such as gender, housing mortgage, age, income, living areas, smoking habits, and attendance of religious services. It has been found that COVID-induced job loss leads to mental

wellbeing deterioration. This study showed that the risk of mental wellbeing loss is high for women, young people, residents of urban and semi-urban areas, as well as smokers.

The third empirical chapter examines the correlation between minimum wage policy and crime rates in the US. A statistical method based on a Bayesian framework; a multi-kink quantile technique is developed to find a threshold for minimum wage policy over each part of the distribution of crime rate. This can give a broad understanding of asymmetric effects of policy action over different segments of the conditional distribution of crime. The findings show that an increase in minimum wage on each segment of violent and property crime rates is negative. Also, results support the asymmetric impact of minimum wage on crime rates in the US.

Declaration

This thesis presents work carried out by myself and does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; to the best of my knowledge, it does not contain any materials previously published or written by another person except where due reference is made in the text; and all substantive contributions by others to the work presented, including jointly authored publications, are clearly acknowledged.

Akbar Zamanzadeh

[AZaman] [December 2022]

Acknowledgments

I would like to thank my Ph.D. supervisors Associate Professor Tony Cavoli, Associate Professor Rajabrata Banerjee and Professor Marc K. Chan, for their insightful comments. In addition, I would like to thank the two thesis examiners, as they provided valuable comments.

Besides providing excellent academic advice, I appreciated the support of my supervisors during my studies. As an ideal supervision panel they have exceeded my expectations. Continuing my Ph.D. studies would not have been feasible without the funding offered by the University of South Australia. This support enabled me to complete my doctoral studies, and I am very grateful for it. I am also thankful to the Business School and Centre for Markets, Values and Inclusion (CMVI) for providing an excellent research environment, valuable feedback from several internal forums, and wonderful administrative assistance. In particular, I would like to express my gratitude to Marie Feo for making the administrative process as easy as possible for me.

I would not be at this stage in my life without my family's support, especially that of my wife, Zara. My deepest gratitude goes out to her for her support and for giving me hope during difficult times. I am very indebted to my children, Adrian and Benyamin, as I was not able to spend enough time with them due to my studies.

Finally, I would like to express my gratitude to my parents and my parents-in-law for their support throughout my Ph.D. study and my life.

Chapter 1 Introduction

This thesis aims to examine effects of health and labour market policies on several ongoing socioeconomic and health challenges across different nations. It provides insights into how appropriate health and labour market policies can mitigate or control crucial social outcomes. This study considers three important social outcomes: pandemic-related infection rate, mental wellbeing loss, and crime rate. This chapter proceeds as follows: Section 1.1 presents the motivations for this Ph.D. research. Section 1.2 explains research objectives and questions. The contribution of the study is given in Section 1.3. Finally, Section 1.4 describes the structure of upcoming parts of the thesis.

1.1. Research Motivation

The World Health Organization (WHO) declared COVID-19 as a pandemic causing death and illness across the globe. This crisis severely impacted lower and middle-income countries (LMCs), characterised by high-income inequality, lack of financial resources, weak governance quality, and fragile health systems. As such, implementing proper policy actions, especially at the initial stage of the spread of the virus, could have saved people's lives and burdened lower cost to communities. Awareness of the impact of different health policies enlightens as to which intervention is more effective for controlling such infectious diseases, particularly if the crisis occurs again in future. Hence, the first empirical study answers the question, "Which types of policy intervention are more effective in controlling the spread of COVID-19?" This information enables policymakers to prevent or mitigate the spread of the virus by implementing suitable public health policies. This study analyses government interventions in LMCs to investigate how different instruments of public health policy decrease the infection risk of COVID-19. Hence, the study is motivated to provide policy guidelines for such vulnerable nations to control the spread of the contingent virus in the early phase of the outbreak.

The COVID-19 pandemic created an unprecedented challenge and affected tens of millions of people across the globe. It not only caused a humanitarian crisis via infecting and killing people but also caused mental health disorders. The World Health Organisation (2020), based on information from 130 countries, indicates that the

coronavirus crisis worsened mental health worldwide. Additionally, a report from the Organization of Economic Cooperation and Development (2021) stresses that the COVID-19 crisis heightens the risk of mental disorders through rising financial insecurity and unemployment as well as the fear of the virus. Even though unemployment caused by the Coronavirus pandemic has an adverse effect on mental health, fewer studies examine the impact of the labour market change on mental illness. In the second empirical chapter, the research is motivated to find the nexus between unemployment induced by the pandemic as a labour market outcome and mental wellbeing during COVID-19. This study answers an important question; what are the mental health effects of job loss imposed by the pandemic? There are several studies like Chatterjee et al. (2021), Posel et al. (2021) and Griffiths et al. (2021) which mention that unemployment can affect the mental wellbeing of people more during the pandemic. As a result, being aware of the association between labour market variables and mental disorders helps policymakers and health authorities to control this problem through implementing suitable labour market policy.

The third research study focuses on labour economics and examines a relationship between minimum wage and crime in the US. Theoretically, an increase in minimum wage has two possible effects on crime rate: on the one hand, increasing minimum wage reduces the likelihood of committing crimes because the relative return of working increases compared to criminal activities (Becker, 1968; Gogger, 1998). On the other hand, raising the minimum wage leads to increased unemployment because labour costs are increased and firm demand for labour is decreased due to the increased minimum wage (Neumark and Wascher, 1992, Baker et al.,1999; Kabetek, 2021). Therefore, the probability of losing jobs surges for vulnerable labour forces such as teens and young adults characterised as low-wage earners or low-skill workers. As a result of increased unemployment; crime rate increases. Since these two effects are opposite, it is unclear what the marginal effect of minimum wage increase is on crime. This study aim to answer an important question; what is the effect of minimum wage on crime? These approaches may be explained by asymmetric effects of minimum wage on crime. In this regard, minimum wage can have a pull effect on crime rate when it is above a threshold, or it might have a push effect when minimum wage is below a tipping point. Awareness of these asymmetric effects may give policymakers a more accurate guideline when the minimum wage exceeds an unknown threshold.

1.2. Research Objectives and Questions

The research covers three important objectives in health and labour economics. The objective of the first study is to answer how governments respond to overcome the Coronavirus challenge in the first 100 days of the outbreak. Implementing appropriate policy is crucial during such a "golden period" when the virus has not spread widely in the community. This study considers a number of policy instruments besides several economic factors to evaluate the impact of all possible variables on the spread of COVD-19. The study answers two important questions, "which factors contribute more towards the spread of the virus in lower and middle-income countries (LMCs)?" and "How do government interventions effectively control the spread in the early phase of the pandemic?". Employing high-dimensional regression methods, the research aims at finding the influential factors that restrict the spread of Coronavirus in lower and middle-income countries (LMCs) during the early stages of the pandemic.

The second project's objective is to learn whether job losses which occurred due to the pandemic impact mental wellbeing. This research aims to find the nexus between unemployment induced by the pandemic and mental wellbeing loss during COVID-19. In this regard, four different indicators of wellbeing, namely anxiety, insomnia, boredom, and loneliness are considered. Six different countries are examined to test the association. They are China, Italy, Japan, South Korea, the UK and the US. Since one group of countries in the sample, like China and South Korea, experienced an early peak of COVID-19 infections, separate analyses were performed for countries with early vs delayed peak infections. This research answers a main question; which type of mental illnesses (based on severity) is impacted more by job loss due to pandemic?. Hence, being aware of the association between unemployment and mental disorders can provide insight to policymakers and health authorities to control this problem via implementing suitable labour market policy. The study also answers several essential questions to identify groups which are more vulnerable during the pandemic. Other important questions addressed are: Does mental wellbeing loss occur more often among females compared to males during the pandemic? Are financially challenged individuals more prone to mental health problems? Does living in urban areas rather than rural ones exacerbate mental health disorders? Are youth more prone to mental issues than older people? Are people with smoking habits prone to mental wellbeing loss?

The third study aims to find asymmetric effects of minimum wage policy on the conditional distribution of violent and property crime in the US. It examines two different asymmetric effects: (1) asymmetries across quantiles of crime rate and (2) asymmetries based on a threshold level of minimum wage. In this regard, the project answers the question, "what is the threshold effect of the minimum wage over the conditional distribution of the crime rate in each state?". Finding state-level thresholds is more informative for policymaking, and it is more efficient than conventional aggregate panel threshold models. In fact, it brings insight to policy makers in each state to understand the critical value of minimum wage across different segments of conditional distribution of crime. This aspect can provide valuable information to both national and local governments about the consequences of the minimum wage policy on the perpetration of criminal activities.

1.3. Research Contribution

This PhD thesis makes several contributions to the body of existing literature in health and labour economics through providing policy implications of controlling COVID-related infections and mental health deteriorations as well as preventing crime. For instance, the first study analyses the effect of government health policy on the spread of COVID-19 through three broad channels. First, it examines how government nonpharmaceutical interventions change the COVID-19 infection rate in LMCs by considering policy actions such as school and business closures, stay-at-home requirements, contact tracing, and testing policy. Secondly, it explores whether government economic support to households diminishes the infection rate in LMCs. Third, the study examines how socioeconomic factors such as density of population, average years of an adult's education, income inequality, international tourism arrivals, health care workers, and institutional quality affect the risk of infection. Rather than focusing on specific variables of interest, a data-driven approach is taken by examining many covariates to uncover the most important determinants of infection rate.

The second study contributes to the literature in several ways. Job loss leads to a series of mental issues because of a grief-like reaction for unemployed people (Archer and Rhodes, 1993). However, there is little known about the multidimensional side effects of job loss on mental health after the pandemic at an international level. This study fills this gap in the literature and analyse the impact of job loss on different measures of mental illness

such as anxiety, boredom, insomnia and loneliness. This approach allows us to understand which aspects of wellbeing are affected more by the labour market variations. As another contribution, this study introduces an indicator of mental wellbeing loss by combining these four dimensions of mental wellbeing loss. Then, the hypothesis is tested based on this combined index to realise how overall individual wellbeing reacts to job loss. Also, many researchers analyse the effect of the pandemic on wellbeing based on one country's information. To have a broad picture of this association, I use a rich set of cross-country microdata. I disentangle the dataset into two groups of countries; one is the countries that overcame the spread of the virus while gathering the data. The second group includes countries struggling with rising or near-peak infection rates when the information was collected. This type of analysis reveals how the mental illness caused by the COVID-19 differs in countries experienced vs early infection peaks.

The third project fills a significant gap in the literature by developing a model in which state-specific thresholds of minimum wages are identified across fifty US states. Since the state governments adjust their minimum wage heterogeneously after the federal decision, an unknown continuous threshold for each state is specified. The value of thresholds in each state determines what the critical value of the minimum wage is across different regions. Accordingly, policymakers can learn how criminal behaviours are heterogeneously changed when the minimum wage exceeds such critical thresholds. This aspect provides valuable information to both national and local governments about the consequences of minimum wage policy on the perpetration of criminal activities. In this project, specifying the unknown continuous heterogenous tipping points, a regression kink design, in a panel model is a notable feature of this research. Finding state-level tipping points is more informative for policymaking, and it is more efficient than conventional panel threshold models. For instance, Hansen (1999, 2017) investigates break points over time. In this context, this research provides a more informative technique compared to the existing literature because it specifies kink designs for each state within a panel data framework. This contribution makes the results more reliable for efficient policymaking. This research adds to the literature by modelling the state-specific tipping points across the conditional distribution of the regression.

1.4. Structure of the Thesis

This thesis provides three studies in health and labour economics. In this regard, each chapter focuses on separate policy relevance to give insights for carrying out suitable economic policy in health and labour markets. Chapter 2 investigates the determinants of COVID-19 infection in the first 100 days of government actions. Using a debiased LASSO estimator, I explore how different measures of government nonpharmaceutical interventions affect new infections of COVID-19 for 37 lower and middle-income countries (LMCs). In this chapter, the debiased LASSO method is based on a panel data framework to show how one can deal with the problem of variable selection when too many variables are included in the model.

Chapter 3 examines the association of mental wellbeing and job loss during the early stages of COVID. Using a rich individual-level dataset from six countries, including China, Italy, Japan, South Korea, the UK and the US, I examine the relationship between job loss and mental wellbeing loss during the early stages of the COVID-19 pandemic. In this regard, four indicators of mental health status based on their severity are considered such as anxiety, insomnia, boredom, and loneliness. Then, an index of mental wellbeing loss is created by combining these four indicators. The sample is also clustered to two sections; countries which faced the peak of the pandemic earlier i.e., China and South Korea vs other countries which experienced the peak of infections later. Chapter 4 analyses the association between minimum wage policy and crime in the US. This chapter examines the asymmetric effects of minimum wage policy on the conditional distribution of violent and property crime in the US. Applying a Bayesian multi-kink panel data method, two different asymmetric effects are investigated: (1) asymmetries across quantiles of an outcome variable and (2) asymmetries below or above a threshold of an explanatory variable. This study adds to the literature by developing multi-kink quantile regression in a Bayesian Panel data framework by specifying heterogenous threshold. Chapter 5 concludes this thesis and recommends future directions.

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Chapter 2 The effect of nonpharmaceutical interventions on COVID-19 infections for lower and middle-income countries: Debiased LASSO Approach[1]

2.1. Introduction

The initial spread of COVID-19 infections presented a series of policy challenges for governments and public health authorities around the world – particularly over the composition and possible magnitude of non-pharmaceutical intervention for policymakers to consider. These policies are important, especially when there is no cure for highly transitive viruses. So, governments enact school and business closures, lockdowns, contact tracing and testing to control the infections in societies. Of all possible options, which are likely to incur economic as well as political costs? Which ones are more effective? This chapter investigates the determinants of COVD-19 infection rates by looking specifically at government actions during the first 100 days of the spread of COVID-19 infections. In fact, analysing the first 100 days in each region is important to understand how governments react to control the spread of the virus when the problem has not heightened. The first 100 days of the coronavirus challenge can be known as a "golden period" for government response because the virus has not prevailed throughout the community.

The study focuses on 37 low to middle-income countries (LMCs) as these countries are characterised by high-income inequality, lack of financial resources, weak governance quality, and fragile health systems. These challenges are said to deepen the health crisis brought about by the pandemic in LMCs.

This study analyses the effect of possible determinants on the spread of COVID-19 through three broad channels. First, the study examines how government nonpharmaceutical interventions might impact the COVID-19 infection rate in LMCs by

[1] A version of this chapter coauthored with Associate Professor Tony Cavoli, my thesis supervisor, is accepted for publication in the PloS One Journal (Scimago Q1 ranked) in 2022. The details of the publication are: "Zamanzadeh, A., & Cavoli, T. (2022). The effect of nonpharmaceutical interventions on COVID-19 infections for lower and middle-income countries: A debiased LASSO approach. *PloS One, 17*(7), e0271586.".

considering policy actions such as school and business closures, stay-at-home requirements, contact tracing, and testing policy. Second, this research explores whether government economic support to households diminishes the infection rate in LMCs. Third, how socio-economic factors such as density of population, average years of an adult's education, income inequality, international tourism arrivals, health care workers, and institutional quality affect the risk of infection has been examined. Rather than emphasizing individual variables of interest and then focusing on issues of causality pertaining to those specific variables, I have taken a data-driven machine learning approach by examining many covariates to uncover the most important potential determinants of infection rate.

It is important to understand whether one can meaningfully reduce the number of covariates that might help to determine infection rates in LMCs. These countries face several challenges such as insufficient education, high income inequality, being deprived of enough health workers, lack of governance quality and so on. Taking into account these features as well as government non-pharmaceutical interventions leads to the issue of facing too many covariates in the model. As such, it is required to firstly deal with the issue of using many covariates in a regression analysis. Tibshirani (1996), Belloni et al. (2014), and Hastie et al. (2015) indicate that applying conventional regression methods like OLS with too many covariates leads to overfitting because the retained variables capture the noise of the regression. These researchers address regularisation of the regression and reduce its dimension by using the least absolute shrinkage and selection operator (LASSO) method. This technique prevents overfitting and generates reliable out-of-sample forecasts when the model has many explanatory variables, and where non-contributing variables are eliminated from the list of potential determinants.

However, more recent studies, such as Zhang and Zhang (2014), Bühlman and van de Geer (2015), van de Geer (2017), Javanmard and Montanari (2018), and Honda (2019) state that the coefficients extracted by LASSO are biased due to the correlation between covariates. To overcome this, they propose the debiased LASSO approach. The asymptotic variance of the debiased LASSO estimator is lower than that of the conventional LASSO estimator (van de Geer, 2017). Although these researchers establish their model relying on time series, this research develops the debiased LASSO model within a panel data framework by taking into account unobserved heterogeneities across sections and over time. This study employs the debiased LASSO method introduced by

Zhang and Zhang (2014) in their paper. This approach produces de-noised coefficients and allows the selection of the most influential variables explaining the variation in COVID-19 infection rates among LMCs, thus providing reliable guidelines for policymaking. There are three major contributions by this study. First, evaluating the effects of government non-pharmaceutical intervention on COVID-related infection rates during the first phase of the COVID. However, no one has looked at this issue yet. Second, this study benefits from a methodological contribution using debiased LASSO to deal with selecting variables efficiently when there are too many covariates in the model. Third, this study provides international evidence of COVID-19 transmission by particular focus on LMCs where people face with socio-economic challenge such as lack of education, insufficient health workers, incompetent governments, and income inequality. Moreover, I perform several robustness tests to ensure the stability of our findings.

This research finds that school closures, stay-at-home restrictions, and contact tracing are particular policies that have the highest effect and can reduce the spread of the Coronavirus in LMCs. However, business closure is not statistically significant for lowering the COVID-19 infection rate as a nonpharmaceutical health intervention. The spread of the virus is negatively correlated with economic support to households, but this effect is not as large as the effects of other nonpharmaceutical interventions. Interestingly, a greater number of health workers leads to a decrease in the number of new infections. Further, our findings show that the greater number of tests infer more infections. Conversely, countries with high-income inequality, a higher arrival rate of tourists, less-educated adults, and poor governance quality experience more infections. Despite using a sample pertaining to the recent infection rates for COVID-19, it has been felt that these results are generalisable and can be used to inform policy actions for other infectious diseases. As a result, sensible policy interventions can reduce infection rates for poorer countries. Further, the economic and institutional environment is also important, thereby justifying the use, and ultimately success, of economic support to households during the initial infection period.

The research is structured as follows: Section 2.2 provides a brief literature survey and some historical context. Section 2.3 provides the empirical model and estimation procedure. Section 2.4 presents the data and the results. Section 2.5 concludes.

2.2. Literature Review

Numerous studies show how infectious diseases like the 1918 influenza, SARS, MRSA, and Avian Flu make human disasters, create economic recessions, change demographic structures, and burden firms, households, and governments with socio-economic costs. However, only the 1918 influenza is comparable with COVID-19 based on the spread and contagion of the virus, the medical limitation, the effect on the respiratory system, and the similarities in government interventions, such as closing public events, locking down societies, and requiring the wearing of masks (Beach et al., 2020). Barro et al. (2020) indicate that the 1918 influenza is the worst-case scenario for COVID-19 outcomes. Therefore, lessons from that great influenza pandemic assist policymakers in controlling current human disaster worldwide. I review public health policy during both the 1918 influenza and COVID-19 to understand how the government responses affect pandemics and the expected health outcomes of these interventions.

Markel et al. (2007) examine how non-pharmaceutical interventions affect the weekly excess death rate during the 1918 influenza in the US. They gather data on the weekly extra death rate for 43 cities over 24 weeks and analyse the impact of three different interventions, namely school closure, cancellation of public gatherings, and isolation (quarantine), on the outcome of the pandemic. According to their findings, non-pharmaceutical interventions significantly mitigate pandemic-related deaths by 74 percent in the United States. Additionally, they state that implementing early non-pharmaceutical health policy leads to a delay of peak mortality. Chapelle (2020) analyses the effect of public restrictions such as school closures and social distancing on the 1918 influenza pandemic. He uses city-level US data and applies the difference-in-differences (DiD) method to evaluate the economic and health benefits of non-pharmaceutical interventions. His medium-run findings reveal that a significant share of people saved during the 1918 pandemic lost their lives during the following years. The research states that in the long term, social distancing probably lowers herd immunity in society. Further, this public health policy reduces the death rate over the short run, especially when the death rate is at its peak. Barro (2020) analyses the impact of three measures of public health interventions, including school closures, prohibitions on public gatherings, and isolation on the excess death rate of 1918 influenza across 45 large US cities. His findings

confirm the negative and significant association between non-pharmaceutical interventions and the peak of the extra death rate. The findings suggest that more interventions flattened the curve for mortality during the 1918 pandemic. However, this effect is weak and insignificant on overall death rates. Barro concludes that government distancing measures for the pandemic probably delay deaths in societies rather than remove them.

Acemoglu et al. (2020) develop the epidemiological Susceptible Infected Recovered (SIR) model to multi-age groups of people above 20 years old, including "young," "the middle-aged," and the "old". Then they show how different government interventions in testing, tracking and group distancing impact infections, deaths, and economic loss. Their specification allows them to evaluate the trade-off between saving lives and GDP due to implementing public health interventions. Their findings reveal that keeping the adult death rate below 0.2 percent needs a strict economic lockdown for more than one year and a half. As a result of this intervention, the US GDP shrinks almost 40 percent in one year. They argue that the government should perform a tough and long lockdown among the most vulnerable group to control infections by maximizing economic benefit. Further, less strict lockdown should be implemented for the young and middle-aged people as the low-risk groups. They show that decreasing the interactions between elders and other groups and increasing testing and isolating the infected ones leads to minimised economic losses and deaths.

Borjas (2020) examines how the spread of Coronavirus is determined via imposing economic and behavioural restrictions in New York City. He uses the fraction of COVID-19 tests yielding a positive result to measure the spread of the virus. The data covers 177 zip codes in New York City. New standards for business activity and stay-at-home indices are defined by using smartphone information. The business activity index is constructed based on the number of people who visited businesses in each zip code. The stay-at-home index is defined by the fraction of smartphones (people) that stayed fixed at their home location during the pandemic. Borjas applies the fixed effects method over calendar date and the zip code of residence to capture unobserved heterogeneities over time and sections. His findings reveal that the number of visits to local businesses is positively correlated with the positivity rate of COVID-19 tests. However, the fixed location of smartphones lowers the likelihood of the positivity rate by 2 percentage points.

Ciminelli and Garcia-Mandico (2020) investigate the effect of business shutdown on COVID-19 deaths in Italy. They gather a substantial dataset across 4,000 Italian municipalities, which covers 222 local labour markets. They define business shutdown as the share of the workers without any essential activities – due to COVID-19 – compared to the total number of employees. Further, some variables like the share of working-age females, the share of high school graduates, and population density are used as other controls. Their findings reveal that business shutdown, especially in the retail trade and hospitality sectors, significantly reduces the COVID-19 death rate. Additionally, the results confirm that performing closure restrictions one week earlier could save 25 percent of the lost lives in Italy. Flaxman et al. (2020) analyse whether public health interventions are efficient in Europe over the first wave of the Coronavirus pandemic. The data covers 11 European countries, including Austria, Belgium, Denmark, France, Germany, Italy, Norway, Spain, Sweden, Switzerland, and the U.K. They use school closure, prohibitions of public events, social distancing, and lockdown decreed as measures of non-pharmaceutical intervention. Their findings demonstrate that economic lockdown has a large impact on reducing virus transmission in Europe.

Overall, the extant literature shows that previous studies have focused on one, or a category of possible determinants of infections. There have been many excellent contributions to this line of research examining the effects of individual variables, including income inequality (e.g., Wildman, 2021), governance quality (Chien and Lin, 2020), tourism flows (Farzanegan et al, 2021), business closures (Ciminelli and Garcia-Mandico, 2020), health care infrastructure (Amdaoud et al., 2021), population density (Hamidi et al., 2020), government interventions (Nader et al., 2021; Liu et al.,2021) and many others. In the sections that follow, a data driven approach is adopted for the selection of the most influential variables that may determine COVID-19 infection rates among LMCs.

2.3. Model and Methodology

A reduced form panel data model with many covariates, following the literature of high-dimensional methods like Zhang and Zhang (2014), Bühlman and van de Geer (2015), van de Geer (2017), Javanmard and Montanari (2018), and Honda (2019), is specified for the first 100 days of the spread of the Coronavirus as follows,

$$Y_{ij,t} = \beta X_{ij,t} + \eta W_{ij,t} + \theta Cou_i + \varphi Con_j + \lambda t + \varepsilon_{ij,t}, \quad (2.1)$$

where Y is the ratio of the new infections per 100,000, X = (X_1, X_2,...,X_n) includes the vector of daily government interventions. Based on Barro (2020), Borjas (2020), Ciminelli and Garcia-Mandico (2020), and Flaxman et al. (2020) several measures of government interventions are considered, such as school and business closures, stay-at-home restrictions, contact tracing, household economic support, and tests per population. W = (W_1,...,W_m) is the vector of country-level socio-economic factors. Based on Hamidi et al. (2020), Chien and Lin (2020), Wildman (2021), Farzanegan et al. (2021), and Amdaoud et al. (2021), W includes population density, average years of adults' education, income inequality, international arrivals per population, and health workers per population in i^{th} country, j^{th} continent and t^{th} period. Accordingly, Cou, Con and t indicate the country, continent and time fixed effects[2]. These fixed effects are utilised to flexibly account for omitted variables within regions and over time. The reason for employing the continent fixed effects is to capture unobserved heterogeneity within regions[3]. The variables are normalised to avoid problems with scaling. Meinshausen and Bühlmann (2006) suggest normalisation of variables because the scale of variables affects regulation of the parameters. This transformation changes the distribution of variables to a normal one with zero mean and unit variance. It means if the model consists of some categorical variables, they will no longer be discontinuous. This normalisation allows us to interpret their coefficients like continuous regressors rather than interpreting each category with regard to a baseline group, case, or condition. Further, due to the normalisation of variables, the model does not include an intercept[4].

Note that these fixed effects do not lead to an unidentifiability issue in the model because the time-invariant variables such as education, income inequality, etc., vary from country to country. Therefore, the time invariants and country or continent fixed effects do not overlap each other. The parameters β, η, θ, φ and λ are the vectors of slopes. ε is the error term.

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[2] There are several studies addressing how employing fixed/random effects for LASSO models leads to more reliable estimates due to capturing unobserved heterogeneities (Ibrahim et al., 2011; Lu and Su, 2016).

[3] I estimate the regression without regional fixed effect as well to show the robustness of the estimates. However, I do not report them for brevity – they are available on request.

[4] Normalised values for a vector of ones are mathematically undefined since bot deviation from mean and standard error of a vector with constant values are zero.

To show the procedure of debiased LASSO, I first simplify our representations and specify the Eq. (2.1) as,

$$Y = Z\psi + \varepsilon. \tag{2.2}$$

Z and ψ reflect for a p-dimensional vector of explanatory variables and their corresponding coefficients, respectively. Based on Zhang and Zhang (2014), firstly, it is necessary to de-correlate the vector of normalised explanatory variables, Z. For this purpose, a LASSO fit is employed on an explanatory variable, Z_j versus all other explanatory variables, Z_{-j}. Here, the dimension of Z_{-j} is $p-1$. Accordingly, the optimisation problem is set as follows,

$$\hat{\gamma}_j = \underset{\gamma \in \mathbb{R}^{p-1}}{\operatorname{argmin}} \left(\frac{\| Z_j - Z_{-j}\gamma \|_2^2}{NT} \right) + \zeta_Z \| \gamma \|_1 . \tag{2.3}$$

Eq. (2.3) satisfies the Karush–Kuhn–Tucker (KKT) optimality condition for the estimates. γ is a vector of coefficients corresponding to Z_{-j}. $\zeta > 0$ is a tuning parameter that is determined by a cross-validation technique. $\|.\|_1$and $\|.\|_2$ are $\ell_1$and ℓ_2 norms[5], respectively. N and T indicate the number of sections (countries) and time. The residuals of Eq. (2.3) are denoted by,

$$M_j = Z_j - Z_{-j}\hat{\gamma}_j. \tag{2.4}$$

Now the vector of residuals defined by Eq. (2.4) is regressed over the response variable in Eq. (2.2) as follows,

$$\psi_j^{\dagger} = \frac{M_j^{Tr}Y}{M_j^{Tr}Z_j} = \psi_j + \sum_{k \neq j} \frac{M_j^{Tr}Z_k}{M_j^{Tr}Z_j}\,\psi_k + \frac{M_j^{Tr}\varepsilon}{M_j^{Tr}Z_j} . \tag{2.5}$$

Eq. (2.5) demonstrates M_j is not orthogonal to Z_j. This issue induces bias in $\psi_j^{\dagger}$. The second part of the decomposition, $\sum_{k \neq j} \frac{M_j^{Tr}Z_k}{M_j^{Tr}Z_j}\,\psi_k$ refers to the bias arising from the existing correlation between the explanatory variables[6]. Here, $M_j^{Tr}Z_k \neq 0$ at least for

[5] $\boldsymbol{\ell_1}$and $\boldsymbol{\ell_2}$ norms are known as "Absolute-value" and "Euclidean" norms, as well. Generally, for a vector of $\boldsymbol{x} = (\boldsymbol{x_1}, \cdots, \boldsymbol{x_i})$, one can define $\boldsymbol{\ell_p}$ norm as, $\| \boldsymbol{x} \|_{\boldsymbol{p}} = (\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} | \boldsymbol{x_i} |^{\boldsymbol{p}})^{\boldsymbol{1/p}}$, where $\boldsymbol{p} \geq \boldsymbol{1}$.

[6] Notes: the correlations among the explanatory variables in models with too many covariates lead to biased estimates using alternative regularisation and variable selection methods, such as Ridge regression and elastic net (Zhang and Politis, 2020; Bascou et al., 2020).

one $k \neq j$. The last term, $\frac{M_j^{Tr}\varepsilon}{M_j^{Tr}Z_j}$ is equal to zero because M_j and ε are orthogonal to each other.

In the second step, Z is regressed over Y through employing the LASSO method. The KKT optimality condition is presented below,

$$\widehat{\psi}^{\,initial} = \underset{\psi \in \mathbb{R}^p}{\operatorname{argmin}} \left(\frac{\| Y - Z\psi \|_2^2}{NT} \right) + \zeta_Z \| \psi \|_1 . \tag{2.6}$$

Now, I deduct the bias term obtained in Eq. (2.5) from each component of the estimated coefficients, $\widehat{\psi}^{\,initial}$. Therefore, the debiased LASSO estimator is shown as follows,

$$\widehat{\psi}_j^{de-biase} = \widehat{\psi}^{\,initial} - \sum_{k \neq j} \frac{M_j^{Tr}Z_k}{M_j^{Tr}Z_j} \widehat{\psi}_k^{initial}, \tag{2.7}$$

where the final bias term is calculated by inserting the coefficient $\widehat{\psi}_k^{initial}$ obtained from Eq. (2.6).

A specific value for each coefficient is obtained after the debiasing procedure because the debiased coefficients now consist of two parts. Then, even though the $\widehat{\psi}^{\,initial}$ is zero, it is likely the second part of Eq. (2.7), $\sum_{k \neq j} \frac{M_j^{Tr}Z_k}{M_j^{Tr}Z_j} \widehat{\psi}_k^{initial}$ will not be zero.

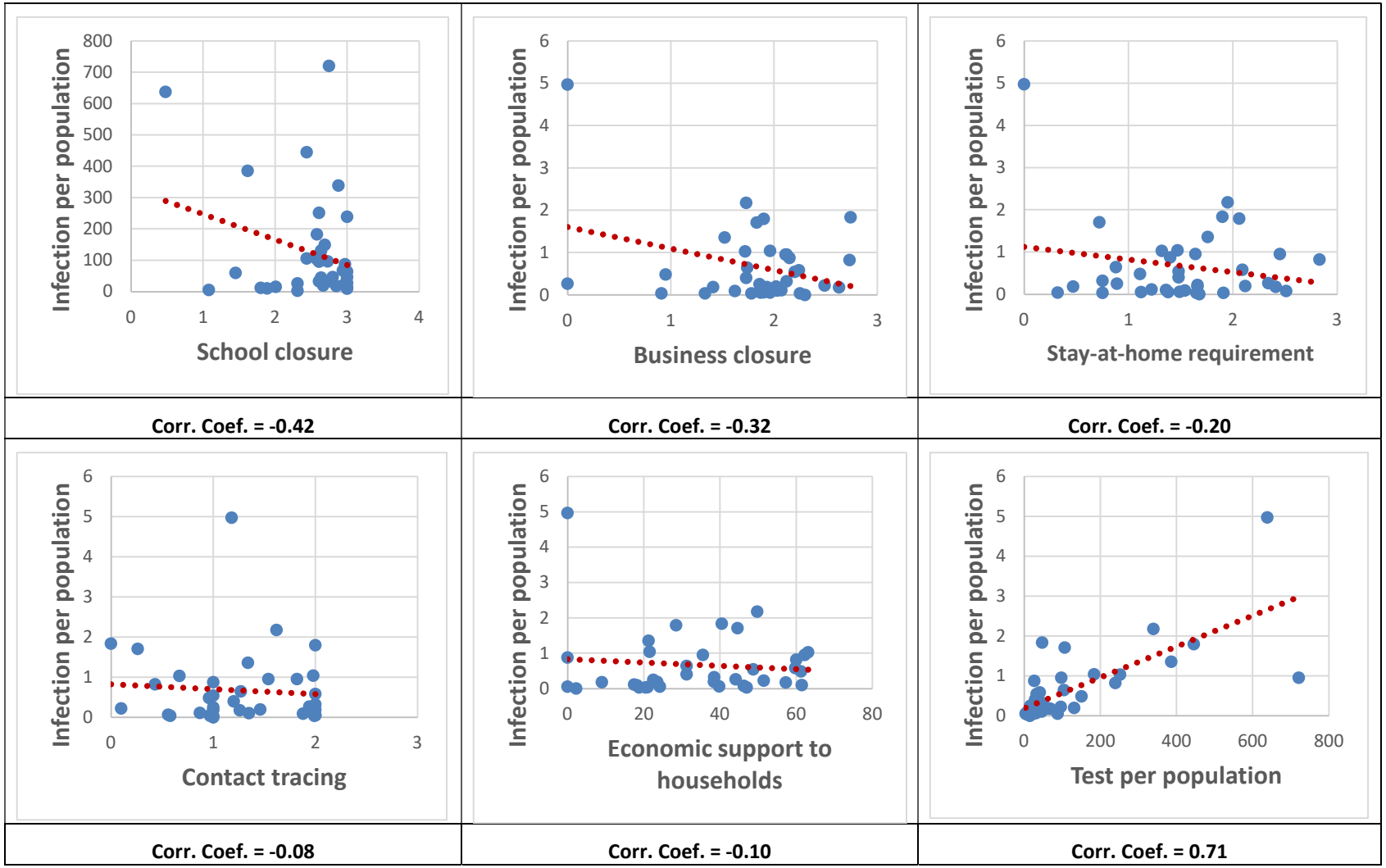
Zhang and Zhang (2014) establish a framework to estimate regression variance for the debiased LASSO method. They show $\tau_j^{-1}\left(\widehat{\psi}_j - \psi_j\right) \approx N(0, \sigma^2)$, where $\tau_j = \frac{\| M_j \|_2}{| M_j^{Tr}Z_j |}$ is known as a "noise factor." Bühlman and van de Geer (2015) show that this condition is satisfied even for misspecified models. Indeed, such inference allows researchers to calculate reliable confidence intervals and p-values for estimates.

2.4. Data, Estimation, and Results

The data covers 37 LMCs across four geographic regions, including 11 African, 12 Asian, 8 Latin American and the Caribbean, and 6 European countries (See Appendix 2A). The sample was chosen based on data availabilities on World Bank and Oxford University websites. The definitions and sources of the data, including measures of interventions and nonpharmaceutical instruments, government support, socio-economic conditions, and health care variables are all reported in Appendix 2B. Figure 2.1 depicts the association between different non-pharmaceutical interventions and the spread of the virus in the

LMCs. The figure reveals that school and business closures, stay-at-home restrictions, contact tracing and economic support have a negative association with the infection rate in the LMCs. In this regard, the highest negative correlation has been seen for school closures. Interestingly, the association between testing policy and infection rate is positive.

Figure 2.1: Scatter plots between infection rate and various instruments of government health policy in LMCs



This chapter considers governance quality as one of the major predictors of COVID-19 infection rate. The intuition for using such a variable is to understand how good or bad governance contributes to the control of the infection rate. As one of the limitations of this research, there is no access to a unique index of governance quality. Accordingly, the governance quality index is created based on Langbein and Knack (2010) by combining six governance dimensions using principal component analysis (PCA). In terms of policy analysis, this unique index is much more informative for policymaking because it reflects the rank of low and middle-income countries in terms of governance quality. As such, countries can learn how their performance in governing societies contributes to combating new diseases. Details of data and method are given in Appendix 2C. In the sample, Iraq has the worst quality of governance with an index value of -1.33, while Malaysia has the best quality of governance with an index value of 1. I also provide a table of descriptive statistics of all covariates in Appendix 2D.

The results are summarised in Table 1 where 9 different models are estimated. Model 1 is the baseline regression in which government nonpharmaceutical interventions explain the infection rate. Model 2 includes government supports to households. I evaluate the effects of other factors one-by-one, Models 3 to 8, to show the robustness of estimates when controls change. Model 9 presents the effects of all policy variables and socio-economic covariates.

Table 2.1. The effects of government interventions on COVID-19 infection rate

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
School closure	**-0.0563****	**-0.0422***	**-0.0608*****	**-0.0511****	**-0.0270**	**-0.0413***	**-0.0395***	**-0.0534***	**-0.0541****
	(0.0226)	(0.0227)	(0.0226)	(0.0230)	(0.0230)	(0.0226)	(0.0226)	(0.0229)	(0.0227)
Business closure	**0.0027**	**0.0010**	**-0.0038**	**0.0104**	**-0.0089**	**-0.0002**	**0.0022**	**-0.0020**	**-0.0158**
	(0.0225)	(0.0223)	(0.0220)	(0.0226)	(0.0225)	(0.0223)	(0.0222)	(0.0223)	(0.0227)
Stay-at-home requirement	**-0.1077*****	**-0.0875*****	**-0.0681*****	**-0.0914*****	**-0.0802*****	**-0.0875*****	**-0.0767*****	**-0.0971*****	**-0.0353**
	(0.0238)	(0.0242)	(0.0240)	(0.0242)	(0.0243)	(0.0241)	(0.0247)	(0.0243)	(0.0251)
Contact tracing	**-0.1347*****	**-0.1436*****	**-0.1273*****	**-0.1354*****	**-0.1771*****	**-0.1486*****	**-0.1445*****	**-0.1053*****	**-0.1008*****
	(0.0254)	(0.0253)	(0.0251)	(0.0255)	(0.0263)	(0.0254)	(0.0252)	(0.0273)	(0.0275)
Test per population	**0.0036*****	**0.0036*****	**0.0039*****	**0.0037*****	**0.0037*****	**0.0036*****	**0.0036*****	**0.0036*****	**0.0039*****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Economic support to households		**-0.0029*****	**-0.0034*****	**-0.0029*****	**-0.0030*****	**-0.0031*****	**-0.0033*****	**-0.0021*****	**-0.0031*****
		(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)
Health care workers			**-0.0455*****						**-0.0348*****
			(0.0063)						(0.0092)
Average years of adults' education				**-0.0274*****					**-0.0321****
				(0.0103)					(0.0168)
Income inequality					**0.0140*****				**0.0269*****
					(0.0028)				(0.0038)
Density of population						**0.0002****			**0.0002***
						(0.0001)			(0.0001)
Tourism arrivals							**0.1263****		**0.6147*****
							(0.0664)		(0.0791)
Governance quality								**-0.1470*****	**-0.3669*****
								(0.0395)	(0.0484)
Africa	**-0.3056*****	**-0.2584*****	**-0.2213*****	**-0.2865*****	**-0.2749*****	**-0.2431*****	**-0.2261*****	**-0.2584*****	**-0.3039*****
	(0.0377)	(0.0374)	(0.0375)	(0.0400)	(0.0375)	(0.0373)	(0.0372)	(0.0374)	(0.0395)
Asia	**-0.1717*****	**-0.1340*****	**-0.0767*****	**-0.1340*****	**-0.1471*****	**-0.1221*****	**-0.1112*****	**-0.1340*****	**-0.0695*****
	(0.0368)	(0.0365)	(0.0360)	(0.0365)	(0.0366)	(0.0364)	(0.0363)	(0.0365)	(0.0357)
Latin America	**0.2136*****	**0.2355*****	**0.2880*****	**0.2355*****	**0.2159*****	**0.2467*****	**0.2515*****	**0.2355*****	**0.2276*****
	(0.0418)	(0.0415)	(0.0409)	(0.0415)	(0.0416)	(0.0413)	(0.0412)	(0.0415)	(0.0406)
Europe	**0.3798*****	**0.3878*****	**0.5324*****	**0.4460*****	**0.4222*****	**0.3884*****	**0.3497*****	**0.3878*****	**0.5170*****
	(0.0468)	(0.0464)	(0.0514)	(0.0508)	(0.0473)	(0.0463)	(0.0477)	(0.0464)	(0.0533)
R^2	**0.033**	**0.066**	**0.069**	**0.069**	**0.059**	**0.062**	**0.073**	**0.067**	**0.093**
F-stat.	**335.36**	**109.54**	**123.66**	**115.17**	**122.81**	**10167**	**106.89**	**95.21**	**168.23**
No. Obs.	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**

Notes: The values between parentheses represent the standard errors. The up scripts "***", "**", "*" reflect statistical significance for each coefficient at 99, 95 and 90 percent of credible intervals, respectively.

Clearly, contact tracing followed by stay-at-home requirements have the highest effect among all policies in LMCs. Further, the results confirm that testing and infection rates are positively correlated with each other. More interestingly, economic support packages to households are negatively associated with the infection rates. However, and notably, there is no evidence of a significant correlation between business closures and infection rates – calling into question the efficacy of that policy action for LMCs.

Since variables are standardised, coefficients must be interpreted based on the changes in standard deviations (Siegel and Wagner, 2022). In Model 1 a one standard deviation hike in the school closure index – keeping other variables fixed -- leads to a 0.056 standard deviation decrease in the infection rate. Also, a positive change of one standard deviation in the contact tracing policy leads to a 0.135 standard deviation decrease in the infection rate. Further, the stay-at-home restriction reduces infections by a 0.108 standard deviation. Regarding testing policy, one standard deviation hike in the testing rate, while keeping other variables fixed, increases the infection rate by 0.4 percent standard deviation.

Model 2 presents the coefficients for government supports to households. The incidence of infection decreases by a 0.3 standard deviation when household economic support increases by one standard deviation while keeping all other variables unchanged. From Model 3, for the effect of health care workers, increasing by one standard deviation the number of nurses and doctors decreases the infection rate by a 0.045 standard deviation. This finding is consistent with the work of Amdaoud et al. (2021) and Perone (2021), which shows that the efficacy of the health care system can contribute to reducing cases.

Model 4 shows that the average years of an adult's schooling is negatively correlated with the infection rate, as per Hoffmann and Lutz (2019), which examines the relationship between schooling and health-related behaviours; an "education gradient". Accordingly, the virus is expected to be less prevalent in more educated countries. If other variables hold constant, a one standard deviation increase in the average schooling years of adults results in a 0.027 standard deviation decrease in infection rates.

Model 5 shows the effect of income inequality on the spread of the virus. Here, the nexus between income inequality and infection rate is positive – consistent with Wildman (2021) and Ginsburgh et al. (2021). People living in countries with extreme income inequality are not able to afford primary health care. Keeping other factors constant, the

infection rate increases by a 0.014 standard deviation when income inequality increases by one standard deviation.

Model 6 reports the reaction of the infection rate to population density. The infection rate increases by 0.02 percent standard deviation when the density of the population changes by one standard deviation, consistent with Hamidi et al. (2020). The magnitude of the coefficient is not considerable, although it is statistically significant. This finding may be due to a significant proportion of the economy living in rural areas characterised by a low density of people.

Model 7 demonstrates the effect of tourism arrivals on the COVID-19 infection rate. The standardised coefficient of this variable reveals that one standard deviation increase in tourism arrivals hikes the infection rates by 0.126 standard deviations. A very similar result is found in Farzanegan et al. (2021). The size of this coefficient is larger than other socio-economic covariates, suggesting that controlling tourism arrivals allows governments to prevent the spread of the virus.

Model 8 shows the importance of the quality of public institutions in controlling COVID-19 outbreaks. The estimated coefficient reveals that the infection rate falls by a 0.147 standard deviation when governance quality rises by one standard deviation, keeping other variables fixed. This result is consistent with Bargain and Aminjonov (2020) and Chien and Lin (2020), highlighting the role of good governance.

Model 9 provides broad estimates of coefficients when all policy variables and socio-economic controls are included in the model. The results for this regression are consistent with the above results. The findings reveal that school closures and contact tracing have the most prominent effects on controlling the spread of the virus. However, business closures cannot help to control the outbreak in LMCs. As a result of these findings, it is suggested that governments in LMCs should prioritise contact tracing and school closures to overcome the spread of the virus rather than other interventions.

2.5. Robustness Checks

I refit the model with other alternative debiased LASSO methods such as scaled debiased LASSO and residual bootstrapping debiased LASSO methods to check the consistency of the estimates. This type of exercise will help to reveal how the signs or magnitudes of

coefficients are firm in different debiased LASSO methods. Both of these approaches are derived from Eq. (2.6) after a few adjustments. The former modifies the penalty function to estimate the regression's noise along with the slopes. The latter resamples the residuals obtained from Eq. (2.6), then approximates the empirical distribution of the outcome variable. This provides more accurate confidence intervals for the estimates (Chatterjee and Lahiri, 2011).

The scaled debiased LASSO is constructed based on Antoniadis (2010) and Sun and Zhang (2010, 2012) to consider variance and coefficient in the optimisation procedure. In light of this, the scaled LASSO technique jointly estimates the regression coefficients and noise level in a linear model as $\frac{\sigma}{2} + \frac{\|Y-Z\psi\|_2^2}{(2\sigma NT)} + \zeta_0 \| \psi \|_1$. According to this scale-invariance analysis, the penalty level is proportional to the noise level of the regression model. Recall that the standard LASSO method assumes that the optimal penalty parameter depends on the error scale, so it is mainly determined by cross-validation. Therefore, the Scaled LASSO offers the advantage of scale-free penalty parameters that are predetermined from purely theoretical considerations (Raninen and Ollila, 2017). Sun and Zhang (2013) present that the Scaled LASSO provides the advantage of automatically adjusting the penalty level in a regression model for yielding optimal convergence. Although this approach uses an alternative optimisation function, it needs to be debiased like the conventional LASSO model (Zhang and Zhang, 2014). Raninen and Ollila (2017) also discuss that the scaled LASSO method performs inappropriately when predictors are strongly correlated with each other. The coefficients must be denoised to obtain reliable estimates. Before estimating the regressions, covariates are firstly de-correlated from each other and then scaled LASSO is implemented. The results of the scaled debiased LASSO are provided in Table 2.2 as follows,

Table 2.2. Robustness test based on the scaled debiased LASSO

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
School closure	**-0.0559*****	**-0.0415****	**-0.0607*****	**-0.0508****	**-0.0266**	**-0.0408***	**-0.0389***	**-0.0530*****	**-0.0543*****
	(0.0219)	(0.0222)	(0.0223)	(0.0225)	(0.0223)	(0.0222)	(0.0222)	(0.0223)	(0.0224)
Business closure	**0.0025**	**0.0007**	**-0.0043**	**0.0102**	**-0.0095**	**-0.0005**	**0.0018**	**-0.0024**	**-0.0157**
	(0.0218)	(0.0218)	(0.0217)	(0.0221)	(0.0219)	(0.0218)	(0.0218)	(0.0218)	(0.0223)
Stay-at-home requirement	**-0.1080*****	**-0.0871*****	**-0.0676*****	**-0.0909*****	**-0.0796*****	**-0.0870*****	**-0.0764*****	**-0.0969*****	**-0.0352**
	(0.0231)	(0.0236)	(0.0237)	(0.0237)	(0.0236)	(0.0236)	(0.0242)	(0.0237)	(0.0247)
Contact tracing	**-0.1347*****	**-0.1435*****	**-0.1272*****	**-0.1354*****	**-0.1773*****	**-0.1486*****	**-0.1446*****	**-0.1051*****	**-0.1007*****
	(0.0247)	(0.0247)	(0.0247)	(0.0249)	(0.0255)	(0.0249)	(0.0247)	(0.0267)	(0.0271)
Test per population	**0.0036*****	**0.0036*****	**0.0039*****	**0.0037*****	**0.0037*****	**0.0036*****	**0.0036*****	**0.0036*****	**0.0039*****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Economic support to households		**-0.0029*****	**-0.0034*****	**-0.0029*****	**-0.0030*****	**-0.0031*****	**-0.0033*****	**-0.0021*****	**-0.0031*****
		(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Health care workers			**-0.0456*****						**-0.0347*****
			(0.0062)						(0.0091)
Average years of adults' education				**-0.0275*****					**-0.0326****
				(0.0101)					(0.0166)
Income inequality					**0.0140*****				**0.0269*****
					(0.0027)				(0.0038)
Density of population						**0.0002***			**0.0002***
						(0.0001)			(0.0001)
Tourism arrivals							**0.1264***		**0.6158*****
							(0.0652)		(0.0779)
Governance quality								**-0.1473*****	**-0.3670*****
								(0.0385)	(0.0477)
Africa	**-0.1250*****	**-0.1246*****	**-0.1744*****	**-0.1584*****	**-0.1811*****	**-0.1257*****	**-0.1219*****	**-0.1475*****	**-0.3362*****
	(0.0366)	(0.0365)	(0.0370)	(0.0391)	(0.0365)	(0.0366)	(0.0365)	(0.0365)	(0.0389)
Asia	**-0.0357**	**-0.0365**	**-0.0371**	**-0.0373**	**-0.0372**	**-0.0373**	**-0.0372**	**-0.0372**	**-0.0398**
	(0.0357)	(0.0356)	(0.0355)	(0.0357)	(0.0356)	(0.0357)	(0.0356)	(0.0356)	(0.0351)
Latin America	**0.3216*****	**0.3314*****	**0.3664*****	**0.3309*****	**0.2550*****	**0.3309*****	**0.3243*****	**0.3328*****	**0.2116*****
	(0.0406)	(0.0405)	(0.0403)	(0.0405)	(0.0405)	(0.0405)	(0.0405)	(0.0405)	(0.0400)
Europe	**0.3743*****	**0.3848*****	**0.5846*****	**0.4382*****	**0.4227*****	**0.3847*****	**0.3496*****	**0.3888*****	**0.5434*****
	(0.0455)	(0.0454)	(0.0507)	(0.0497)	(0.0460)	(0.0454)	(0.0468)	(0.0453)	(0.0525)
R^2	**0.019**	**0.053**	**0.068**	**0.057**	**0.053**	**0.050**	**0.063**	**0.055**	**0.097**
F-stat.	**335.36**	**90.01**	**133.07**	**92.24**	**101.44**	**86.03**	**92.75**	**82.11**	**172.09**
No. Obs.	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**

Notes: the values between parenthesizes represent the standard errors. The up scripts "***", "**", "*" reflect statistical significance for each coefficient at 99, 95 and 90 percent of credible intervals, respectively.

To show the stability of the results after applying the debiased LASSO method, I change an assumption in the estimating procedure and re-estimate the model. As another robustness check, a residual bootstrapping method for the debiased LASSO regression is implemented. As Dezeure-Bühlmann and Zhang (2017) present, this process starts with estimating coefficients from the conventional LASSO method. Then, initial residuals are calculated through $\hat{\varepsilon} = Y - Z\hat{\psi}$. Accordingly, centered residuals are computed by $\hat{\varepsilon}_{it}^{centered} = \hat{\varepsilon}_{it} - \bar{\hat{\varepsilon}}$ for $(i = 1, \cdots, N)$ and $(t = 1, \cdots, T)$. Also, an expected value for residuals equals $\bar{\hat{\varepsilon}} = NT^{-1/2} \sum_{t=1}^{T} \sum_{n=1}^{N} \hat{\varepsilon}_{it}$. Note that the expected value for residuals is not zero in the original LASSO because the type of penalty applied for regularizing the parameters differs from the OLS.

Then, the bootstrapped errors $(\varepsilon_{11}^*, \cdots, \varepsilon_{NT}^*)$, are obtained from centred residuals. After that, the bootstrapped response variable is produced as follows,

$$Y^* = Z\hat{\psi} + \varepsilon^*. \quad (9)$$

Here, Y^* is non-random and the sample has a fixed design now. Dezeure-Bühlmann and Zhang (2017) show that the estimates obtained from the residual bootstrapping debiased LASSO method are asymptotically consistent. Also, Chatterjee (2017) indicates that the residual bootstrapping debiased LASSO estimates are more efficient than other debiased methods. The estimates for the residual bootstrapping debiased LASSO method after 500 replications are represented below,

Table 2.3. Robustness test by applying the bootstrapping debiased LASSO

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
School closure	**-0.0563****	**-0.0423***	**-0.0609*****	**-0.0511****	**-0.0270**	**-0.0415***	**-0.0394***	**-0.0533*****	**-0.0540****
	(0.0226)	(0.0228)	(0.0228)	(0.0232)	(0.0229)	(0.0228)	(0.0225)	(0.0228)	(0.0228)
Business closure	**0.0027**	**0.0011**	**-0.0036**	**0.0104**	**-0.0089**	**-0.0002**	**0.0021**	**-0.0020**	**-0.0158**
	(0.0225)	(0.0224)	(0.0223)	(0.0228)	(0.0224)	(0.0224)	(0.0221)	(0.0222)	(0.0227)
Stay-at-home requirement	**-0.1077*****	**-0.0876*****	**-0.0683*****	**-0.0914*****	**-0.0802*****	**-0.0875*****	**-0.0767*****	**-0.0971*****	**-0.0353**
	(0.0238)	(0.0243)	(0.0243)	(0.0244)	(0.0242)	(0.0243)	(0.0245)	(0.0242)	(0.0251)
Contact tracing	**-0.1347*****	**-0.1436*****	**-0.1275*****	**-0.1355*****	**-0.1771*****	**-0.1485*****	**-0.1443*****	**-0.1053*****	**-0.1008*****
	(0.0254)	(0.0254)	(0.0253)	(0.0257)	(0.0262)	(0.0255)	(0.0250)	(0.0272)	(0.0276)
Test per population	**0.0036*****	**0.0036*****	**0.0039*****	**0.0037*****	**0.0037*****	**0.0036*****	**0.0036*****	**0.0036*****	**0.0039*****
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Economic support to households		**-0.0029*****	**-0.0034*****	**-0.0029*****	**-0.0030*****	**-0.0031*****	**-0.0033*****	**-0.0021*****	**-0.0031*****
		(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Health care workers			**-0.0455*****						**-0.0348*****
			(0.0063)						(0.0092)
Average years of an adult's education				**-0.0273****					**-0.0319****
				(0.0104)					(0.0169)
Income inequality					**0.0140*****				**0.0269*****
					(0.0028)				(0.0038)
Density of population						**0.0002***			**0.0002****
						(0.0001)			(0.0001)
Tourism arrivals							**0.1260****		**0.6145*****
							(0.0660)		(0.0793)
Governance quality								**-0.1471*****	**-0.3668*****
								(0.0393)	(0.0485)
Africa	**-0.3056*****	**-0.2915*****	**-0.2821*****	**-0.3315*****	**-0.2584*****	**-0.2749*****	**-0.2003**	**-0.2292**	**-0.2952*****
	(0.0377)	(0.0376)	(0.0379)	(0.0403)	(0.0374)	(0.0375)	(0.0370)	(0.0372)	(0.0396)
Asia	**-0.1717*****	**-0.1614*****	**-0.1221*****	**-0.1717*****	**-0.1340*****	**-0.1471*****	**-0.0923*****	**-0.1112*****	**-0.0763*****
	(0.0368)	(0.0367)	(0.0364)	(0.0368)	(0.0365)	(0.0366)	(0.0361)	(0.0363)	(0.0358)
Latin America	**0.2136*****	**0.2183*****	**0.2467*****	**0.2136*****	**0.2268*****	**0.2247*****	**0.2687*****	**0.2571*****	**0.2368*****
	(0.0418)	(0.0417)	(0.0413)	(0.0418)	(0.0415)	(0.0416)	(0.0410)	(0.0412)	(0.0407)
Europe	**0.3798*****	**0.3813*****	**0.5404*****	**0.4398*****	**0.4233*****	**0.3862*****	**0.3497*****	**0.3887*****	**0.5204*****
	(0.0468)	(0.0467)	(0.0520)	(0.0513)	(0.0471)	(0.0466)	(0.0475)	(0.0462)	(0.0534)
R^2	**0.033**	**0.067**	**0.074**	**0.071**	**0.058**	**0.065**	**0.071**	**0.064**	**0.093**
F-stat.	**335.36**	**114.65**	**136.29**	**123.11**	**120.27**	**105.82**	**102.79**	**91.29**	**168.32**
No. Obs.	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**	**3700**

Notes: the values between parenthesizes represent the standard errors. The up scripts "***", "**", "*" reflect statistical significance for each coefficient at 99, 95 and 90 percent of credible intervals, respectively.

As seen in Table 2.3, all coefficients obtained from the residual bootstrapping debiased LASSO method are in line with the estimates obtained from the debiased LASSO method. The important point about the debiased LASSO method here is the results are close to each other. Appendix 2E reports the initial estimates for Model 9 based on these different approaches.

The findings show that the estimates of the conventional and bootstrapping LASSO models are similar to each other in terms of variable selection with slight differences in the magnitude of coefficients. The results with the other method, the Scaled LASSO, differ from the conventional and bootstrapping LASSO techniques. The results reveal that the Scaled LASSO selects more variables compared to the other two methods. Additionally, the magnitude of coefficients selected by the Scaled LASSO method is slightly larger than the other two methods. These differences are due to the different penalty functions employed for selecting covariates.

Further, I check the robustness of the models by changing the sample size and implementing an extreme bounds analysis (EBA). Finding robust results by changing samples can reveal how the results are generalisable to other countries not included in the sample. Based on Abadie et al. (2015), the sample size is first changed through the *leave-one-out method* and the models re-estimated to ensure that the estimates are robust and are not sensitive to the sample size. For example, the first country, i.e., Argentina, is removed from our sample and we re-estimate the coefficients throughout Models 1 to 9. Then, the estimating procedure is carried out by removing the second country and replacing it with the first country. This leave-one-out approach is continued to remove the last country, namely, Zimbabwe, and refit all models. Hence, I estimate 37 (samples with leaving a country out) x 9 (models) = 333 regressions through the debiased LASSO method. To perform the EBA, I calculate the average value of each coefficient, $Avg\left(\hat{\psi}_j^{de-biased}\right)$ and the corresponding standard error $Avg(\ \hat{\sigma}_j^{de-biased})$, relying on 37 different estimated regressions for each model. Then the extreme bounds are constructed for 95 percent of the credible interval via $Avg\left(\hat{\psi}_j^{de-biased}\right) \mp 1.96 \times Avg(\ \hat{\sigma}_j^{de-biased})$. In which, $Avg\left(\hat{\psi}_j^{de-biased}\right) - 1.96 \times Avg(\ \hat{\sigma}_j^{de-biased})$ and $Avg\left(\hat{\psi}_j^{de-biased}\right) +$

$1.96 \times Avg(\hat{\sigma}_j^{de-biased})$ are the lower and upper extreme bounds, respectively[7]. In this sense, a coefficient is fragile when the lower outer bound is negative while the upper extreme bound is positive. Table 2.4 reports the average coefficient values and the corresponding lower and upper bounds.

[7] This approach outlined here is much similar to Sala-i-Martin (1997) because the extreme bounds are constructed based on the average values of coefficients obtained from different design matrices. He considers different combinations of variables and attains the average values for each coefficient. Then, he establishes the lower and upper extreme bounds for estimates. Likewise, I calculate these bounds relying on the average value of coefficients by altering the sample size.

Table 2.4. Robustness test based on the extreme bounds analysis

	Model 1			Model 2			Model 3			Model 4			Model 5		
	Coefficient	Lower extreme bound	Upper extreme bound	Coefficient	Lower extreme bound	Upper extreme bound	Coefficient	Lower extreme bound	Upper extreme bound	Coefficient	Lower extreme bound	Upper extreme bound	Coefficient	Lower extreme bound	Upper extreme bound
School closure	-0.0613	-0.0801	-0.0426	-0.0413	-0.0604	-0.0221	-0.0597	-0.0790	-0.0404	-0.0498	-0.0695	-0.0301	-0.0263	-0.0457	-0.0069
Business closure	0.0076	-0.0111	0.0262	0.0017	-0.0169	0.0203	-0.0033	-0.0218	0.0151	0.0105	-0.0086	0.0296	-0.0082	-0.0268	0.0104
Stay-at-home requirement	-0.1070	-0.1278	-0.0861	-0.0866	-0.1084	-0.0648	-0.0673	-0.0892	-0.0454	-0.0898	-0.1117	-0.0679	-0.0789	-0.1007	-0.0571
Contact tracing	-0.1273	-0.1511	-0.1035	-0.1428	-0.1667	-0.1189	-0.1266	-0.1505	-0.1027	-0.1350	-0.1592	-0.1107	-0.1762	-0.2016	-0.1508
Test per population	0.0036338	0.0036335	0.0036341	0.0036174	0.0036171	0.0036177	0.0038609	0.0038606	0.0038612	0.0036757	0.0036754	0.0036760	0.0036898	0.0036895	0.0036901
Economic support to households				-0.00289	-0.00291	-0.00287	-0.00336	-0.00338	-0.00334	-0.00286	-0.00288	-0.00284	-0.00297	-0.00299	-0.00294
Health care workers							-0.0448	-0.0463	-0.0433						
Average years of adults' education										-0.0263	-0.0303	-0.0263			
Income inequality													0.01395	0.01367	0.01395
Density of population															
Tourism arrivals															
Governance quality															
AFRICA	-0.2270	-0.2793	-0.1747	-0.2614	-0.3134	-0.2094	-0.2768	-0.3301	-0.2236	-0.2873	-0.3468	-0.2277	-0.2510	-0.3027	-0.1993
ASIA	-0.1095	-0.1592	-0.0598	-0.1322	-0.1816	-0.0828	-0.1156	-0.1646	-0.0666	-0.1307	-0.1801	-0.0813	-0.1219	-0.1710	-0.0727
AMERICA	0.2562	0.1918	0.3206	0.2380	0.1740	0.3020	0.2512	0.1878	0.3147	0.2368	0.1729	0.3008	0.2326	0.1687	0.2965
EUROPE	0.3867	0.3059	0.4674	0.3828	0.3025	0.4630	0.5306	0.4297	0.6315	0.4395	0.3433	0.5357	0.4196	0.3373	0.5019

Table 2.4. continued: Robustness test based on the extreme bound analysis

	Model 6			Model 7			Model 8			Model 9		
	Coefficient	Lower extreme bound	Upper extreme bound	Coefficient	Lower extreme bound	Upper extreme bound	Coefficient	Lower extreme bound	Upper extreme bound	Coefficient	Lower extreme bound	Upper extreme bound
School closure	-0.0407	-0.0599	-0.0215	-0.0384	-0.0576	-0.0191	-0.0525	-0.0719	-0.0330	-0.0524	-0.0717	-0.0331
Business closure	0.0006	-0.0181	0.0192	0.0028	-0.0158	0.0214	-0.0013	-0.0199	0.0172	-0.0154	-0.0346	0.0038
Stay-at-home requirement	-0.0861	-0.1079	-0.0642	-0.0757	-0.0987	-0.0527	-0.0960	-0.1181	-0.0740	-0.0333	-0.0568	-0.0098
Contact tracing	-0.1467	-0.1709	-0.1224	-0.1435	-0.1675	-0.1196	-0.1053	-0.1331	-0.0776	-0.0995	-0.1279	-0.0711
Test per population	0.0036383	0.0036380	0.0036386	0.0035853	0.0035851	0.0035856	0.0036287	0.0036285	0.0036290	0.0039079	0.0039076	0.0039082
Economic support to households	-0.00305	-0.00307	-0.00303	-0.00321	-0.00323	-0.00319	-0.00208	-0.00211	-0.00206	-0.00306	-0.00309	-0.00304
Health care workers										-0.0345	-0.0378	-0.0313
Average years of adults' education										-0.0308	-0.0415	-0.0201
Income inequality										0.02654	0.02598	0.0271
Density of population	0.0001446	0.0001442	0.0001449							0.0001530	0.0001526	0.0001534
Tourism arrivals				0.1263	-0.0409	0.2934				0.6077	0.3719	0.8435
Governance quality							-0.1448	-0.2030	-0.0866	-0.3612	-0.4496	-0.2728
AFRICA	-0.2642	-0.3163	-0.2122	-0.2669	-0.3190	-0.2148	-0.2565	-0.3084	-0.2047	-0.2989	-0.3570	-0.2407
ASIA	-0.1323	-0.1818	-0.0828	-0.1377	-0.1872	-0.0881	-0.1276	-0.1769	-0.0783	-0.0733	-0.1207	-0.0260
AMERICA	0.2371	0.1730	0.3012	0.2285	0.1643	0.2926	0.2405	0.1767	0.3043	0.2311	0.1695	0.2926
EUROPE	0.3861	0.3057	0.4665	0.3459	0.2600	0.4318	0.3841	0.3040	0.4642	0.5104	0.4036	0.6172

According to the magnitudes and signs of the coefficients, the values in Table 2.4 are broadly consistent with those in Table 2.1. All estimates related to the government interventions have significant impact on infection rate except the business closure. This is consistent over different models. It has also been demonstrated that other socio-economic factors associated with the spread of the virus are robust across all models, as none of the structured credible intervals contain a zero value.

2.6. Conclusions

I examine the effects of several government nonpharmaceutical interventions, as well as the socio-economic environment, on the spread of the virus in LMCs. A data-driven machine learning and multivariate approach is taken in order to identify the important factors determining infection rates.

In order to deal with a dataset with too many predictors involving correlation between covariates, a debiased LASSO method is applied along with several robustness exercises. Our findings suggest that school closures and contact tracing are the most effective interventions compared to other government responses to the spread of COVID-19. In fact, school closures can reduce the virus transmission and contact tracing can help to prevent additional unknown transmissions. Curiously, findings reveal that a policy involving business closures is statistically insignificant in affecting infection rates. Further, our results reveal that economic support to households and the number of healthcare workers negatively affect the spread of the virus. As a result of these findings, it is suggested that governments in the LMCs should support household income during the pandemic to control the spread of the virus.

Finally, the density of population, income inequality, and tourism arrivals contribute to infections in those countries. In contrast, the average years of education of adults and governance quality impact the infection rate negatively.

Closing schools and universities, limiting people to staying at home, and tracing the contacts of infected individuals are all effective policy interventions. Further, strengthening public institutions and increasing the number of health care workers are vital to assisting these countries in overcoming future health crisis.

While this paper has employed a sample pertaining to infection rates for the recent COVID-19 pandemic, these results can be generalised to inform policy actions for other contagious infectious diseases. It is concluded that, for the most part, sensible policy interventions can reduce infection rates for poorer countries. In this regard, school closures and contact tracing had the highest effects on controlling COVID-19 cases in the LMCs during the early stage of the pandemic. Hence, policymakers should effectively limit virus transmissions by closing educational centres and tracing infected people. Further, this research revealed that socio-economic factors, and the economic and institutional environments are also important in impacting the spread of infections.

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Appendix 2A. List of low and middle-income countries and the date of the first incidence of COVID-19 infection

Africa		Asia		Latin America & Caribbeans		Europe	
Country	**Date of the first infection**	**Country**	**Date of the first infection**	**Country**	**Date of the first infection**	**Country**	**Date of the first infection**
Cote d'Ivoire	12/03/2020	**Bangladesh**	9/03/2020	**Argentina**	4/03/2020	**Belarus**	28/02/2020
Ethiopia	14/03/2020	**India**	30/01/2020	**Bolivia**	12/03/2020	**Bulgaria**	8/03/2020
Kenya	14/03/2020	**Indonesia**	2/03/2020	**Colombia**	7/03/2020	**Romania**	27/02/2020
Morocco	3/03/2020	**Iran**	20/02/2020	**Costa Rica**	7/03/2020	**Russia**	1/02/2020
Nigeria	28/02/2020	**Iraq**	25/02/2020	**Cuba**	12/03/2020	**Serbia**	7/03/2020
Rwanda	15/03/2020	**Kazakhstan**	15/03/2020	**El Salvador**	19/03/2020	**Ukraine**	4/03/2020
Senegal	3/03/2020	**Malaysia**	25/01/2020	**Mexico**	29/02/2020		
South Africa	6/03/2020	**Myanmar**	24/03/2020	**Paraguay**	8/03/2020		
Togo	15/03/2020	**Pakistan**	27/02/2020				
Tunisia	3/03/2020	**Philippines**	30/01/2020				
Zimbabwe	21/03/2020	**Thailand**	13/01/2020				
		Turkey	12/03/2020				

Appendix 2B. Definitions and sources of variables

Variable Name	Definition	Source
Infection rate	The ratio of covid-19 new infections per 100000 population	*Our World in Data*
Average years of adults' schooling	The average schooling years for adults over 25 years old	*World Bank*
Income Inequality	The Gini coefficient	*World Bank*
Density of population	The number of people per square kilometre	*World Bank*
Governance Quality	The combination of six dimensions of governance quality including, control of corruption, the rule of law, government effectiveness, rule quality, political stability, and voice and accountability. The weight of each factor is calculated via principal component analysis (PCA).	*World Bank*
Health Care Workers	The number of doctors and nurses per 1000 people	*World Health Organization (WHO)*
Tourism arrivals per population	The proportion of foreign tourism arrivals to1000 people	*World Bank*
School closure	An ordinal variable recording school and university closures. It is indicated as 0 when a government does not recommend closing, 1 when a government requires closures (only some levels or categories, e.g., just high school, or just public schools), 2 when a government requires closing all levels.	*Oxford COVID-19 Government Response Tracker* (OxCGRT)
Business closure	An ordinal measure of closure of workplaces. It is indicated as 0 when a government does not recommend closing 1 when a government recommends closing (or work from home) 2 when a government requires closing (or work from home) for some sectors or categories of workers 3 when a government requires closing (or work from home) all-but-essential workplaces (e.g., grocery stores, doctors).	*Oxford COVID-19 Government Response Tracker* (OxCGRT)
Stay-at-home requirements	An ordinal measure confining people to their homes. It is indicated as, 0 when there is no intervention.	*Oxford COVID-19 Government Response Tracker* (OxCGRT)

	1 when a government recommends people not to leave their houses. 2 when a government requires people not to leave their houses with exceptions for daily exercise, grocery shopping, and 'essential' trips. 3 when a government requires people not to leave their houses with minimal exceptions (e.g., allowed to leave only once a week, or only one person can leave at a time, etc.)	
Economic support to households	This index is a combination of 2 measures including: A) income support for households: 0 - no income support, 1 - the government is replacing less than 50% of lost salary (or if a flat sum, it is less than 50% median salary), 2 - the government is returning 50% or more of lost pay (or if a flat sum, it is greater than 50% median salary) B) debt or contract relief for households: 0 - No 1 - Narrow relief, specific to one kind of contract 2 - broad debt/contract relief	*Oxford COVID-19 Government Response Tracker* (OxCGRT)
Contact tracing	An Ordinal measure of government contact tracing. It is indicated as, 0 when there is no contact tracing 1 when there is limited contact tracing - not done for all cases 2 when there is comprehensive contact tracing - done for all identified cases	*Oxford COVID-19 Government Response Tracker* (OxCGRT)
Testing rate	The ratio of the daily COVID-19 tests per 100000 population	*Our World in Data*

Notes: There is a small number of missing observations in the testing rate series where some data are presented weekly rather than daily, and for the infection rate, where authorities reported accumulated infections information. For the testing rate, an interpolation method is used based on geometric growth rates to fill these gaps. For infections, I interpolated based on the trend of the data. The data file is available on request.

Appendix 2C. Principal components analysis for indexing governance quality

First, the Principal Components Analysis (PCA) is used to diminish the number of variables in a dataset into fewer dimensions. PCA initially constructs uncorrelated components obtaining from weighted linear combinations of the original variables. Assume a vector of variables, $X = (X_1, \cdots, X_n)$, hence, m principal components can be defined as follows,

$$PC_1 = \alpha_{11}X_1 + \alpha_{12}X_2 + \cdots + \alpha_{1n}X_n$$

$$\vdots$$

(1)

$$PC_m = \alpha_{m1}X_1 + \alpha_{m2}X_2 + \cdots + \alpha_{mn}X_n \,,$$

in which $(\alpha_{11}, \cdots, \alpha_{ij})$, *i=(1, ..., n)* and *j=(I, ..., m)*, are the corresponding weights to the i[th] variable into the j[th] principal component. Weights can be obtained by calculating the eigenvalues of the correlation matrix or the covariance matrix if the original variables are standardised. Eq. (1) satisfies three conditions as,

I. All principal components, $(PC_1, \cdots, PC_m)$, are orthogonal to each other.

II. The first principal component captures the greatest proportion of the variance of the variables. Accordingly, the second component accounts for most of the remaining variance. This will continue until the final principal component absorbs all of the difference not covered by the preceding component.

III. The sum of all squared weights equals one, i.e., $\alpha_{11}^2 + \alpha_{12}^2 + \cdots + \alpha_{ij}^2 = 1$. For more detailed review, see *Nardo et al. (2005)* and *Vyas* and *Kumaranayake (2006)*.

I use the *World Governance Indicators* dataset covering 214 countries from 1996 to 2019. *STATA 16* software is used to calculate the weights of six dimensions of governance quality, including control of corruption, the rule of law, government effectiveness, rule quality, political stability, and voice and accountability. Table C1 provides the weights of different dimensions of public institutional quality in each principal component below.

Table C1. Weights of variables in each principal component

Variable	PC1	PC2	PC3	PC4	PC5	PC6
X1	0.3860	0.0796	0.9059	-0.0516	0.1435	-0.0276
X2	0.3627	0.8685	-0.2281	0.2269	0.0770	0.0684
X3	0.4238	-0.2878	-0.2653	0.0966	0.6314	-0.5091
X4	0.4153	-0.3780	-0.0600	0.6536	-0.2052	0.4601
X5	0.4335	-0.0519	-0.0920	-0.1933	-0.7214	-0.4931
X6	0.4235	-0.1046	-0.2119	-0.6870	0.1112	0.5296

Notes: X1 to X6 refers to voice and accountability, political stability and absence of violence, government effectiveness, regulatory quality, the rule of law, and control of corruption, respectively.

The estimated eigenvalues and their shares of the variation of the governance quality are presented in Table C2 as,

Table C2. Eigenvalues of the correlation matrix

Component	Eigenvalue	Difference	Proportion	Cumulative
PC1	5.08707	4.67747	0.8478	0.8478
PC2	0.409606	0.119645	0.0683	0.9161
PC3	0.289961	0.169124	0.0483	0.9644
PC4	0.120837	0.0728232	0.0201	0.9846
PC5	0.0480135	0.0035043	0.0080	0.9926
PC6	0.0445092	0	0.0074	1.0000

As can be seen, PC1 explains more than 84 percent of the variation of six dimensions of governance quality. However, the second and third principal components respectively define less than 7 and 5 percent of the variation of the governance quality.

Appendix 2D. Descriptive statistics of variables

	Mean	Median	Maximum	Minimum	Std. Dev.
Infection per population	0.67	0.15	10.3	0.0001	1.41
School closure	2.5	3	3	0	1.06
Business closure	1.83	2	3	0	1.12
Stay-at-home requirement	1.51	2	3	0	1.01
Contact tracing	1.25	1	2	0	0.74
Economic support to households	34.08	37.5	100	0	30.11
Test per population	125.6	37.82	1821.66	0.001	241
Income inequality	40.74	41.2	62.5	25.5	8.17
Health care workers	4.57	2.88	17.28	0.35	4.28
Governance quality	-0.24	-0.15	1	-1.33	0.5
Tourism arrivals per population	0.28	0.17	1.33	0.004	0.32
Average years of adults' education	8.06	8.2	12.3	2.7	2.62
Density of population	143.63	85.11	1116.01	6.89	195.41

Chapter 3 Mental wellbeing and job loss during the early stages of COVID: International evidence[8]

3.1. Introduction

The World Health Organisation (2020) report, based on information from 130 countries, provides sufficient evidence that the coronavirus crisis worsens mental health worldwide. Also, a report commissioned by the Organisation of Economic Cooperation and Development (2021) stresses that the COVID-19 crisis heightens the risk of mental disorders through rising financial insecurity and unemployment as well as the fear of the virus. The International Labour Organization (2020) highlights that job loss during the COVID-19 pandemic led to a series of mental disorders among unemployed. Numerous studies have showed that the coronavirus related unemployment increased during the first phase of the outbreak (Kong and Prinz, 2020; Şahin et al., 2020; Su et al., 2020). Also, voluminous papers examine the negative association between job loss or job search and people's mental health and wellbeing in general (Clark and Oswald, 1994; Winkelmann and Winkelmann,1998). However, evidence suggests that job loss during harder downturns, such as a GFC or a health crisis, has a more substantial and persistent effect on people's mental health and wellbeing (Frasquilho et al., 2016; Avdic et al., 2020). Avdic et al. (2020) argue that the COVID-19 crisis, like the GFC, profoundly impacts people's mental health. After the COVID-19 crisis, many studies investigate the nexus between government non-pharmaceutical interventions such as lockdown on mental health and wellbeing. For instance, Wang et al. (2020), Rossi et al. (2020) and Tull et al. (2020) analyse the association of lockdown with the mental health of people in China, Italy and the US during the early stage of the pandemic. Their findings confirm the negative impact of government intervention on people's mental health, especially for women.

Additionally, job loss leads to a series of mental health issues because it causes a grief-like reaction for unemployed people (Archer and Rhodes, 1993). However, there is little

[8] A version of this chapter with the same title coauthored with Associate Professors Rajabrata Banerjee and Tony Cavoli, my thesis supervisors, is submitted to the 'Stress and Health' journal and is currently under review.

known about the multidimensional association of job loss and mental health resulting from the pandemic. To fill this gap in the literature of COVID-19 and mental health, I analyse the impact of job loss on different measures of mental illness such as anxiety, boredom, insomnia and loneliness. This approach allows us to understand which aspects of wellbeing are correlated more by the labour market variable. Despite the fact that unemployment caused by the Coronavirus pandemic has an adverse effect on mental health, fewer studies examine the impact of the labour market change on mental illnesses. A limited number of research studies investigate the association between unemployment and mental health during the COVID-19 pandemic. Chatterji et al. (2021), Posel et al. (2021) and Griffiths et al. (2021) are among notable studies analysing the correlation of unemployment and mental health in rural India, South Africa, Australia and the US, respectively, during the pandemic. They analyse the association between unemployment and mental health in a single country and find that unemployment increases the probability of mental illness. Compared to these studies, our investigation covers multi-country analysis. Also, this research examines how "being unemployed as a result of the pandemic" has been associated with a different range of psychological symptoms. This feature, in line with Archer and Rhodes (1993), which contributes to the literature on how the adverse impact of the pandemic on the job market leads to a series of mental health issues.

This research aims to find the nexus between unemployment induced by the pandemic and mental wellbeing during COVID-19. Being aware of the association between labour market variables and mental disorders helps policymakers and health authorities to control this problem by implementing suitable labour market and mental wellness policies in future. To find more vulnerable groups during the pandemic, I answer several essential questions: Does being unemployed as a result of COVID-19 exacerbate mental health disorders? Does unemployment have varying impacts on different aspects of mental wellbeing? Do mental health issues occur more often among women compared to men? Are financially challenged individuals more prone to mental health problems during crisis periods?

In addition, I aggregate these four aspects of mental disorders to create a mental disorder index using a factor analysis method. Then, the hypothesis of "a positive association between job loss and poorer mental health" is tested based on this combined index to realise how overall individual wellbeing reacts to job loss. Also, many researchers analyse

the effect of the pandemic on wellbeing based on one country's information. To have a broad picture of this association, a rich micro dataset from six countries is used. I split the dataset into two groups of countries based on early peak vs delayed peak in the spread of the virus. This type of analysis differentiates the effect of a mental illness caused by COVID-19 between those countries which experienced an early peak of the pandemic in comparison with others which faced delayed peaks.

This research uses individual-level data from six countries, including China, Italy, Japan, Korea, the UK, and the US, then applies a logistic regression method to evaluate the association between job loss and different outcomes of mental illness. Our results are robust to different specifications and show that losing jobs as a result of the pandemic leads to poor mental health, including anxiety, boredom, insomnia and loneliness. The clustered estimates suggest that unemployed people experience more anxiety, insomnia, and loneliness in countries which faced an early peak compared to those which experienced delayed peak infections.

Financially stressed individuals, such as people with housing mortgages, are likely to be more anxious. Notably, the findings reveal that women are more vulnerable than men during the pandemic. In countries that have overcome the spread of the virus, women are more prone to anxiety. Also, there is evidence that women suffer greatly from anxiety, insomnia, and loneliness in countries with delayed infection peak. Furthermore, mental health issues are more common among urban residents, youth, low-income groups, and tobacco users. However, religious activities decrease the chance of mental illness.

This study contributes significantly to the literature by providing reliable guidelines in public mental health for policymakers by analysing different measures of mental disorders, including anxiety, boredom, insomnia and loneliness during the pandemic. This research enlightens as to which type of mental disorder is sensitive to an important economic factor like unemployment. Also, it examines which demographics are more vulnerable. So, the government can lessen the impact of the COVID-19 crisis on vulnerable groups by implementing suitable labour market policies during or after the pandemic. OECD (2021) indicates that authorities should prioritise mental health support to workplaces that have been disrupted by the pandemic.

Using multi-country individual-level information to analyse the effect of labour market changes, i.e., being unemployed because of COVID-19, on mental health issues is another

advantage of this research. This study further contributes to the current literature by creating a mental disorder index (MDI) by combining different mental illnesses, i.e., anxiety, boredom, insomnia, and loneliness. This index can be utilised by policymakers to monitor the mental health status of countries over time and rank the countries across regions. This has substantial policy implications for thinktanks, such as World Bank and the UN, to implement mental health policies around wellbeing and psychological coping strategies. Accordingly, it demonstrates how job loss as a result of the pandemic is associated with the MDI. Finally, splitting the sample based on the location of living and different income groups to show the consistency of the estimates is the other contribution added to the literature.

This paper proceeds as follows. First, Section 3.2 provides the existing literature regarding the effects of socioeconomic determinants of mental disorders, particularly during a crisis such as the COVID pandemic. Section 3.3 specifies the empirical strategy to show the association between job loss and mental wellbeing. Section 3.4 presents data, a summary of statistics, and results. In this section, I offer how different aspects of mental illnesses react to unemployment induced by the COVID-19 pandemic and in countries faced with early vs delayed infection peaks. The findings for each group of nations are compared and interpreted in this section. Section 3.5 concludes the results and provides policy directions.

3.2. Literature Review

There is extensive literature suggesting that unemployed people and unemployment periods affect mental health negatively. Many of these studies examine the pre-pandemic condition of wellbeing, such as Clark and Oswald (1994), Winkelmann and Winkelmann (1998), and Krueger et al. (2011). Clark and Oswald (1994) analyse the association between labour market status and unhappiness as a measure of mental disorder in Great Britain. They use more than six thousand individual-level details provided by the British Household Panel Study in 1991. They use marital status, age, and gender as the controls in the model. Their fixed-effects estimates reveal that unemployed people have poorer mental health than those who work. They show that, in terms of lost utility units, being unemployed has a worse effect on mental health than divorce or separation. Further, the findings show that men suffer more than women from a mental disorder. However, older

people tend to be less unhappy compared to young people. Winkelmann and Winkelmann (1998) examine the association between unemployment and life satisfaction as a measure of wellbeing in Germany. They consider unemployment duration and household income as controls. They use the information of 20,994 individuals from 1984 to 1989 and employ a fixed-effects logit regression. Their findings reveal that unemployment and its duration negatively impact the quality of life substantially. However, household income does not significantly affect wellbeing. Additionally, younger unemployed are at more risk of mental illness than older people. Krueger et al. (2011) use information from 6,025 American unemployed workers and demonstrate that the 2008-09 recession and the increase in numbers of unemployed people leads to extreme negative emotional wellbeing. The unemployed workers feel much dissatisfaction and unhappiness, especially when they experience more prolonged spells of unemployment. These individuals tend to feel sad during job searches, and their sadness grows when the job search lasts longer.

Interestingly, several studies examining the effect of unemployment or economic downturn on mental health during a crisis, such as the GFC, show that this impact on people's mental health is persistent and more profound (Frasquilho et al., 2016; Farré et al., 2018; Avdic et al., 2020). On the other hand, most pro-pandemic researchers focus on non-pharmaceutical interventions and compulsory health advice over mental illnesses instead. To understand the effects of the COVID-19 pandemic on mental health, I closely examine all these studies. A few pro-pandemic exemptions exist closer to the work presented here. They are Posel et al. (2021), Chatterji et al. (2021) and Griffiths et al. (2021). Posel et al. (2021) examine the loss depression effect of job loss in South Africans. According to their findings, people who remained employed during the pandemic are less depressed compared to those who lost their jobs. Chatterji et al. (2021) evaluate the association between job loss and mental health in rural India. Their results suggest that job loss leads to poor mental health. Griffiths et al. (2021) investigate whether losing a job is associated with psychological distress, mental disease, or physical health problems. Their findings show that losing jobs deteriorates psychological and physical disorders.

However, all these studies focused on the effect of unemployment on mental disorders on a single country-level basis and do not examine that effect on different measures of mental disorders. Also, the aggregate index that is created in this research is absent among other

studies. These studies do not show how unemployment induced by COVID-19 heterogeneously impacts different nations that faced an early peak compared with a delayed peak of the virus. Thus, a significant gap still exists in the literature in examining the effect of job loss on mental health during the early stages of the pandemic.

The next two sub-sections, the literature is discussed giving particular attention to two groups of studies: related to GFC and COVID-19, respectively. Former summarises studies investigating economic changes on wellbeing during more recent GFC. The later examines suome studies evaluated the impact of being jobless during the COVID-19 pandemic on individuals' mental health.

3.2.1. **GFC, unemployment and mental health**

The World Health Organization (2011) summarises several studies related to the effects of economic downturn and unemployment on wellbeing. The review shows that there is a substantial increase in mental health problems among people experiencing unemployment as a result of the GFC. Also, the likelihood of suffering from mental illness is greater for those with more debt during the GFC. The report reveals that mental health problems are likely to cause more deaths in times of economic crisis[9].

Jenkins et al. (2008) use the private household microdata in England, Scotland, and Wales to analyse the correlation between mental disorders and debt. The sample covers the information of 8,580 participants between the ages of 16 and 74 years. They consider specific measures of mental illnesses such as Psychosis, Neurosis, and alcohol and drug addiction. Their results reveal that low-income and indebted people are more likely to have poor mental health.

Fitch et al. (2011) systematically review numerous studies to understand what types of personal debt affect mental health. They used 14 databases in the areas of medicine, business, law, and social sciences from 1980 to 2009. Their findings support that an increase in debt level is associated with a substantially poor state of mental health. The researchers mentioned that debts could have different effects on mental health based on

[9] Several studies have identified significant improvements in physical health during periods of economic downturn and the channels of such cyclical relationships (; Van den Berg et al., 2017; Ruhm , 2000; Ariizumi. et al., 2012; Afoakwah, et al., 2021).

the interest rate, repayment period, and non-payment penalties. They conclude that consumption and housing debts have heterogeneous effects on wellbeing. Also, higher debt leads to poorer mental health. Finally, they suggest that debtors should be aware of the potential risk of mental illness or diminished wellbeing.

Mucci et al. (2016) systematically examine several research articles to determine the effects of the 2008-09 global financial crisis on the wellbeing of labour forces in various countries. They analyse 19 studies to understand how the changes in the labour market affect wellbeing. The authors state that a rise in unemployment, increased workload, staff reductions, and wages cuts worsen mood disorders, anxiety, depression, dysthymia, and suicides. Further, the research indicates that the labour market changes as a result of the 2008-2009 economic crisis impact the labour force's physical health by increasing the risk of cardiovascular diseases as well as respiratory illnesses. Their investigation also reveals that suicide attempts resulting from mental disorders are high among the unemployed due to the severe economic downturn.

Frasquilho et al. (2016) explore how economic recessions and mental health outcomes are related by summarizing more than a hundred published studies from 2004 to 2014. The evidence consistently sheds light on economic recession and its induced effects on societies via increasing unemployment, diminishing income, and unmanageable debts, all of which are significantly linked to poor mental wellbeing, increased substance use, and suicide attempts. They conclude that governments can manage the side effects of recessions on mental health by implementing policies as follows: activating the labour market, assisting low-income families, regulating the alcohol market, providing quality and fair access to primary healthcare for patients with severe mental illnesses, and finally, easing debts.

Farré et al. (2018) show that the 2008-09 economic crisis through high unemployment rate leads to widespread mental disorders among Spanish people. They mention that job losses in each segment of the labour market are affected by the collapse of the construction sector. Therefore, a decline in employment results from a negative labour demand shock. They argue this phenomenon leads to prolonged unemployment, stress, desperation, and feelings of worthlessness. The results suggest that an increase in unemployment by 10 percentage points is associated with a 3-percentage point worsening of mental health in affected populations.

Navarro-Carrillo et al. (2019) examine how unemployment is associated with lower levels of subjective wellbeing and self-perceived health during an economic crisis. Their sample spans microdata of 245 adults with ages ranging from 18 to 69 in Spain. Their findings show that unemployment substantially lowers life satisfaction, happiness, and self-perceived health. The effect of age and gender is not significant on mental health; however, income significantly and positively affects wellbeing.

Avdic et al. (2020) analyse that economic downturn impacts mental disorders and life satisfaction via income reduction and fear of job loss profoundly. They collect information from the German Socio-Economic Panel Study (GSOEP) from 2000 to 2016, then examine whether the global financial crisis in 2009 has a long-lasting impact on people's mental health. Their findings support that economic downturn lowers life satisfaction and mental health status. The authors argue that fear of job loss and income reduction mediate mental health issues. Finally, they highlight that the economic downturn due to the COVID-19 pandemic possibly has the same effect on mental health and wellbeing of people.

3.2.2. COVID-19, unemployment and mental health

Burchell et al. (2020) explore how changes in employment status and working hours explain the mental health disorders of workers during the COVID-19 pandemic in the UK. They mention that government responses to the pandemic via implementing a closure policy hike the risk of unemployment for millions of employees and businesses. They gathered the individual-level data for 7,149 British workers before the pandemic and after lockdown, April 2020. They measure the mental health disorders of workers through the General Health Questionnaire (GHQ) index. Their findings confirm that leaving paid employment is associated with a worse mental health condition. Additionally, government intervention in the labour market via the Coronavirus Job Retention Scheme (CJRS) reduces mental issues. This is due to increased labour market opportunities for people and reducing potential financial hardship in the future. However, decreasing working hours via transition from full-time to part-time work is not statistically influential on mental illness, neither for men nor women. Their results also suggest that mental illness prevails among women and people with pre-existing

conditions. However, the likelihood of having mental disorders is less for higher-income and older people.

Posel et al. (2021) analyse how employment loss affects depression among South Africans during the COVID-19 pandemic. They use the individual-level data of 2,213 people gathered from two waves of the National Income Dynamics Coronavirus Rapid Mobile Survey collected from May to August 2020. Their findings show that people who remained at their jobs suffer less depression than those who lost their jobs during the pandemic. Further, they consider age, gender and living area as control variables. They show that people living in urban environments are more prone to mental disorders than villagers. However, the effects of age and gender are not statistically significant. Chatterji et al. (2021) investigated the mental health consequences of job loss in rural India. They use the information of 1,021 women and 1,020 men from February 1 to March 31, 2021. Their findings show that women have a higher probability of having mental illnesses than men. The study also revealed that financial hardship and job loss are associated with higher levels of mental illness among rural Indians. They suggest that the government can help families recover their mental health through financial relief and job creation programs.

Griffiths et al. (2021) examine the effect of job loss on the mental and physical health status of Australians. They use the information of 2,603 people, then apply a logistic regression method to assess whether losing a job is associated with psychological distress, mental disease, or physical health problems. Their results reveal that losing jobs exacerbates psychological and physical disorders. Additionally, they present that female and aged Australians are more likely to suffer from mental disorders than men and people between the ages of 35 and 44.

3.3. Empirical Strategy

This study examines the effect of job loss on different mental disorders based on a logistic regression model. It divides people into two groups, $Y \in \{0, 1\}$. Y=1 indicates individuals with mental disorders; in contrast, Y=0 reflects people with no sign of mental illness. Consequently, the probability of having a mental disorder is Pr(Y=1) = p, whereas the

likelihood of not being diagnosed mentally ill is Pr(Y=0) = 1-p. Accordingly, the empirical specification for this binary outcome based on the odds ratio is written below,

$$\log(P_{ijk}) = X'_{ijk}\beta + Z'_{ijk}\theta + \alpha_j + \gamma_k + \varepsilon_{ijk}, \quad (3.1)$$

where $P = \frac{\mathrm{p}}{1-\mathrm{p}}$ indicates the odds ratio. X is a binary variable that takes a value of 1 when a person loses his/her job; otherwise, it equals zero. Z reflects a vector of other controls covering different aspects of socioeconomic, demographic, geographical, and behavioural factors. Based on Fitch et al. (2011), Holingue et al. (2020), Ettman et al. (2021), Cheng et al. (2021), Griffiths et al. (2021) and Posel et al. (2021), this vector consists of housing mortgage, gender, age and income groups, location of living, risky behaviour such as smoking cigarettes, and finally attending religious activities. β and θ are regression coefficients. The scripts i, j and k refer to individual, country and region, respectively. α_j and γ_k are the country and regional fixed effects[10] to capture the effect of unobserved heterogeneities in the model. Regions here indicates the states or provinces in each country. ε_{ij} indicates the regression error term.

Since interpreting coefficients based on the odds ratio may not be informative for policymaking, I calculate the marginal effects of the discrete explanatory variables on the conditional probability of Y=1. In fact, obtaining the marginal effects relying on the change of explanatory variables facilitates interpreting the results based on chance instead of the odds ratios. The marginal effect is defined as a change in the likelihood of success of the dependent variable, Pr(Y=1), when a dichotomous variable like job loss, $X \in \{0, 1\}$, changes from zero to one, keeping other variables constant. The value of the marginal effect is calculated as follows,

$$ME = \Pr(Y = 1 \mid X = 1, Z) - \Pr(Y = 1 \mid X = 0, Z), \quad (3.2)$$

where Z is considered constant while X changes from zero to one. As seen from Eq. (2), interpreting results is much easier and informative than odds ratios (Cameron and Trivedi, 2005). In comparison with odds ratios, the estimates provide straightforward interpretations that are relevant for policy purposes.

[10] Note that other potential factors such as losing families and lack of receiving mental care affect mental disorders. Since the microdata does not cover these factors, I capture their effects by applying regional fixed effects.

3.4. Data and Estimates

3.4.1. Data

Rich multi-country microdata from six countries are used; China, Italy, Japan, South Korea, the UK, and the US. Belot et al. (2020) collected the data with the cooperation of two market research companies "Lucid" and "dataSpring". The former gathered the data for the Western countries (Italy, the UK, and the USA) and the latter collected the same information for the Asia-Pacific region (China, Japan, and Korea). Participant information was surveyed online by a cloud-based platform, "Qualtrics". The sample is representative of the population across those six countries along with the three aspects of age, gender, and household income. Since the dataset properly varies across countries, regions, age and income groups, these variations allow one to make reliable inferences based on the provided data. The dataset was collected during the early stages of the pandemic between 15 and 23 April 2020. 6,089 people were surveyed in total, and almost 1,000 observations were taken in each country. Among these countries, China and South Korea faced early peaks of the virus compared to the other countries which experienced delayed infection peaks. Based on John Hopkins University CSSE COVID-19 data, the incidence of new COVID-19 cases on 23 April in China and South Korea was 0.05 and 0.27 per million people. However, this rate in Japan, Italy, the UK and the US at the same time was 3.48, 49.77, 70.87 and 87.48 per million people.

The data covers different aspects of the demographic (age and gender), geographic (living area), behavioural (smoking behaviour and attending religious activities), and, finally, economic (having a mortgage) characteristics of respondents. The dataset also contains some non-economic consequences of the pandemic such as psychological aspects like happiness or household conflicts. The survey reports information regarding beliefs and how people feel about the effectiveness of government intervention. Four different aspects of mental disorders are considered: boredom, loneliness, insomnia (trouble in sleeping), and anxiety.[11] In this survey, questions indicate that mental illness and losing

[11] Among these countries, the ethical information is just available for the US, and the survey does not cover the educational features of the respondents. However, this effect is captured by employing sectional fixed effects and treating these factors as unobserved variables.

jobs result from the COVID-19 pandemic. The questionnaire asks people: (i) "*Have you experienced any negative non-financial effects from the societal changes occurring due to the epidemic*?" This question was asked for different mental health problems*, such as Boredom, Loneliness, Trouble sleeping and anxiety.* On unemployment, interviewees were asked (ii) "*Have you lost your job or has your activity (as self-employed) been stopped as a consequence of the COVID-19 pandemic*?". Therefore, our sample does not have a sample selection issue because both mental disorders and job loss, in this study, are induced by the coronavirus pandemic. Appendix 3A provides the list of variables and their definitions precisely.

3.4.1.1. Data description

Reviewing the main features of the dataset allows us to have a better understanding of the distribution of information in the sample population. The descriptive values of this dichotomous data, such as the number of incidences and the proportion of each event, allow us to know which groups are more vulnerable or which types of mental disorders prevail. Table 3.1 provides the count and proportion of different characteristics of the dataset across different countries.

Table 3. 1. Descriptive statistics

	China		Italy		Japan		Korea		the UK		the US		Total	
Variable	Count	Proportion	Count	Proportion	Count	Proportion	Count	Proportion	Count	Proportion	Count	Proportion	Count	Proportion
Sample Size	996	1	1044	1	1015	1	963	1	1016	1	1055	1	6089	1
Anxiety	450	0.45	482	0.46	491	0.48	460	0.48	440	0.43	457	0.43	2780	0.46
Boredom	534	0.54	462	0.44	424	0.42	492	0.51	489	0.48	530	0.5	2931	0.48
Insomnia	299	0.3	314	0.3	88	0.09	128	0.13	342	0.34	333	0.32	1054	0.17
Loneliness	290	0.29	328	0.31	137	0.13	175	0.18	310	0.31	347	0.33	1587	0.26
Losing Jobs	430	0.43	385	0.37	147	0.14	241	0.25	291	0.29	341	0.32	1835	0.3
Mortgage	266	0.27	233	0.22	221	0.22	251	0.26	323	0.32	386	0.37	1680	0.28
Gender	508	0.51	513	0.49	525	0.52	480	0.5	516	0.51	596	0.56	3138	0.52
Age group 18-25 years	150	0.15	119	0.11	107	0.11	129	0.13	109	0.11	122	0.12	736	0.12
26-35 years	192	0.19	186	0.18	168	0.17	170	0.18	177	0.17	184	0.17	1077	0.18
36-45 years	227	0.23	209	0.2	162	0.16	189	0.2	186	0.18	183	0.17	1156	0.19
46-55 years	183	0.18	190	0.18	206	0.2	200	0.21	192	0.19	161	0.15	1132	0.19
56-65 years	127	0.13	158	0.15	170	0.17	139	0.14	191	0.19	163	0.15	948	0.16

above 65 years	117	0.12	180	0.17	200	0.2	135	0.14	161	0.16	242	0.23	1035	0.17
Income group														
1st quantile	201	0.2	170	0.16	207	0.2	198	0.21	180	0.18	181	0.17	1137	0.19
2nd quantile	199	0.2	179	0.17	209	0.21	163	0.17	180	0.18	196	0.19	1126	0.18
3rd quantile	198	0.2	244	0.23	214	0.21	199	0.21	196	0.19	218	0.21	1269	0.21
4th quantile	198	0.2	263	0.25	187	0.18	200	0.21	222	0.22	245	0.23	1315	0.22
5th quantile	198	0.2	165	0.16	165	0.16	159	0.17	217	0.21	199	0.19	1103	0.18
Living area														
Rural	70	0.07	159	0.15	281	0.28	56	0.06	143	0.14	113	0.11	822	0.13
Semi-urban	202	0.2	269	0.26	451	0.44	335	0.35	525	0.52	512	0.49	2294	0.38
Urban	724	0.73	616	0.59	283	0.28	572	0.59	348	0.34	430	0.41	2973	0.49
Smoking	266	0.27	444	0.43	202	0.2	309	0.32	265	0.26	272	0.26	1758	0.29
Religious	104	0.1	81	0.08	29	0.03	82	0.09	106	0.1	205	0.19	607	0.1

As shown in Table 3.1, the distribution of mental disorders is quite unique to countries. The prevalence of anxiety and boredom in the sample is 46 and 48 percent and is more than those for insomnia and loneliness, with 17 and 26 percent, respectively. China, South Korea, the UK, and the US suffer severely from boredom, whereas Japan and Italy struggle with anxiety. The highest rates of insomnia belong to the UK and US, with 34 and 32 percent, respectively. In contrast, Japan and Korea have the lowest rates of insomnia among all countries during this period, with 9 and 13 percent of prevalence, respectively. Americans suffer from loneliness more than other nations, with an incidence of 33 percent among individuals. Despite this, the Japanese experienced loneliness at 13 percent, which is lowest among the countries.

The job loss incidence is 30 percent in the sample. Given this low rate of job loss during the early stage of the pandemic, the null hypothesis is "*job loss does not influence mental health*". According to the dataset, China and Italy have the highest rates with 43 and 37 percent, respectively. In comparison, this rate among Japanese is less than in other nations with a rate of 14 percent. Regarding gender distribution, 52 percent of the sample consists of women. Also, 28 percent of people in the survey have financial liabilities such as housing mortgages.

In terms of income distribution, 19, 18, 21, 22, and 17 percent of people are classified as the first to fifth income groups. Regarding the living area, 13, 38, and 49 percent of respondents live in rural, semi-urban, and urban areas, respectively. Smoking prevalence as a measure of behavioural risk factors is 29 percent in the sample. Furthermore, 19 percent of Americans participate in religious activities, which makes them the most religious nation. Comparatively, the Japanese adhere to religion with only 3 percent participation, which is at the lowest rate than other countries.

3.4.2. Empirical results

This section evaluates the effect of the job loss induced by the COVID-19 on different aspects of mental disorders. Lu and White (2014) propose an approach to make sure the estimates are robust and do not change in the presence or absence of controls. In this case, the "core regression", a regression with a focus variable, should be estimated. The regression specification is then modified by adding or removing non-core explanatory

variables. One can conclude the estimates are robust and not fragile in the presence or absence of controls if the core regressor does not change across different specifications. To employ this approach, first, different regressions are estimated by inclusion and exclusion of controls on a one-by-one basis in the models. For example, I first estimate Eq (1) without any controls as a baseline regression. Then each covariate adds to the baseline regression one by one to estimate the model with all covariates, e.g., the second model includes housing mortgage. The third regression adds gender and refits the model. This process continues by considering age categories and income groups, living areas, smoking prevalence, and attendance of religious activities. Then, finally, I include all controls and re-estimate a complete specification. Therefore, 36 = (4 mental disorders) x (9 models) regressions are estimated. I employed this approach to show the results are not sensitive to the inclusion or exclusion of variables. Results are presented by two models: (i) a baseline model and (ii) a model with a complete set of controls[12].

3.4.2.1. Estimates for all countries

Table 3.2 provides the estimated marginal effects of coefficients for all countries as follows,

[12] Each mental wellbeing index is examined by LASSO regression to make sure that job loss is an influential variable in the model. The findings confirm the validity of the specification. The results are reported in Appendix 3B.

Table 3.2. Marginal effects of the logit regression for six countries

	Anxiety		Boredom		Insomnia		Loneliness	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Job Loss	0.0721***	0.0548***	0.0613***	0.0341**	0.115***	0.0927***	0.127***	0.106***
	(0.0142)	(0.0146)	(0.0142)	(0.0147)	(0.0123)	(0.0126)	(0.0127)	(0.0132)
Mortgage		0.0317**		0.00890		0.0172		-0.0183
		(0.0148)		(0.0149)		(0.0125)		(0.0127)
Gender		0.147***		-0.00276		0.0697***		0.0443***
		(0.0130)		(0.0130)		(0.0110)		(0.0114)
Age group Baseline: above 65 =0								
18-25 years		0.126***		0.290***		0.156***		0.135***
		(0.0242)		(0.0240)		(0.0209)		(0.0226)
26-35 years		0.149***		0.197***		0.116***		0.0679***
		(0.0220)		(0.0225)		(0.0184)		(0.0198)
36-45 years		0.152***		0.104***		0.108***		0.0287
		(0.0216)		(0.0222)		(0.0179)		(0.0190)
46-55 years		0.155***		0.0301		0.0660***		0.00406
		(0.0214)		(0.0218)		(0.0173)		(0.0186)
56-65 years		0.0938***		0.00169		0.0850***		-0.00541
		(0.0219)		(0.0223)		(0.0181)		(0.0190)
Income group Baseline: 1st quantile=0								
2nd quantile		0.0425**		-0.0150		-0.0128		-0.0262
		(0.0206)		(0.0207)		(0.0176)		(0.0182)
3rd quantile		0.0146		0.0365*		-0.0107		-0.0369**
		(0.0201)		(0.0203)		(0.0173)		(0.0178)
4th quantile		0.0130		0.00813		-0.00986		-0.0274
		(0.0202)		(0.0203)		(0.0173)		(0.0180)
5th quantile		0.00563		0.0169		0.0000254		-0.0334
		(0.0215)		(0.0218)		(0.0186)		(0.0192)
Living area Baseline: Rural								
Semi-urban		0.0650***		0.0260		0.0608***		0.0221
		(0.0204)		(0.0207)		(0.0178)		(0.0183)
Urban		0.0531**		0.0148		0.0233		0.0159
		(0.0210)		(0.0214)		(0.0176)		(0.0185)
Smoking		0.0472***		0.0344**		0.0351***		0.0328**
		(0.0146)		(0.0146)		(0.0125)		(0.0130)
Religious services		-0.107***		-0.0599***		-0.0194		0.0525***
		(0.0212)		(0.0217)		(0.0172)		(0.0195)
N	**6089**	**5945**	**6089**	**5945**	**6074**	**5916**	**6082**	**5938**
Pseudo R^2	**0.0173**	**0.0508**	**0.0168**	**0.0469**	**0.0787**	**0.1007**	**0.0571**	**0.0714**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals. There are eight specifications for each mental disorder, e.g., adding each control to the baseline model, Model 1, and estimating the regression to ensure that the effect of job loss does not change by including an additional variable. I report the baseline and completer models.

As is evident, the four aspects of mental disorders are positively and significantly associated with losing jobs. Considering the full specification in model 2, the estimates reveal that the probability of anxiety, boredom, insomnia and loneliness increase by 0.055, 0.034, 0.093 and 0.106, respectively, for job losers compared to employed people, given the other variables in the model are constant. This suggests that effective labour market policies creating jobs lead to better mental health. Further, these findings show that job loss is associated more with insomnia and loneliness than other mental disorders. It may be due to social isolation and lack of communication induced by restrictions during the pandemic (Pietrabissa and Simpson, 2020).

Regarding the effect of financial liabilities on mental health, it should be noted that housing mortgage has a positive and significant impact only on anxiety. In this regard, the probability of anxiety is 0.032 higher for home mortgage debtors in comparison to non-debtors, considering the other variables constant. This finding aligns with Jenkins et al. (2008) and Fitch et al. (2011).

Interestingly, findings reveal that women are subject to all the same mental disorders as men except boredom during the pandemic. In accordance with WHO (2002), socially imposed inequalities between women and men in terms of roles and duties, status, and power, interact with biological differences between sexes to lead to an increased risk of mental disorders among women. The estimated marginal effects reveal that women's likelihood of experiencing anxiety, insomnia, and loneliness is 0.147, 0.070, and 0.044, respectively, more than men.

The marginal effect of all age groups compared to the older age group (> 65 years) is positive and significant for anxiety and insomnia. Regarding boredom and loneliness, the first two and the first three groups of ages are impacted. It may be due to a longer job search period that young unemployed experience than older and experienced people. This finding is in line with Winkelmann and Winkelmann (1998) and Holingue et al. (2020).

The results also show that individuals at the second quantile of income are more subject to anxiety. For boredom and loneliness, people in the third quantile are more prone to mental illness.

Living in semi-urban and urban areas compared to rural regions increases the probability of getting anxiety compared to the first income quantile. However, the effect of the location of living on boredom and loneliness is insignificant.

Results show that engaging in risky behaviour like smoking cigarettes increases the chance of all types of mental disorders than non-tobacco users. The value of the marginal effect reveals that the probability of experiencing anxiety for smokers is 0.047 is higher than for non-smokers, given the other variable is fixed. Also, anxiety is a prevalent mental problem among smokers. Increased anxiety among smokers may happen because of the side effects of nicotine on the brain system[13] (Moylan et al., 2013).

Finally, engaging in religious activities at least once a week reduces the chance of all mental disorders except insomnia. Again, this effect is more prominent for anxiety compared to other mental illnesses. Hill et al. (2018) argue that religious involvement can benefit mental health in some aspects: (i) promoting social resources such as social integration, social ties and engagements, as well as social support. (ii) increasing psychological resources, including optimism, hope, and a sense of purpose and meaning. As a result of these benefits, religious people take advantage of a high quality of health and a better state of mental health.

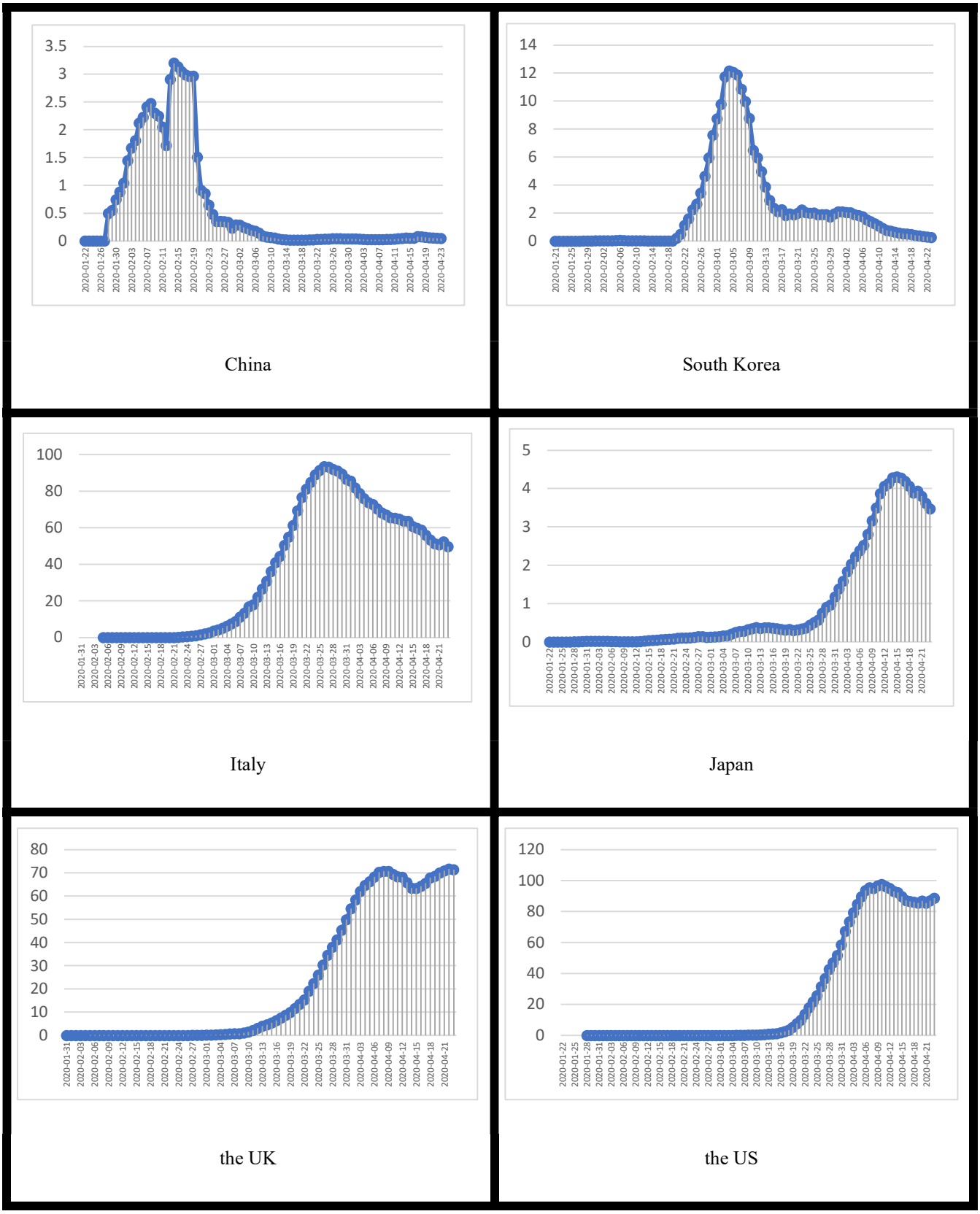
3.4.2.2. Estimates for the countries with delayed peak of the virus

At the next step, I cluster the countries based on the trajectory of the COVID-19 outbreak in each. This type of grouping shows how the wellbeing of individuals varies in different societies when the spread of the virus is under control in comparison with when the infection is near the peak. In light of this fact, mental disorders may heterogeneously vary in countries where individuals are less concerned about the outbreak in comparison with those struggling with high infection rates in their societies. In fact, when the incidence of new COVID-19 cases peaked the respondents would have felt more anxious and would have gone through more stressful conditions, i.e., lower mental wellbeing, particularly when the state was going through an extreme health crisis, higher hospitalisation rates, and deaths. However, after the peak date when the new infections

[13] Specifically, Moylan et al. (2013) discuss smoking cigarettes by increasing nicotine in blood negatively impacts neurotransmitter systems, mitochondrial dysfunction, neurotrophins and neurogenesis, and epigenetics.

rate fell, the adverse impact on mental wellbeing would have dampened. Therefore, we treat these two groups of countries separately and conjecture that the effect of job loss on mental health status is different between countries experiencing early spike of new infections and countries experiencing delayed spike of new infections in the sample. Moreover, the group of delayed peak infection rate countries, i.e., Italy, Japan, the UK, and the US can be categorised as advanced economies as compared to the early peak infections rate countries, i.e., China and South Korea, which are emerging economies in our sample. Figure 3.1 shows the trajectories of COVID-19 infection rates from January 2020 to the date the survey was completed.

Figure 3.1: Trajectories of the smoothed daily infection rate



Source: the Center for Systems Science and Engineering (CSSE), Johns Hopkins University. Notes: The smoothed daily infection rate represents the rolling average of infections per million people over the past week. The smoothing technique, in fact, calculates the 7-day average on a lagging basis when the current value for day t matches the average of days t, t-1, t-2, t-3, t-4, t-5, and t-6.

The trajectories of COVID-19 infection rates reveal that the advanced countries in the sample, i.e., Italy, Japan, the UK and the US were faced with delayed infection peak compared to the emerging countries in the sample, China and South Korea.

Table 3.3 reports the marginal effects of job loss estimates over different mental disorders in a group of high infection countries, i.e., Italy, Japan, the UK, and the US. These countries can also be categorised as advanced economies as compared to the low infection countries, i.e., China and South Korea, which are emerging economies in our sample. To satisfy the purposes of Lu and White (2014) regarding robust estimates of mental health effects of job loss, 64 = (2 clusters) x (4 mental disorders) x (8 models) regressions are estimated. Although the effects of all job losses on mental health have not been changed over different specification, I report the core regression and the model with a complete set of controls as follows.[14]

[14] A complete picture of estimates is available upon request. Further, the models are tested with interactional effects between (gender x job loss) and (gender x mortgage). However, I could not find reliable and significant results for interactional effects. These estimates are accessible as well upon request.

Table 3.3. Marginal effects of the logit regression for countries with delayed infection peak

	Anxiety		Boredom		Insomnia		Loneliness	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Job Loss	0.0714***	0.0435**	0.106***	0.0523***	0.104***	0.0669***	0.128***	0.0856***
	(0.0175)	(0.0181)	(0.0175)	(0.0184)	(0.0153)	(0.0156)	(0.0159)	(0.0164)
Mortgage		0.00508		-0.0218		0.0279*		-0.0204
		(0.0178)		(0.0178)		(0.0154)		(0.0155)
Gender		0.168***		-0.00271		0.0859***		0.0540***
		(0.0156)		(0.0156)		(0.0135)		(0.0139)
Age group								
Baseline: above 65 =0								
18-25		0.140***		0.333***		0.199***		0.170***
		(0.0296)		(0.0293)		(0.0265)		(0.0280)
26-35 years		0.169***		0.245***		0.148***		0.104***
		(0.0262)		(0.0268)		(0.0225)		(0.0239)
36-45 years		0.173***		0.136***		0.122***		0.0528**
		(0.0258)		(0.0266)		(0.0218)		(0.0229)
46-55 years		0.189***		0.0583**		0.0646***		0.0326
		(0.0253)		(0.0258)		(0.0207)		(0.0224)
56-65 years		0.117***		0.0144		0.101***		0.0297
		(0.0253)		(0.0256)		(0.0215)		(0.0225)
Income group								
Baseline: 1st quantile=0								
2nd quantile		0.0533**		-0.0242		-0.00469		-0.0130
		(0.0250)		(0.0252)		(0.0218)		(0.0224)
3rd quantile		0.00814		0.0265		-0.0250		-0.0251
		(0.0244)		(0.0247)		(0.0210)		(0.0218)
4th quantile		0.00991		-0.00349		0.0114		-0.00739
		(0.0245)		(0.0247)		(0.0214)		(0.0221)
5th quantile		-0.0123		0.000560		0.0119		-0.0193
		(0.0262)		(0.0266)		(0.0231)		(0.0236)
Living area								
Baseline: Rural								
Semi-urban		0.0478**		0.0237		0.0507**		0.0215
		(0.0222)		(0.0226)		(0.0202)		(0.0206)
Urban		0.0450*		0.0185		0.0240		0.0215
		(0.0233)		(0.0236)		(0.0206)		(0.0213)
Smoking		0.0404**		0.0172		0.0336**		0.0254
		(0.0176)		(0.0177)		(0.0153)		(0.0157)
Religious services		-0.113***		-0.0666**		-0.0384*		0.0789***
		(0.0260)		(0.0263)		(0.0206)		(0.0246)
N	4130	4033	4130	4033	4127	4026	4127	4030
Pseudo R^2	**0.0154**	**0.0589**	**0.0171**	**0.0537**	**0.0715**	**0.1043**	**0.0573**	**0.0745**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals. There are eight specifications for each mental disorder, e.g., adding each control to the baseline model, Model 1, and estimating the regression to ensure that the effect of job loss does not change by including an additional variable. I report the baseline and completer models.

According to the results, there is a positive association between job loss from all types of mental illness, especially loneliness. In this context, the marginal effects for anxiety, boredom, insomnia and loneliness are 0.043, 0.052, 0.067, and 0.086, respectively.

Assuming that all other variables in the model remain constant, the chances of anxiety, boredom, insomnia, and loneliness are 0.043, 0.052, 0.067, and 0.086, respectively higher for people who lost jobs compared to non-job losers. This finding is consistent with the idea that an effective labour market policy leads to better mental health in countries experiencing delayed infection peak.

In terms of the marginal effect of financial obligations on mental health, it is noteworthy that housing mortgage has a positive and significant effect only on insomnia. Accordingly, the probability of insomnia is expected to be 0.028 more for people who are in housing debt than for people who do not have mortgages, assuming the other variables remain constant.

Notably, I find that women are at a higher risk for mental disorders, except boredom at the time of the outbreak. According to the marginal effects, women are more likely to be anxious, insomniacs, and lonely than men, by 0.168, 0.086, and 0.054 points, respectively, keeping other factors constant.

All age groups significantly experience anxiety and insomnia compared to adults older than 65 years across the nations facing the peak of the outbreak. For boredom and loneliness, the age effect is not significant for the last age group. It indicates that the psychological impact of COVID-19 hits young adults consistently.

In addition, the results suggest that people at the second quantile of earnings have a greater tendency to feel anxious than individuals who are in the first income quantile. However, there is no evidence on the effects for other income groups on mental disorders compared to the first earning quantile in countries with delayed infection peak.

Interestingly, a semi-urban or urban lifestyle increases the risk of anxiety compared with the countryside. Despite this, boredom and loneliness are not affected significantly by place of residence.

Findings show that engaging in risky behaviours like using tobacco elevates the risk of anxiety and insomnia in countries with delayed infection peak. The value of the marginal effects suggests that the likelihood of experiencing anxiety and insomnia for smokers is 0.040 and 0.034 greater than for those not smoking, keeping other variables constant.

Lastly, engaging in spiritual activities at least once a week diminishes the risk of all mental disorders, especially anxiety in countries that have struggled with the spread of the virus.

3.4.2.3. Estimates for the countries with early infection peak

To gain a comprehensive understanding of how the Coronavirus pandemic has affected people's mental health in countries that overcame the spread of the virus at an early stage, model (1) is fitted for China and South Korea, where the infection rates had an early peak at the time of data collection. Lievens (2020) mentions that these two emerging countries achieve this goal due to implementing effective public health policies.

In Table 3.4, I present the estimates of the marginal effects of job loss and other socioeconomic, demographic, and behavioural factors on mental health for countries with low COVID-19 prevalence:

Table 3.4. Marginal effects of the logit regression for countries with early infection peak

	Anxiety		Boredom		Insomnia		Loneliness	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Job Loss	0.0734***	0.0758***	-0.0246	-0.0157	0.134***	0.129***	0.123***	0.131***
	(0.0241)	(0.0249)	(0.024)	(0.0251)	(0.020)	(0.0212)	(0.021)	(0.0222)
Mortgage		0.0866***		0.0728***		-0.0079		-0.0210
		(0.0268)		(0.0268)		(0.0214)		(0.0223)
Gender		0.0922***		-0.000427		0.0321		0.0314
		(0.0243)		(0.0244)		(0.0200)		(0.0207)
Age group Baseline: above 65 =0								
18-25		0.101**		0.170***		0.102***		0.0621
		(0.0442)		(0.0438)		(0.0360)		(0.0411)
26-35 years		0.108***		0.0648		0.0646*		-0.0140
		(0.0420)		(0.0427)		(0.0337)		(0.0380)
36-45 years		0.115***		0.0194		0.0869**		-0.0292
		(0.0404)		(0.0413)		(0.0323)		(0.0361)
46-55 years		0.0873**		-0.0415		0.0548*		-0.0687**
		(0.0406)		(0.0414)		(0.0315)		(0.0350)
56-65 years		0.0382		-0.0332		0.0430		-0.0916**
		(0.0437)		(0.0445)		(0.0340)		(0.0366)
Income group Baseline: 1st quantile=0								
2nd quantile		0.0145		0.0118		-0.0205		-0.0418
		(0.0366)		(0.0367)		(0.0289)		(0.0310)
3rd quantile		0.0418		0.0650*		0.0399		-0.0454
		(0.0360)		(0.0361)		(0.0302)		(0.0311)
4th quantile		0.0271		0.0368		-0.0359		-0.0582*
		(0.0364)		(0.0366)		(0.0292)		(0.0314)
5th quantile		0.0509		0.0736		0.00814		-0.0470
		(0.0389)		(0.0392)		(0.0325)		(0.0338)
Living area Baseline: Rural								
Semi-urban		0.155***		0.0186		0.0902**		0.00878
		(0.0509)		(0.0518)		(0.0383)		(0.0427)
Urban		0.121**		-0.0213		0.0446		-0.00479
		(0.0498)		(0.0512)		(0.0353)		(0.0412)
Smoking		0.0339		0.0533**		0.0317		0.0380
		(0.0268)		(0.0268)		(0.0226)		(0.0236)
Religious services		-0.0651*		-0.0570		0.0267		-0.00142
		(0.0382)		(0.0390)		(0.0319)		(0.0322)
N	1959	1912	1959	1912	1947	1890	1955	1908
Pseudo R^2	**0.0209**	**0.046**	**0.0155**	**0.0396**	**0.0912**	**0.1071**	**0.0533**	**0.0714**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals. There are eight specifications for each mental disorder, e.g., adding each control to the baseline model, Model 1, and estimating the regression to ensure that the effect of job loss does not change by including an additional variable. I report the baseline and completer models.

The findings indicate that job loss is positively associated with mental health issues, except boredom in countries experiencing early infection peak. Considering this, the incidences of anxiety, insomnia, and loneliness rise by 0.076, 0.129, and 0.131, respectively, for job losers, compared with those who do not lose their jobs when all other variables are held constant. Therefore, a favourable labour market policy promotes mental health, which is consistent with the findings.

However, these figures are consistently higher than for the countries with early infection peak presented earlier in Table 3.3. Since those countries are among emerging nations, losing jobs has more considerable effects on mental disorders as compared to developed economies. There are three possible reasons for this: (i) timing: China and Korea were hit by COVID-19 much earlier than Italy, the UK, or the US[15]. As a result, businesses in those two emerging economies struggled longer than those in advanced economies where COVID-19 prevalence emerged later. Consequently, in societies that were exposed to the pandemic earlier, the business effect is greater. (ii) restrictions: Relying on the *Oxford COVID-19 Government Response Tracker* (OxCGRT), the average ratio of the stringency index as the measure of government nonpharmaceutical interventions is 50.27 and 33.99 out of 100 in the countries with early and delayed infection peaks from 1 January 2020 to the date the data is collected. The average values of the stringency index and government economic supports for each country are reported in Appendix 3C. (iii) economic supports: in spite of the lower change of unemployment rate in China and Korea than the countries with delayed infection peak[16], Japan, Italy and the UK and the US performed a comprehensive job retention scheme during the pandemic (OECD, 2020). Further, the information provided by the OxCGRT indicates that Chinese and Korean governments provided less economic support compared to the advanced ones. For example, based on the OxCGRT, the average government financial support index is 7.6 out of 100 in China and South from 1 January to 23 April 2021; however, this value in Italy, Japan, the UK and the US equals 21.66 out of 100. It shows that when an economy experiences a lockdown, businesses and households receive lower economic support from

[15] First cases were identified in China on 31 December 2019, from South Korea on 20 January 2020, from Japan on 15 January 2020, from Italy and the UK on 31 January, and from the United States on 21 January.

[16] Unemployment rate was changed a year after pandemic from 4.6 to 5 percent in China, from 3.75 to 4.1 percent in Korea, from 2.4 to 3 percent in Japan, from 9.9 to 9.3 percent in Italy, from 3.7 to 4.3 percent in the UK, and finally from 3.7 to 8.3 percent in the US.

the government. In fact, when people lose their jobs as a result of the pandemic, they cannot expect the government to compensate a part of their lost income. Therefore, losing jobs has a more significant impact on individual wellbeing. There is also another reason causing more mental issues among people who lost their jobs in emerging countries: the countries perform more stringent nonpharmaceutical interventions than advanced countries (Nelson, 2021). In fact, low- and middle-income countries have more authoritarian governments compared to advanced ones. As a result of lack of democracy in such countries, governments implement harder restrictions like lockdown, and school and business closures to control the spread of the virus.

Considering the marginal effect of financial commitments on mental well-being, it highlights that mortgage debt significantly affects anxiety and boredom in nations that faced early infection peak. Consequently, the probability of anxiety and boredom are 0.087 and 0.073 more for people who are in housing debt than for people who do not have mortgages, keeping the other variables constant. Comparing the results with the countries characterised by delayed infection peak reveals that housing mortgage affects mental health in these two groups in different ways. In nations with delayed infection peak, those with mortgages suffer insomnia by 0.028 points more than those without mortgages.

Furthermore, it is found that women are at a higher risk for anxiety. Based on the marginal effect, the probability of anxiety becoming more prevalent among women than men is 0.092 when all other factors are kept constant. Comparing this result with the findings for countries with delayed infection peak reveals that, first, women suffer from different mental issues such as anxiety, insomnia and loneliness in advanced countries compared to emerging countries during the COVID-19 pandemic. Second, the probability of women being at risk of mental health issues is much higher in advanced countries than in emerging ones.

More interestingly, it is revealed that youth who have the highest probability of boredom and insomnia are those in countries with early infection peak. The likelihood of anxiety for all age groups except people at 56-65 years is significantly positive. I find a significantly negative relationship between age and loneliness for people between the ages of 46 to 65 years old in these nations. This finding is in line with Holingue et al. (2020) mentioning prime-age adults are more vulnerable than older groups.

The results also confirm that people at the third quantile of earnings have a larger propensity to boredom than those among the first income quantile. The likelihood of feeling lonely for the fourth quantile of income is less than for the baseline group. However, there is no statistical evidence on the effects of income on anxiety and insomnia in countries with early infection peak.

Living in semi-urban or urban environments exacerbates the risk of anxiety compared with the countryside. This is in line with Posel et al. (2021) showing that living in urban environments leads to mental disorders. This result is also consistent with our findings for countries characterised by delayed infection peak. When comparing semi-urban and urban areas, the coefficients demonstrate that semi-urban residents suffer more mental degeneration than urban residents. This phenomenon may occur due to the lack of health facilities in semi-urban areas compared to urban ones. Despite this, home location does not affect loneliness and boredom.

Findings suggest no association between risky habits like smoking and three aspects of mental disorders, including anxiety, insomnia, and loneliness in countries with early infection peak. This result differs entirely from the evidence that those countries have struggled with the spread of the virus.

Lastly, engaging in spiritual activities at least once a week diminishes only the risk of anxiety and does not affect other types of mental illness.

3.4.2.4. Estimates for overall wellbeing measure

Since different factors of mental disorders exist, it is worthwhile to know how mental health overall reacts to job loss and other socioeconomic factors in the model. Each type of mental health indicator is unique to its own determinants, and it may react to socioeconomic variables in different ways in each country. However, from a macroeconomic perspective of government policy, an overall measure of wellbeing would help policymakers to understand the relationship of job loss with mental health in each of these countries.

To accomplish that, a mental disorder index (MDI) is created by combining the different aspects of mental illness in this study, including anxiety, boredom, insomnia, and loneliness. A factor analysis method is applied. Factor Analysis (FA) is a statistical

method that explains a set of variables in terms of a few latent factors. This technique is widely used among psychologists to create a unique behavioural index of several psychological outcomes. The first example of using this method goes back to Spearman (1904); he shows how different educational outcomes — e.g., "verbal skills" and "knowledge of mathematics" — can be combined to measure educational achievement as a measure of general intelligence. He establishes FA to show how several branches of intellectual activities are modelled based on "common groups of Functions."

To fix to notation, an m-factor model is specified as follows,

$$x_1 = \theta_{11}F_1 + \theta_{12}F_2 + \cdots + \theta_{1m}F_m + \varepsilon_1$$

(3.3)

$$x_n = \theta_{n1}F_1 + \theta_{n2}F_2 + \cdots + \theta_{nm}F_m + \varepsilon_n \,,$$

where x_i for $i = (1, \cdots, n)$ is a set of random variables that need to be diminished in some aspects. Here, it includes four aspects of mental disorders such as anxiety, boredom, loneliness, and insomnia. F_j for $j = (1, \cdots, m)$ is a vector of uncorrelated common factors that are not directly observable. It has been identified with a zero mean and unity variance. Technically, the factors present the relationship between variables in a condensed form. θ_{ij} is the factor loadings corresponding to the correlation between the factors and mental disorders. ε_i for $i = (1, \cdots, n)$ is the error term assumed as independent and identically distributed (iid) random variables.

It is important to note that the variance of x_i can be written as $Var(x_i) = \theta_{i1}^2 + \theta_{i2}^2 + \cdots + \theta_{im}^2 + Var(\varepsilon_i)$. The error variance in the model, $Var(\varepsilon_i)$ is named the specificity of x_i. The variance of the common factors, $\theta_{i1}^2 + \theta_{i2}^2 + \cdots + \theta_{im}^2$ is called common variance or communality. The common variance is crucial because it determines how many factors should be extracted from the original data.

Accordingly, the MDI, the dependent variable is no longer a discrete variable because it is a combination of different measures of mental disorder. Thus, the ordinary least square (OLS) method is employed instead of logistic regression. After calculating the MDI, I estimate the following regression,

$$MDI_{ijk} = X'_{ijk}\beta + Z'_{ijk}\theta + \alpha_j + \gamma_k + \varepsilon_{ijk}, \qquad (3.4)$$

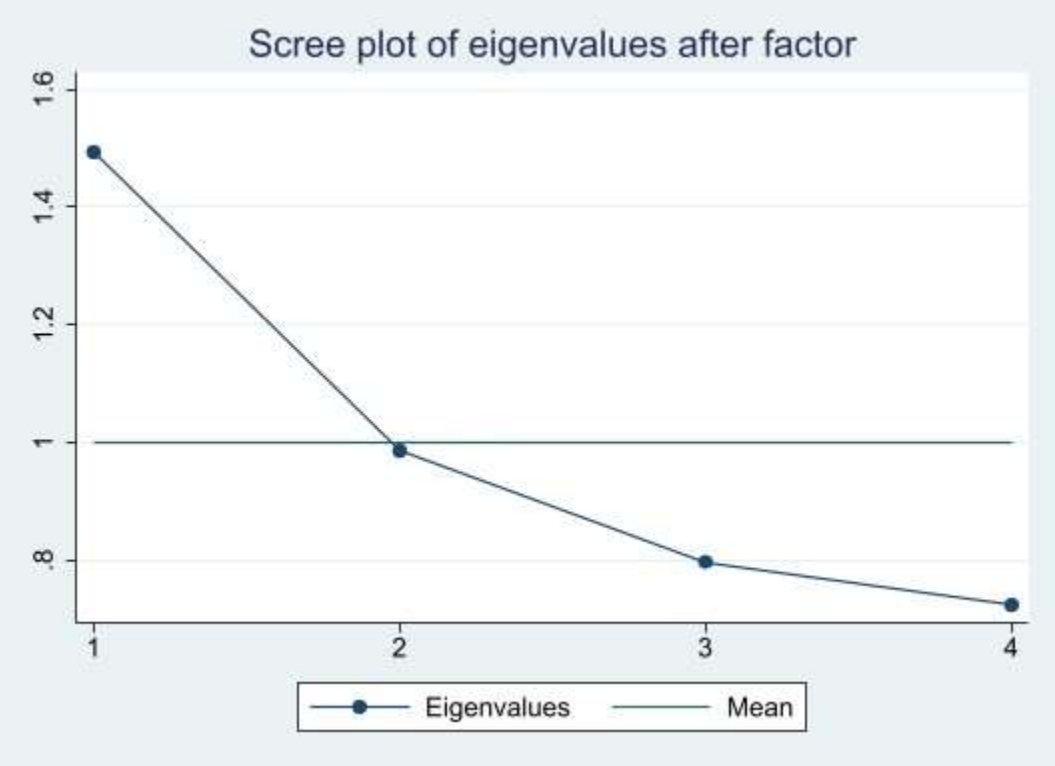
Here, the coefficients β and θ reveal the overall effect of job loss and other determinants on mental health of individuals.

Before implementing factor analysis, it should be ensured that our data suits factor analysis. To do this, I apply the Kaiser-Meyer-Olkin (KMO) criterion. It is defined as follows,

$$KMO = \frac{\sum\sum_{i \neq j} r_{ij}^2}{\sum\sum_{i \neq j} r_{ij}^2 + \sum\sum_{i \neq j} p_{ij}^2}, \tag{3.5}$$

Where r_{ij} and p_{ij} are the correlation and the partial covariance matrices, respectively. The value of this measure ranges from zero to one. A value below 0.5 indicates insufficiency for performing the factor analysis. The value of KMO for anxiety, boredom, insomnia and loneliness is 0.61, 0.59, 0.59 and 0.59, respectively. Since the average of this measure for all random variables equals 0.6, applying the FA is suitable for creating a reliable composite index indicating the overall mental disorder of each individual. Based on the fact that four random variables are incorporated in the model, it implies that there can be four factors that are feasible. One common approach to obtain factors and factor loadings is the principal-component factor analysis (PCF). The PCF assumes the common variance equals one. This measure provides a principal for a factor selection method. Figure 3.2 shows the "Scree Plot" in which eigenvalues for different factors are depicted.

Figure 3.2: Scree Plot



Source: Calculation method

As shown, the first factor captures the highest variance in the model. The horizontal line reflects the average values of the eigenvalues. Based on the Kaiser-Guttman criterion, I employ the "eigenvalue-one rule". In this case, eigenvalues larger than one explain greater proportions of the variance of the model. This fact is also known as the eigenvalue-one rule. The findings reveal that there is only one factor that exists in the model.

Table 3.5 shows the values of the estimated eigenvalues and their shares of the variation of mental disorders as follows:

Table 3.5. Estimated factors and their shares of the model variance

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	**1.4937**	**0.50830**	**0.3734**	**0.3734**
Factor2	0.9854	0.18810	0.2464	0.6198
Factor3	0.7973	0.07370	0.1993	0.8191
Factor4	0.7236	.	0.1809	1.0000

LR test: independent vs. saturated: chi2(6) = 995.15 Prob>chi2 = 0.0000

Notes: above LR test, known as the sphericity test, checks whether a matrix of correlations meaningfully differs from an identity matrix (Bartlett, 1951). When the test is not statistically significant, the correlation matrix cannot be utilised to perform a factor analysis because the random variables are not sufficiently correlated.

As seen, the first factor explains over 37.4 percent of the variation of mental disorder. However, the other factors cannot explain this variation adequately. Accordingly, the estimated factor loading for anxiety, boredom, insomnia and loneliness equal 0.5613, 0.5133, 0.659, and 0.6935, respectively. The composite measure of mental disorders, MDI, is produced by these coefficients[17].

The estimates of the association between job loss on the MDI are provided in Table 3.6 as follows,

[17] Appendix 3D reports the observed correlation coefficients among wellbeing indices. Appendix 3E reports the anti-image covariance coefficients of each index in the factor model.

Table 3.6. the effect of job loss on the Mental disorder index (MDI) in the countries with early and delayed infection peaks

	Grand Total		Countries with delayed infection peak		Countries with early infection peak	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Job Loss	0.357***	0.287***	0.381***	0.246***	0.312***	0.323***
	(0.0277)	(0.0283)	(0.0358)	(0.0369)	(0.0424)	(0.0436)
Mortgage		0.0286		-0.005		0.0851*
		(0.0289)		(0.0364)		(0.0468)
Gender		0.224***		0.265***		0.129***
		(0.0253)		(0.0317)		(0.0426)
Age group Baseline: above 65 =0						
18-25		0.590***		0.708***		0.346***
		(0.0476)		(0.0609)		(0.0777)
26-35 years		0.432***		0.548***		0.160**
		(0.0434)		(0.0542)		(0.0738)
36-45 years		0.319***		0.391***		0.150**
		(0.0425)		(0.0533)		(0.0711)
46-55 years		0.201***		0.271***		0.0119
		(0.0421)		(0.0523)		(0.0716)
56-65 years		0.145***		0.219***		-0.0524
		(0.0432)		(0.0525)		(0.0766)
Income group Baseline: 1st quantile=0						
2nd quantile		-0.0141		0.0144		-0.0443
		(0.0400)		(0.0509)		(0.0636)
3rd quantile		-0.00926		-0.0233		0.0744
		(0.0392)		(0.0499)		(0.0628)
4th quantile		-0.0219		0.00771		-0.0399
		(0.0394)		(0.0500)		(0.0635)
5th quantile		-0.0174		-0.0162		0.0554
		(0.0422)		(0.0538)		(0.0680)
Living area Baseline: Rural						
Semi-urban		0.145***		0.120***		0.216**
		(0.0400)		(0.0455)		(0.0899)
Urban		0.0856**		0.0861*		0.105
		(0.0412)		(0.0477)		(0.0886)
Smoking		0.131***		0.106***		0.129***
		(0.0284)		(0.0359)		(0.0470)
Religious services		-0.0787*		-0.0837		-0.0558
		(0.0429)		(0.0552)		(0.0679)
Constant	-0.319**	-0.748***	-0.209	-0.858***	-0.300**	-0.600***
	(0.132)	(0.137)	(0.226)	(0.227)	(0.119)	(0.153)
N	**6089**	**5945**	**4130**	**4033**	**1959**	**1912**
R^2	**0.078**	**0.130**	**0.075**	**0.138**	**0.088**	**0.130**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals. There are eight specifications for each mental disorder, e.g., adding each control to the baseline model, Model 1, and estimating the regression to ensure that the effect of job loss does not change by including an additional variable. I report the baseline and completer models.

The results indicate that job loss and the mental disorder index (MDI) are positively associated. These results are robust to our baseline findings. In model 2, the coefficients for countries experiencing delayed and early infection peaks are 0.246 and 0.323, respectively. Thus, people who have lost their jobs are at a higher risk of the MDI in the countries where controlled the virus than the regions experiencing the pick of the virus. This issue may be due to fewer economic support, high levels of restrictions or inadequate job retention schemes in China and Korea (Lievens, 2021). The estimates show that the housing mortgage cannot affect the overall index of mental illness, the MDI. Notably, similar to our baseline findings, women are more vulnerable than men to mental illness, especially in countries with a high Coronavirus prevalence. This phenomenon may be because women deal with additional responsibilities such as handling their children's homework, cooking, and taking care of family members who have stayed home during pandemics and lockdowns (Rossi et al., 2020; Tull et al., 2020).

Most interestingly, findings show that mental illness is more likely to occur when one is younger. This age effect diminishes for older groups. Consider the grand total, the MDI for 18-25, 26-35, 36-45, 46-55 and 56-65 is 0.590, 0.432, 0.319, 0.201 and 0.145 units higher, respectively, when compared to the baseline group. The age effect is greater for the nations experiencing the peak of the pandemic than for those that have been able to manage the spread of the virus.

The living location has a greater impact on MDI in countries with early infection peak than in nations with high rates. This effect in semi-urban environments is bigger than in urban areas. The results also reveal that smoking tobacco increases the MDI by 0.106 and 0.129 units compared to non-smokers in the countries with delayed and early infection peaks, respectively.

Last but not least, participating in religious activities at least once a week dramatically reduces the risk of mental illness by 0.078 units when compared with non-religious people in grand total. Although after subgrouping, the sample the effect is statistically negligible.

3.5. Endogeneity checks

There could be potential endogeneity biases on how job loss can impact the mental health status of an individual. Endogeneity bias can arise due to reverse causality as we can argue that people with weaker mental health are more likely to lose their jobs in the first place. Also, there could be omitted variable bias, as jobless and mental wellbeing could be jointly determined by unknown factors in the model, potentially impacting both variables. Following Angrist and Pischke (2009), a two-step least squares (2SLS) method is employed to solve the potential endogeneity of job loss.

3.5.1. First stage estimates for countries faced early vs delayed infection peak

In the first step, we identify an instrument from the survey which is exogenous to the specification but can influence the mental health status of an individual only through the channel of job loss. This variable is defined as the pre-pandemic working status of an individual. This variable includes four categories: no employment, full-time employment, part-time employment, and self-employment. The working status of an individual in the pre-pandemic period is exogenous as it has no association with the mental health status developed during the COVID-19 pandemic. However, people's pre-pandemic contractual job conditions affect the probability of being unemployed as a result of the pandemic (i.e., job loss). In other words, he instrumental variable (pre-pandemic employment status) works as a lag for current employment status. People with full-time contracts are expected to be less vulnerable to losing their jobs than those with part-time contracts or who are self-employed. Thus, the variable satisfies both the relevancy and the exogeneity conditions of a valid instrument. We further test these conditions empirically by running the first stage regression (relevancy condition) and checking the Cragg-Donald F statistic provided by Stock and Yogo (2005) for exogeneity in the second order regressions (exogeneity condition). To pass the second stage of exclusion restrictions, the value of the Cragg-Donald F-statistic is required to be greater than 10 (Kaufmann, Mehrez, and Gurgur, 2019).

In order to capture the variation in job loss in the first stage regression, I consider demographic characteristics such as gender, age, and location of residence, along with country and regional fixed effects. The estimates of the first stage regression are presented as follows:

Table 3.7. first stage estimates for countries with early and delayed infection peaks

	Grand Total	Countries with delayed infection peak	Countries with early infection peak
Labour Statues			
Baseline: no employment			
Full-time employment	0.0795***	0.0997***	-0.00157
	(0.0152)	(0.0179)	(0.0287)
Part-time employment	0.258***	0.265***	0.184***
	(0.0204)	(0.0234)	(0.0419)
Self-employment	0.384***	0.394***	0.283***
	(0.0217)	(0.0269)	(0.0380)
Gender	-0.00267	0.00702	-0.0172
	(0.0113)	(0.0131)	(0.0210)
Age group			
Baseline: above 65 =0			
18-25	0.187***	0.265***	0.0152
	(0.0212)	(0.0258)	(0.0382)
26-35 years	0.169***	0.221***	0.0332
	(0.0203)	(0.0237)	(0.0391)
36-45 years	0.166***	0.180***	0.115***
	(0.0195)	(0.0227)	(0.0373)
46-55 years	0.128***	0.120***	0.120***
	(0.0187)	(0.0209)	(0.0375)
56-65 years	0.0625***	0.0650***	0.0545
	(0.0172)	(0.0182)	(0.0402)
Living area			
Baseline: Rural			
Semi-urban	0.0236	-0.0000147	0.0912**
	(0.0160)	(0.0170)	(0.0429)
Urban	0.0302*	0.0476**	-0.0212
	(0.0174)	(0.0188)	(0.0442)
Constant	0.129*	-0.0192	0.283***
	(0.0730)	(0.0894)	(0.0867)
N	**6080**	**4122**	**1958**
R^2	**0.155**	**0.189**	**0.127**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals.

The findings reveal that the probability of job loss for part-time and self-employed is much higher than for people who had full-time contracts. According to the estimates, the chance of being unemployed as a result of the pandemic for individuals who worked full-time before the pandemic was 0.0795. This likelihood was 0. 258 and 0.384 for people with part-time contracts and self-employed, respectively. It is also shown that the probability of job loss for younger people is more than for the older or more experienced cohort.

When the sample is clustered to the countries with early and delayed infection peaks, it is observable that full-time employees are not significantly affected in the countries with early infection peak. Conversely, all groups of the active workforce have been affected by the pandemic in those countries characterised by delayed infection peak.

3.5.2. 2SLS estimates for six countries

The second stage regression is estimated for different wellbeing measures. The following table reports the estimates after controlling the endogeneity of job loss for all six countries.

Table 3.8. 2SLS estimates for six countries

	Anxiety	Boredom	Insomnia	Loneliness	MDI
Job Loss	0.133**	0.122**	0.0755*	0.157***	0.427***
	(0.0529)	(0.0538)	(0.0459)	(0.0481)	(0.104)
Mortgage	0.0262*	0.00230	0.0190	-0.0214	0.0182
	(0.0155)	(0.0156)	(0.0135)	(0.0134)	(0.0301)
Gender	0.147***	-0.00336	0.0681***	0.0427***	0.223***
	(0.0130)	(0.0131)	(0.0110)	(0.0113)	(0.0251)
Age group					
Baseline: above 65 =0					
18-25	0.109***	0.272***	0.156***	0.126***	0.561***
	(0.0264)	(0.0262)	(0.0224)	(0.0243)	(0.0526)
26-35 years	0.133***	0.180***	0.115***	0.0595***	0.404***
	(0.0245)	(0.0247)	(0.0202)	(0.0215)	(0.0474)
36-45 years	0.135***	0.0869***	0.107***	0.0190	0.291***
	(0.0240)	(0.0246)	(0.0196)	(0.0208)	(0.0456)
46-55 years	0.140***	0.0141	0.0646***	-0.00512	0.176***
	(0.0235)	(0.0238)	(0.0187)	(0.0200)	(0.0441)
56-65 years	0.0843***	-0.00800	0.0814***	-0.0106	0.130***
	(0.0224)	(0.0227)	(0.0181)	(0.0188)	(0.0427)
Income group					
Baseline: 1st quantile=0					
2nd quantile	0.0435**	-0.0136	-0.00934	-0.0240	-0.0115
	(0.0205)	(0.0206)	(0.0172)	(0.0185)	(0.0413)
3rd quantile	0.0185	0.0413**	-0.00828	-0.0331*	-0.00108
	(0.0203)	(0.0205)	(0.0173)	(0.0180)	(0.0401)
4th quantile	0.0209	0.0169	-0.0112	-0.0217	-0.00705
	(0.0210)	(0.0211)	(0.0178)	(0.0187)	(0.0413)
5th quantile	0.0177	0.0305	-0.00274	-0.0251	0.00502
	(0.0232)	(0.0235)	(0.0201)	(0.0206)	(0.0457)
Living area					
Baseline: Rural					
Semi-urban	0.0616***	0.0227	0.0566***	0.0186	0.140***
	(0.0204)	(0.0203)	(0.0161)	(0.0173)	(0.0391)
Urban	0.0499**	0.0123	0.0205	0.0135	0.0813**
	(0.0209)	(0.0209)	(0.0170)	(0.0183)	(0.0407)
Smoking	0.0417***	0.0290*	0.0373***	0.0309**	0.122***
	(0.0151)	(0.0152)	(0.0130)	(0.0134)	(0.0291)
Religious services	-0.126***	-0.0794***	-0.0127	0.0495**	-0.110**
	(0.0253)	(0.0257)	(0.0222)	(0.0234)	(0.0468)
Constant	0.00667	0.285***	0.0638	0.145**	-0.784***
	(0.0674)	(0.0727)	(0.0611)	(0.0638)	(0.130)
N	5945	5945	5945	5945	5945
R^2	**0.063**	**0.058**	**0.104**	**0.078**	**0.127**
Cragg-Donald F statistic	**156.117**	**156.117**	**156.117**	**156.117**	**156.117**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals. There are eight specifications for each mental disorder, e.g., adding each control to the baseline model, Model 1, and estimating the regression to ensure that the effect of job loss does not change by including an additional variable. I report the baseline and completer models.

The results show that all types of well-being indices are positively correlated with job loss. It means that unemployment increases the probability of mental issues across all countries. In this direction, being unemployed increases the probability of feeling anxious, bored, insomniac and lonely by 0.133, 0.122, 0.075 and 0.157 units. Also, the probability of the MDI increases by 0.427 units when people lose their jobs. As a result of these findings, job loss has a causal effect on mental wellbeing of people during the pandemic.

3.5.3. 2SLS estimates for countries with delayed infection peak

The second stage estimates for the countries characterised by delayed infection peak are provided in Table 3.9.

Table 3.9. 2SLS estimates for countries with delayed infection peak

	Anxiety	Boredom	Insomnia	Loneliness	MDI
Job Loss	0.137**	0.0494	0.0664	0.0974*	0.308**
	(0.0638)	(0.0648)	(0.0569)	(0.0584)	(0.131)
Mortgage	-0.00136	-0.0220	0.0287*	-0.0209	-0.00892
	(0.0185)	(0.0186)	(0.0165)	(0.0164)	(0.0377)
Gender	0.167***	-0.00280	0.0831***	0.0524***	0.265***
	(0.0156)	(0.0157)	(0.0135)	(0.0138)	(0.0314)
Age group					
Baseline: above 65 =0					
18-25	0.111***	0.333***	0.194***	0.168***	0.689***
	(0.0349)	(0.0347)	(0.0308)	(0.0326)	(0.0737)
26-35 years	0.144***	0.246***	0.143***	0.101***	0.531***
	(0.0314)	(0.0316)	(0.0270)	(0.0281)	(0.0642)
36-45 years	0.149***	0.136***	0.116***	0.0478*	0.376***
	(0.0303)	(0.0309)	(0.0254)	(0.0262)	(0.0602)
46-55 years	0.170***	0.0587**	0.0585**	0.0285	0.259***
	(0.0284)	(0.0287)	(0.0232)	(0.0242)	(0.0561)
56-65 years	0.104***	0.0147	0.0927***	0.0262	0.211***
	(0.0265)	(0.0266)	(0.0219)	(0.0224)	(0.0529)
Income group					
Baseline: 1st quantile=0					
2nd quantile	0.0515**	-0.0240	0.00227	-0.0109	0.0131
	(0.0252)	(0.0250)	(0.0215)	(0.0228)	(0.0524)
3rd quantile	0.00926	0.0263	-0.0212	-0.0244	-0.0224
	(0.0247)	(0.0247)	(0.0209)	(0.0219)	(0.0500)
4th quantile	0.0145	-0.00409	0.0107	-0.00800	0.0106
	(0.0250)	(0.0248)	(0.0215)	(0.0226)	(0.0510)
5th quantile	-0.00361	0.000232	0.0115	-0.0187	-0.0106
	(0.0273)	(0.0275)	(0.0239)	(0.0243)	(0.0557)
Living area					
Baseline: Rural					
Semi-urban	0.0470**	0.0237	0.0460***	0.0197	0.120***
	(0.0222)	(0.0219)	(0.0176)	(0.0186)	(0.0430)
Urban	0.0400*	0.0189	0.0188	0.0196	0.0831*
	(0.0236)	(0.0233)	(0.0192)	(0.0203)	(0.0463)
Smoking	0.0346*	0.0174	0.0362**	0.0263	0.103***
	(0.0181)	(0.0181)	(0.0159)	(0.0164)	(0.0366)
Religious services	-0.134***	-0.0663**	-0.0419	0.0880***	-0.0964
	(0.0306)	(0.0308)	(0.0275)	(0.0294)	(0.0597)
Constant	0.219*	0.228**	-0.134*	0.151	-0.859***
	(0.125)	(0.113)	(0.0696)	(0.103)	(0.207)
N	4033	4033	4033	4033	4033
R^2	**0.072**	**0.072**	**0.106**	**0.084**	**0.137**
Cragg-Donald F statistic	**115.071**	**115.071**	**115.071**	**115.071**	**115.071**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals. There are eight specifications for each mental disorder, e.g., adding each control to the baseline model, Model 1, and estimating the regression to ensure that the effect of job loss does not change by including an additional variable. I report the baseline and completer models.

The findings suggest that job loss significantly increases the probability of anxiety, loneliness and the MDI in the countries with delayed infection peak. In this regard, job loss increases the probability of anxiety, loneliness and the MDI by 0.137, 0.097 and 0.308 units. According to the results, job loss has a causal effect on individuals' wellbeing during the pandemic.

3.5.4. 2SLS estimates for countries with early infection peak

Finally, the second stage estimates are reported for the countries experiencing early infection peaks below.

Table 3.10. 2SLS estimates for countries with early infection peak

	Anxiety	Boredom	Insomnia	Loneliness	MDI
Job Loss	0.136	0.211*	0.0555	0.225**	0.543***
	(0.114)	(0.119)	(0.0961)	(0.101)	(0.207)
Mortgage	0.0820***	0.0512*	-0.00227	-0.0290	0.0640
	(0.0291)	(0.0299)	(0.0239)	(0.0243)	(0.0507)
Gender	0.0912***	-0.00435	0.0317	0.0261	0.126***
	(0.0245)	(0.0250)	(0.0196)	(0.0208)	(0.0425)
Age group					
Baseline: above 65 =0					
18-25	0.0989**	0.166***	0.0916***	0.0565	0.342***
	(0.0440)	(0.0447)	(0.0353)	(0.0391)	(0.0781)
26-35 years	0.106**	0.0595	0.0525	-0.0180	0.156**
	(0.0421)	(0.0436)	(0.0322)	(0.0356)	(0.0738)
36-45 years	0.109***	0.000459	0.0847***	-0.0350	0.132*
	(0.0408)	(0.0428)	(0.0323)	(0.0353)	(0.0702)
46-55 years	0.0791*	-0.0666	0.0559*	-0.0789**	-0.0124
	(0.0421)	(0.0435)	(0.0325)	(0.0354)	(0.0702)
56-65 years	0.0351	-0.0471	0.0395	-0.0944***	-0.0653
	(0.0423)	(0.0450)	(0.0331)	(0.0355)	(0.0705)
Income group					
Baseline: 1st quantile=0					
2nd quantile	0.0171	0.0262	-0.0254	-0.0337	-0.0306
	(0.0364)	(0.0377)	(0.0302)	(0.0330)	(0.0691)
3rd quantile	0.0469	0.0921**	0.0335	-0.0308	0.100
	(0.0379)	(0.0390)	(0.0331)	(0.0340)	(0.0708)
4th quantile	0.0366	0.0792*	-0.0447	-0.0337	0.000688
	(0.0415)	(0.0432)	(0.0351)	(0.0361)	(0.0753)
5th quantile	0.0639	0.127***	-0.00675	-0.0207	0.107
	(0.0466)	(0.0483)	(0.0394)	(0.0415)	(0.0848)
Living area					
Baseline: Rural					
Semi-urban	0.142***	-0.00758	0.0942**	-0.00727	0.190**
	(0.0507)	(0.0537)	(0.0395)	(0.0475)	(0.0932)
Urban	0.116**	-0.0172	0.0439	-0.0114	0.108
	(0.0474)	(0.0511)	(0.0383)	(0.0460)	(0.0904)
Smoking	0.0300	0.0393	0.0329	0.0300	0.115**
	(0.0282)	(0.0290)	(0.0231)	(0.0243)	(0.0489)
Religious services	-0.0777*	-0.0996**	0.0474	-0.0172	-0.0968
	(0.0448)	(0.0472)	(0.0375)	(0.0383)	(0.0745)
Constant	-0.0196	0.298***	0.0948	0.217***	-0.687***
	(0.0912)	(0.0993)	(0.0804)	(0.0842)	(0.170)
N	1912	1912	1912	1912	1912
R^2	**0.058**	**0.012**	**0.109**	**0.069**	**0.118**
Cragg-Donald F statistic	**29.875**	**29.875**	**29.875**	**29.875**	**29.875**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals. There are eight specifications for each mental disorder, e.g., adding each control to the baseline model, Model 1, and estimating the regression to ensure that the effect of job loss does not change by including an additional variable. I report the baseline and completer models.

According to the results, in countries with early infection peak, job loss increases the likelihood of boredom, loneliness, and MDI. As such, the likelihood of feeling bored and lonely is 0.211 and 0.225 units more for people who lost their jobs compared to those employed during the COVID-19 pandemic. Also, the probability of the MDI is 0.543 units higher for people who lost their jobs as a result of the pandemic. These findings confirm causal effects from job loss to mental wellbeing in countries that experienced early peaks of the pandemic.

3.6. Sensitivity Check

I apply various sensitivity checks through changing assumptions and splitting the sample based on income and living locations.

3.6.1. Marginal effect of losing jobs on mental disorders in each country

I first estimate several individual-country regressions for various wellbeing indicators. Here, 24 = 6 (countries) x 4 (mental disorders) more regressions are estimated. The results support the positive associations between losing jobs and mental disorders for country-level estimates.

The estimated association between job loss and mental health for each country is provided in Table 3.11 as follows:

Table 3.11.Marginal effect of losing jobs on mental disorders in each country

	China				South Korea				Japan			
	Anxiety	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**
Job Loss	0.0735**	-0.0006	0.161***	0.141***	0.0847**	-0.0371	0.0747***	0.0925***	0.0973**	0.0622	0.0766***	0.0594**
	(0.0322)	(0.0328)	(0.0282)	(0.0288)	(0.0383)	(0.0389)	(0.0234)	(0.0268)	(0.0460)	(0.0431)	(0.0195)	(0.0259)
Mortgage	0.133***	0.0934**	-0.0131	0.00326	0.0262	0.0523	0.00507	-0.0348	0.0156	-0.0356	0.0203	0.0138
	(0.0359)	(0.0377)	(0.0343)	(0.0349)	(0.0386)	(0.0386)	(0.0262)	(0.0306)	(0.0398)	(0.0374)	(0.0205)	(0.0258)
Gender	0.0570*	0.000168	-0.0116	0.0340	0.139***	0.0133	0.0697***	0.0312	0.0926***	0.0863***	0.0222	0.0570**
	(0.0342)	(0.0346)	(0.0322)	(0.0320)	(0.0337)	(0.0350)	(0.0237)	(0.0266)	(0.0322)	(0.0307)	(0.0183)	(0.0228)
Age group Baseline: above 65 =0												
18-25 years	0.140**	0.220***	0.101	0.0107	0.0648	0.148**	0.0769*	0.0704	0.0772	0.376***	0.0712**	0.0819**
	(0.0660)	(0.0655)	(0.0652)	(0.0584)	(0.0642)	(0.0644)	(0.0410)	(0.0466)	(0.0628)	(0.0571)	(0.0332)	(0.0400)
26-35 years	0.139**	0.118*	0.105	-0.0975	0.0901	0.0544	0.0145	0.0364	0.161***	0.312***	0.0532*	0.0993***
	(0.0660)	(0.0649)	(0.0657)	(0.0604)	(0.0588)	(0.0585)	(0.0412)	(0.0443)	(0.0542)	(0.0484)	(0.0317)	(0.0354)
36-45 years	0.151**	0.0911	0.164***	-0.0870	0.0936	-0.0141	0.0124	0.0303	0.129**	0.133***	0.0006	-0.0043
	(0.0603)	(0.0589)	(0.0597)	(0.0543)	(0.0572)	(0.0571)	(0.0406)	(0.0440)	(0.0544)	(0.0508)	(0.0359)	(0.0411)
46-55 years	0.109*	-0.0461	0.155***	-0.105*	0.0833	-0.00194	-0.0117	-0.0341	0.150***	0.0483	0.0272	0.0211
	(0.0615)	(0.0602)	(0.0597)	(0.0546)	(0.0564)	(0.0561)	(0.0410)	(0.0452)	(0.0515)	(0.0497)	(0.0314)	(0.0370)
56-65 years	0.00586	-0.0267	0.113*	-0.128**	0.0917	-0.0362	0.000451	-0.0665	0.0920*	0.0259	0.00139	-0.0461
	(0.0674)	(0.0633)	(0.0641)	(0.0584)	(0.0607)	(0.0606)	(0.0436)	(0.0519)	(0.0531)	(0.0516)	(0.0355)	(0.0441)
Income group Baseline: 1st quantile=0												
2nd quantile	0.0548	-0.0826	0.0598	-0.0359	-0.0337	0.0914*	-0.0823**	-0.0276	0.0622	0.0175	-0.0134	0.0119
	(0.0513)	(0.0507)	(0.0475)	(0.0459)	(0.0528)	(0.0526)	(0.0353)	(0.0373)	(0.0493)	(0.0477)	(0.0254)	(0.0331)
3rd quantile	0.0749	-0.0247	0.0973**	-0.0413	-0.00473	0.130**	0.00256	-0.0296	-0.0116	0.116**	-0.0711**	-0.0103
	(0.0527)	(0.0528)	(0.0479)	(0.0483)	(0.0512)	(0.0509)	(0.0311)	(0.0369)	(0.0489)	(0.0460)	(0.0316)	(0.0339)
4th quantile	0.0391	-0.0475	0.0539	-0.0480	0.00381	0.0891*	-0.0915**	-0.0493	0.0299	0.0799*	-0.0142	0.0361
	(0.0531)	(0.0527)	(0.0501)	(0.0487)	(0.0521)	(0.0521)	(0.0370)	(0.0391)	(0.0512)	(0.0486)	(0.0267)	(0.0332)
5th quantile	0.0483	0.0100	0.0990*	0.0180	0.0383	0.0891	-0.0440	-0.0729*	0.0269	0.0870*	0.0112	0.0293
	(0.0583)	(0.0594)	(0.0543)	(0.0539)	(0.0558)	(0.0557)	(0.0365)	(0.0431)	(0.0542)	(0.0512)	(0.0270)	(0.0363)
Living area Baseline: Rural												

Semi-urban	0.286***	0.00145	0.0291	0.0174	0.0189	0.122	0.244**	0.0287	0.0357	-0.0433	-0.0120	-0.0270
	(0.0738)	(0.0697)	(0.0631)	(0.0601)	(0.0815)	(0.0825)	(0.111)	(0.0677)	(0.0388)	(0.0369)	(0.0223)	(0.0261)
Urban	0.185***	-0.0903	-0.0132	-0.0341	0.0393	0.159*	0.213*	0.0805	0.00361	-0.0238	0.0130	-0.0132
	(0.0696)	(0.0637)	(0.0578)	(0.0551)	(0.0887)	(0.0898)	(0.114)	(0.0727)	(0.0445)	(0.0421)	(0.0235)	(0.0293)
Smoking	0.0590	0.0612	0.0455	0.0337	0.00893	0.0336	0.0184	0.0348	0.000769	0.00765	-0.0117	0.00977
	(0.0386)	(0.0391)	(0.0355)	(0.0357)	(0.0372)	(0.0373)	(0.0253)	(0.0281)	(0.0406)	(0.0386)	(0.0237)	(0.0282)
Religious services	-0.120**	-0.123**	-0.0147	0.0224	-0.0107	0.0229	0.0714**	-0.0345	-0.169	0.0164	0.0239	0.209***
	(0.0521)	(0.0515)	(0.0461)	(0.0460)	(0.0593)	(0.0595)	(0.0362)	(0.0490)	(0.104)	(0.0959)	(0.0432)	(0.0466)
N	**994**	**994**	**986**	**990**	918	918	904	918	**981**	**981**	**981**	**981**
Pseudo R^2	**0.0809**	**0.0684**	**0.0832**	**0.0611**	**0.0311**	**0.0263**	**0.0949**	**0.0627**	**0.0344**	**0.0929**	**0.0948**	**0.1036**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals.

Table 3.11. continued: Marginal effect of losing jobs on mental disorders in each country

	Italy				**UK**				**US**			
	Anxiety	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**
Job Loss	0.0428	0.0368	0.0389	0.104***	0.0575	0.0664*	0.0703**	0.110***	0.00476	0.0497	0.0650**	0.0426
	(0.0320)	(0.0326)	(0.0300)	(0.0301)	(0.0357)	(0.0363)	(0.0332)	(0.0311)	(0.0340)	(0.0352)	(0.0310)	(0.0320)
Mortgage	-0.0132	-0.0743**	-0.0112	0.0121	0.0208	0.0671*	0.0382	-0.0439	0.0134	-0.0352	0.0522*	-0.0261
	(0.0364)	(0.0372)	(0.0347)	(0.0354)	(0.0361)	(0.0364)	(0.0340)	(0.0335)	(0.0322)	(0.0331)	(0.0301)	(0.0312)
Gender	0.175***	-0.0556*	0.108***	0.0261	0.169***	-0.0251	0.105***	0.0741***	0.217***	0.00535	0.0901***	0.0596*
	(0.0282)	(0.0303)	(0.0279)	(0.0289)	(0.0293)	(0.0316)	(0.0295)	(0.0286)	(0.0305)	(0.0333)	(0.0311)	(0.0317)
Age group Baseline: 65 >0												
18-25	0.160***	0.348***	0.173***	0.0199	0.131**	0.309***	0.279***	0.298***	0.207***	0.255***	0.285***	0.230***
	(0.0598)	(0.0592)	(0.0577)	(0.0572)	(0.0638)	(0.0630)	(0.0630)	(0.0576)	(0.0550)	(0.0572)	(0.0508)	(0.0511)
26-35 years	0.111**	0.232***	0.159***	0.00683	0.167***	0.247***	0.220***	0.158***	0.272***	0.138***	0.212***	0.168***
	(0.0529)	(0.0516)	(0.0509)	(0.0511)	(0.0584)	(0.0575)	(0.0602)	(0.0568)	(0.0499)	(0.0514)	(0.0491)	(0.0484)
36-45 years	0.116**	0.124**	0.125**	-0.0475	0.219***	0.133**	0.241***	0.138**	0.269***	0.131**	0.180***	0.157***
	(0.0514)	(0.0513)	(0.0503)	(0.0505)	(0.0555)	(0.0563)	(0.0580)	(0.0556)	(0.0513)	(0.0522)	(0.0508)	(0.0497)
46-55 years	0.238***	0.0921*	0.0302	-0.000178	0.172***	0.0941*	0.162***	0.0680	0.180***	0.00366	0.0898*	0.0541

	(0.0507)	(0.0520)	(0.0533)	(0.0504)	(0.0545)	(0.0550)	(0.0588)	(0.0566)	(0.0493)	(0.0506)	(0.0512)	(0.0504)
56-65 years	0.0505	-0.0374	0.0846	0.0130	0.119**	0.106**	0.200***	0.142***	0.182***	-0.0504	0.171***	0.000339
	(0.0541)	(0.0558)	(0.0531)	(0.0517)	(0.0542)	(0.0536)	(0.0570)	(0.0535)	(0.0480)	(0.0504)	(0.0481)	(0.0514)
Income group Baseline: 1st quantile=0												
2nd quantile	0.0760	0.0174	-0.00901	0.0515	-0.0055	-0.117**	0.0359	-0.109**	0.0644	0.0227	-0.0290	0.0114
	(0.0508)	(0.0522)	(0.0472)	(0.0473)	(0.0509)	(0.0516)	(0.0493)	(0.0465)	(0.0487)	(0.0507)	(0.0475)	(0.0472)
3rd quantile	0.0466	0.0187	-0.0309	-0.0336	-0.0468	-0.0994*	-0.0133	-0.0442	0.0358	0.0781	-0.0122	-0.0150
	(0.0489)	(0.0502)	(0.0459)	(0.0471)	(0.0500)	(0.0508)	(0.0488)	(0.0445)	(0.0482)	(0.0499)	(0.0465)	(0.0470)
4th quantile	0.0161	0.00979	-0.0145	-0.00181	-0.0765	-0.154***	-0.0067	-0.0911**	0.0509	0.0381	0.0542	0.00507
	(0.0492)	(0.0502)	(0.0461)	(0.0469)	(0.0495)	(0.0496)	(0.0486)	(0.0451)	(0.0477)	(0.0494)	(0.0450)	(0.0461)
5th quantile	0.00669	-0.00300	-0.0247	-0.0114	-0.0380	-0.172***	0.0403	-0.0625	-0.0469	0.0764	-0.00434	-0.0423
	(0.0552)	(0.0562)	(0.0521)	(0.0528)	(0.0513)	(0.0515)	(0.0493)	(0.0462)	(0.0533)	(0.0545)	(0.0501)	(0.0510)
Living area Baseline: Rural												
Semi-urban	0.128***	0.0720	0.0591	0.120**	0.0270	0.0310	0.0618	0.0342	0.0176	0.0636	0.0992	-0.00742
	(0.0491)	(0.0495)	(0.0483)	(0.0493)	(0.0471)	(0.0477)	(0.0465)	(0.0448)	(0.0506)	(0.0524)	(0.0509)	(0.0497)
Urban	0.133***	0.0417	0.0594	0.0852*	0.0290	0.0124	0.0244	0.0366	0.00884	0.0672	0.0116	-0.0164
	(0.0445)	(0.0450)	(0.0441)	(0.0457)	(0.0525)	(0.0531)	(0.0517)	(0.0490)	(0.0530)	(0.0550)	(0.0537)	(0.0518)
Smoking	0.0559*	0.0504	0.0557*	0.00002	0.0197	0.0476	0.0341	0.0541*	0.0613*	-0.0303	0.0497	0.0366
	(0.0301)	(0.0307)	(0.0285)	(0.0293)	(0.0356)	(0.0360)	(0.0337)	(0.0317)	(0.0364)	(0.0377)	(0.0341)	(0.0347)
Religious services	-0.0114	-0.109*	-0.0411	0.123**	-0.212***	-0.158***	-0.100*	0.0548	-0.102**	-0.00778	-0.0240	0.0243
	(0.0552)	(0.0576)	(0.0538)	(0.0499)	(0.0562)	(0.0550)	(0.0523)	(0.0471)	(0.0422)	(0.0431)	(0.0397)	(0.0392)
N	**1020**	**1020**	**1013**	**1017**	994	994	994	994	1038	1038	1038	1038
Pseudo R^2	**0.0948**	**0.0666**	**0.0554**	**0.0490**	**0.0629**	**0.0566**	**0.0611**	**0.0823**	**0.0764**	**0.0472**	**0.0662**	**0.0497**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals.

The results show that job loss has been positively associated with different aspects of mental disorders in each country. For example, job loss is significantly correlated with anxiety, insomnia and loneliness in China (0.073, 0.161, 0.141), South Korea(0.085, 0.075, 0.092) and Japan (0.097, 0.077, 0.059) compared to people have not lost their jobs. In Italy, job loss and loneliness are statistically correlated with each other with the marginal effect of 0.104. In the UK, boredom, insomnia and loneliness are significantly associated with job loss with marginal effects of 0.66, 0.070 and 0.110, respectively. Finally, the evidence shows that job loss increases insomnia by 0.065 units compared to people who have not lost their jobs in the US. However, the marginal effect of housing debts is not statistically significant over other mental disorders across different countries.

Interestingly, women are more subject to all types of mental disorders than men across all nations except China. It may be due to high labour force participation for women in China compared to other countries. For example, based on the information released by the International Labour Organization (ILO), women's participation rate is 60.6 percent in China in 2019. However, this rate equals 53.4, 53.6, 41, 58.1 and 56.8 in Korea, Japan, Italy, the UK and the US, respectively. Therefore, lack of job market opportunity causes more mental disorders in those countries.

The age effect reveals that Japanese, Italians, British, and Americans substantially experience more mental disorders than Chinese and Koreans, particularly among young people. This may be because of the hard-hitting impact of COVID-19 in these advanced countries during the collection of data.

Estimates regarding the effect of the living environment show that this variable has a dominant impact on anxiety in China. There is, however, no significant association between this variable and mental health in the UK, Japan and the United States.

Interestingly, religious activities at least once a week dimmish the probability of anxiety considerably in China, Japan, the U.K, and the US.

3.6.2. Marginal effect of losing jobs on mental disorders across regions

As another robustness test, I split our sample based on different living locations and several income groups to determine whether the results are varied by changing the sample and dividing it into different subgroups. This robustness test is necessary because

rural group was considered the baseline group in previous estimates. Hence, splitting the sample allows one to understand how job loss and wellbeing are associated with each other based on another geographical classification. Table 3.12 reports the estimates based on different living locations as follows:

Table 3.12. The Marginal effect of losing jobs on mental disorders across regions

	Rural				Semi-Urban				Urban			
	Anxiety	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**
Job Loss	0.0836*	0.0269	0.0949**	0.0751*	0.0742***	0.0745***	0.0686***	0.118***	0.0281	0.00513	0.101***	0.0983***
	(0.0461)	(0.0450)	(0.0397)	(0.0402)	(0.0249)	(0.0252)	(0.0214)	(0.0228)	(0.0202)	(0.0203)	(0.0180)	(0.0184)
Mortgage	-0.0194	-0.0377	0.0518	0.00113	0.0292	0.0288	-0.00074	-0.0380*	0.0439**	0.00992	0.0215	-0.0159
	(0.0424)	(0.0424)	(0.0396)	(0.0374)	(0.0242)	(0.0242)	(0.0207)	(0.0207)	(0.0212)	(0.0213)	(0.0184)	(0.0184)
Gender	0.118***	0.00405	0.0741**	0.0655**	0.168***	0.0148	0.0908***	0.0433**	0.145***	-0.0005	0.0531***	0.0461***
	(0.0361)	(0.0352)	(0.0310)	(0.0313)	(0.0214)	(0.0214)	(0.0184)	(0.0188)	(0.0188)	(0.0189)	(0.0165)	(0.0167)
Age group Baseline: above 65 =0												
18-25	0.272***	0.408***	0.256***	0.173***	0.112***	0.318***	0.224***	0.158***	0.103***	0.241***	0.103***	0.124***
	(0.0698)	(0.0661)	(0.0682)	(0.0646)	(0.0387)	(0.0371)	(0.0341)	(0.0357)	(0.0371)	(0.0374)	(0.0327)	(0.0349)
26-35 years	0.251***	0.266***	0.113*	0.0402	0.163***	0.185***	0.175***	0.113***	0.126***	0.183***	0.0938***	0.0607**
	(0.0653)	(0.0666)	(0.0654)	(0.0591)	(0.0366)	(0.0370)	(0.0315)	(0.0332)	(0.0326)	(0.0336)	(0.0282)	(0.0297)
36-45 years	0.218***	0.236***	-0.00310	0.0673	0.143***	0.0539	0.119***	0.0139	0.135***	0.107***	0.121***	0.0467
	(0.0592)	(0.0606)	(0.0475)	(0.0543)	(0.0358)	(0.0363)	(0.0295)	(0.0300)	(0.0325)	(0.0336)	(0.0286)	(0.0296)
46-55 years	0.194***	0.0324	0.00682	0.000890	0.135***	0.0107	0.106***	0.0338	0.161***	0.0422	0.0448	-0.00511
	(0.0542)	(0.0542)	(0.0457)	(0.0470)	(0.0334)	(0.0338)	(0.0269)	(0.0286)	(0.0335)	(0.0344)	(0.0286)	(0.0298)
56-65 years	0.0967*	-0.0591	0.0266	-0.0127	0.123***	0.0348	0.116***	0.0309	0.0842**	-0.00496	0.0699**	-0.0228
	(0.0524)	(0.0507)	(0.0450)	(0.0444)	(0.0347)	(0.0352)	(0.0286)	(0.0299)	(0.0344)	(0.0353)	(0.0301)	(0.0302)
Income group Baseline: 1st quantile=0												
2nd quantile	0.0885*	-0.0282	-0.0173	0.0207	0.0330	-0.0139	-0.0188	-0.0591*	0.0307	-0.00905	-0.0104	-0.0136
	(0.0525)	(0.0505)	(0.0457)	(0.0447)	(0.0331)	(0.0333)	(0.0290)	(0.0293)	(0.0315)	(0.0317)	(0.0275)	(0.0283)
3rd quantile	-0.0111	0.0515	-0.0851	-0.0267	-0.0197	0.0211	-0.0399	-0.0388	0.0420	0.0485	0.0245	-0.0431
	(0.0532)	(0.0528)	(0.0469)	(0.0462)	(0.0319)	(0.0322)	(0.0277)	(0.0289)	(0.0308)	(0.0310)	(0.0273)	(0.0275)
4th quantile	-0.0148	0.0225	0.0165	0.0610	-0.0129	0.0319	-0.00353	-0.0637*	0.0336	-0.00711	-0.0181	-0.0290
	(0.0531)	(0.0533)	(0.0488)	(0.0483)	(0.0330)	(0.0331)	(0.0292)	(0.0295)	(0.0301)	(0.0303)	(0.0263)	(0.0272)
5th quantile	-0.0432	-0.0873	0.0221	-0.00989	0.0154	0.0229	0.00451	-0.0293	0.0100	0.0324	-0.00228	-0.0367
	(0.0656)	(0.0643)	(0.0622)	(0.0574)	(0.0363)	(0.0364)	(0.0325)	(0.0332)	(0.0307)	(0.0310)	(0.0268)	(0.0275)
Smoking	-0.0329	0.0254	-0.0232	0.0270	0.0521**	0.0417*	0.0370*	0.0285	0.0598***	0.0272	0.0469***	0.0337*
	(0.0425)	(0.0430)	(0.0369)	(0.0387)	(0.0249)	(0.0251)	(0.0221)	(0.0224)	(0.0203)	(0.0204)	(0.0179)	(0.0182)

Religious services	-0.0147	-0.0469	-0.0489	0.174**	-0.148***	-0.0851**	-0.0458	0.00111	-0.091***	-0.0509*	-0.00951	0.0610**
	(0.0738)	(0.0679)	(0.0563)	(0.0720)	(0.0395)	(0.0413)	(0.0324)	(0.0353)	(0.0279)	(0.0284)	(0.0233)	(0.0258)
N	751	761	654	726	2218	2199	2172	2190	2912	2910	2849	2899
Pseudo R^2	**0.1018**	**0.1292**	**0.1782**	**0.1247**	**0.066**	**0.068**	**0.1306**	**0.0845**	**0.0486**	**0.0454**	**0.0884**	**0.0752**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals.

It has been found that job loss is positively associated with all types of mental disorders in semi-urban areas. The association between losing jobs and boredom is not significant in both rural and urban environments. The magnitude of the marginal impact of losing jobs shows that the rural population experiences more anxiety than urban or semi-urban residents. Job loss is also associated with insomnia and loneliness in the urban environment in comparison with the other groups. This may be because of the busy lifestyle that people follow in urban areas. These findings are in line with Jia and Yuan (2020) and Voitsidis et al. (2020) who argue that inactivity, limited access to natural environments, and fewer social activities and less emotional contact with others contribute to insomnia and loneliness.

Housing mortgage has a positive and significant impact only on anxiety in urban areas. Accordingly, the probability of anxiety is 0.044 higher for home mortgage debtors than non-debtors when all other factors are held constant. This could be due to the higher volume and value of mortgages in urban areas rather than rural ones (Paykel et al., 2003).

Notably, I find that women are more subject to all mental disorders than men except boredom during the pandemic. The estimated marginal effects reveal that the likelihood of experiencing anxiety and insomnia for women is 0.168 and 0.091 more than men, respectively, in semi-urban areas.

It is also found that young groups show a significant, positive association with all forms of mental illness. This suggests that COVID-19 has a psychological impact on youth consistently. As for boredom and loneliness, this association tends to be greater in rural areas than in other locations.

People who engage in risky behaviour such as smoking cigarettes have a higher risk of mental disorders than people who do not smoke in semi-urban and urban areas. However, this variable does not have a statistically significant effect on the people who live in the rural environment.

Last but not least, religious activities at least once a week reduce anxiety and boredom in semi-urban and rural areas. However, it does not significantly lower the chances of experiencing mental disorders in rural areas.

3.6.3. Marginal effect of losing jobs on mental disorders based on household income

Grouping households based on their income provides additional information to this study because the low- or high-income households do not characterise the rural or urban habitats. The distributions of urban and rural people show that all villagers are not necessarily poor. So, splitting the sample based on the income of the households, then refitting regressions can provide informative policy implications on how job loss across different income-level families impacts mental health. To do that, it is assumed there are three groups of families: low-income covering the 1st and 2nd quantiles, the middle-income equivalent to the 3rd quantile, and finally high-income incorporating the 4th and 5th quantiles, respectively. The joint distribution of the data based on income and location of living is provided in Appendix 3F. Table 3.13 reports the estimates for three groups of households' incomes as follows.

Table 3.13. The Marginal effect of losing jobs on mental disorders based on households' income

	Low-income				Middle-income				High-income			
	Anxiety	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**	**Anxiety**	**Boredom**	**Insomnia**	**Loneliness**
Job Loss	0.0436*	0.0872***	0.112***	0.116***	0.0463	0.0348	0.0858***	0.103***	0.0678***	-0.0210	0.0776***	0.0932***
	(0.0232)	(0.0235)	(0.0200)	(0.0217)	(0.0317)	(0.0320)	(0.0289)	(0.0291)	(0.0238)	(0.0238)	(0.0212)	(0.0215)
Mortgage	0.0489*	-0.00576	-0.0179	-0.0239	0.0247	0.0145	0.0189	-0.0256	0.0273	0.0281	0.0356*	-0.0205
	(0.0278)	(0.0279)	(0.0229)	(0.0248)	(0.0320)	(0.0321)	(0.0283)	(0.0273)	(0.0211)	(0.0212)	(0.0185)	(0.0182)
Gender	0.170***	0.0114	0.0869***	0.0635***	0.104***	0.00346	0.0503*	0.0435*	0.127***	-0.00800	0.0647***	0.0459**
	(0.0213)	(0.0214)	(0.0181)	(0.0194)	(0.0287)	(0.0289)	(0.0259)	(0.0255)	(0.0207)	(0.0207)	(0.0181)	(0.0181)
Age group Baseline: 65 >0												
18-25	0.111***	0.259***	0.199***	0.0893***	0.238***	0.338***	0.176***	0.251***	0.0711	0.323***	0.0809**	0.154***
	(0.0357)	(0.0354)	(0.0312)	(0.0341)	(0.0535)	(0.0530)	(0.0510)	(0.0501)	(0.0443)	(0.0427)	(0.0375)	(0.0420)
26-35 years	0.128***	0.186***	0.128***	0.0328	0.215***	0.186***	0.121***	0.131***	0.131***	0.222***	0.0864***	0.0740**
	(0.0362)	(0.0368)	(0.0302)	(0.0335)	(0.0484)	(0.0509)	(0.0450)	(0.0426)	(0.0355)	(0.0357)	(0.0302)	(0.0324)
36-45 years	0.210***	0.0607*	0.123***	0.00394	0.208***	0.163***	0.0912**	0.100**	0.0792**	0.121***	0.0843***	0.0113
	(0.0362)	(0.0370)	(0.0302)	(0.0329)	(0.0478)	(0.0502)	(0.0435)	(0.0407)	(0.0342)	(0.0347)	(0.0292)	(0.0304)
46-55 years	0.108***	0.0244	0.0981***	0.0148	0.242***	0.0447	0.0567	0.134***	0.152***	0.0422	0.0392	-0.0561*
	(0.0346)	(0.0349)	(0.0282)	(0.0319)	(0.0474)	(0.0498)	(0.0421)	(0.0411)	(0.0346)	(0.0348)	(0.0291)	(0.0295)
56-65 years	0.0422	-0.0474	0.0890***	-0.00469	0.200***	0.0559	0.0682	0.0461	0.0998***	0.0319	0.0961***	-0.0273
	(0.0335)	(0.0333)	(0.0272)	(0.0306)	(0.0477)	(0.0500)	(0.0430)	(0.0397)	(0.0372)	(0.0374)	(0.0329)	(0.0324)
Living area Baseline: Rural												
Semi-urban	0.0512*	0.0104	0.0593**	0.0294	0.0336	-0.0280	0.104**	0.0438	0.109***	0.0724**	0.0495	-0.0259
	(0.0302)	(0.0304)	(0.0269)	(0.0282)	(0.0458)	(0.0456)	(0.0405)	(0.0423)	(0.0351)	(0.0365)	(0.0312)	(0.0332)
Urban	0.0105	-0.0235	0.00698	0.0237	0.0439	-0.00719	0.107***	0.0193	0.112***	0.0610*	0.00984	-0.0301
	(0.0318)	(0.0319)	(0.0269)	(0.0290)	(0.0478)	(0.0478)	(0.0407)	(0.0428)	(0.0352)	(0.0368)	(0.0307)	(0.0332)
Smoking	0.0401*	0.0731***	0.0621***	0.0169	0.0661**	0.0285	0.0204	0.00479	0.0360	0.000697	0.0284	0.0683***
	(0.0237)	(0.0239)	(0.0208)	(0.0218)	(0.0316)	(0.0320)	(0.0287)	(0.0283)	(0.0233)	(0.0233)	(0.0207)	(0.0212)
Religious	-0.0512	-0.0740**	-0.0260	-0.0246	-0.125***	-0.0410	-0.0401	0.0724	-0.130***	-0.0455	-0.00633	0.0920***
	(0.0371)	(0.0368)	(0.0296)	(0.0319)	(0.0471)	(0.0499)	(0.0393)	(0.0456)	(0.0317)	(0.0329)	(0.0274)	(0.0306)
N	2253	2245	2211	2218	1252	1254	1179	1216	2400	2408	2357	2354
Pseudo R^2	**0.0743**	**0.0703**	**0.1295**	**0.0723**	**0.0863**	**0.0836**	**0.122**	**0.1007**	**0.0566**	**0.0565**	**0.0941**	**0.0497**

Notes: The scripts *, **, and *** refer to the significance level of coefficients at 90, 95, and 99 percent credible intervals.

As shown in Table 3.13, our results align with the previous findings. Hence, losing jobs as the primary variable of the study is a consistently significant determinant of mental disorders. Accordingly, job loss and anxiety are more severely associated among high-income families than in low- and middle-income households. On the other hand, low-income families experience more boredom, insomnia, and loneliness compared to middle- and high-income families.

Financial liabilities like housing mortgage have a positive and significant association with anxiety of low-income families. However, it is more associated with insomnia in high-income households.

The study shows that women suffer from more mental disorders than men except for boredom in all income groups. Notably, women from low-income families experience more severe mental issues than wealthier ones.

The age effect reveals that younger people suffer from higher mental health issues. In this regard, middle-income families suffer more from cognitive problems induced by COVID-19 than other groups.

The location of living effect reveals that living in semi-urban environments increases the risk of anxiety and insomnia for low-income families. However, the probability of insomnia is high for middle-income households living in cities or semi-urban areas compared to villagers. The effect of living environment on anxiety and boredom is statistically significant for high-income families.

The results show that smoking behaviour increases the risk of anxiety, boredom and insomnia among low-income households in comparison to non-smokers. This effect significantly hikes the probability of anxiety for middle-income people.

Religious activities diminish the risk of anxiety among middle and high-income families. This variable significantly decreases the likelihood of boredom for low-income households.

3.7. Conclusion

The COVID-19 crisis poses one of the most significant challenges in our recent memory. It has negatively affected both physical and mental wellbeing worldwide. Since mental disorders impose additional socioeconomic costs on societies by affecting

families and burdening private and public health expenditures, this research explored how labour market conditions affect this factor. Due to the importance of mental health, implementing effective economic policies to diminish the negative impact of COVID-19 on mental health has become one of the central political subjects across nations. Therefore, it is crucial to know how unemployment induced by COVID-19 leads to mental crisis besides other socioeconomic variables. Being aware of the magnitudes of these factors helps health authorities and governments mitigate mental health disorders through suitable economic policies.

This study evaluated the impact of unemployment induced by COVID-19 on several mental health issues over two groups of countries, the environments with early and delayed infection peaks. Our findings confirm that job loss induced by the COVID-19 pandemic leads to different types of mental illness, including anxiety, boredom, insomnia and loneliness. The marginal effects of the clustered estimates demonstrate that people experience more anxiety, insomnia and loneliness in the countries that controlled the pandemic compared to the countries experiencing delayed infection peak. Results show that women are more prone to anxiety in the countries that overcome the spread of the virus. However, the gender effect shows that women severely suffer from anxiety, insomnia and loneliness in countries with delayed infection peak. This study showed that the risk of mental illness is high for young people, residents of urban and semi-urban areas, as well as smokers.

For policy implications, it is proposed that governments can reduce the risk of mental illness among people, especially the unemployed, in several ways as follows: performing effective labour market policies by increasing employment opportunities, especially for younger generations, and providing mental health supports, especially for people who lost their jobs. In addition to these, implementing job retention schemes, paying job-keeper employment benefits for employers to retain their employees, and establishing job training funds for those who lost their jobs can increase employability in the countries hit by COVID-19 (OECD, 2020). There are other remedies for mitigating the wellbeing effects of the pandemic such as allocating financial support by paying unemployment benefits to unemployed people until they find jobs, providing debt facilitators and postponing payment of mortgages during the outbreak, and finally providing social supports to people who lost their jobs, indebted households, and women and youth (Chatterji et al., 2021). Since our analysis was performed during the tough

economic conditions, these policy recommendations can be helpful for future recessions or pandemics.

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Appendix 3A. Names and definitions of variables

Variable name	Survey question	Values
Boredom	Have you experienced any boredom due to the COVID-19 pandemic?	It is a bivariate variable. It equals 1 when a respondent has boredom; otherwise, it takes 0 value. (No= 0; Yes= 1)
Loneliness	Have you experienced any loneliness due to the COVID-19 pandemic?	It is a bivariate variable. It equals 1 when a respondent feels loneliness; otherwise, it takes 0 value. (No= 0; Yes= 1)
Insomnia	Have you experienced any trouble sleeping due to the COVID-19 pandemic?	It is a bivariate variable. It equals 1 when a respondent has trouble sleeping; otherwise, it takes 0 value. (No= 0; Yes= 1)
Anxiety	Have you experienced any anxiety due to the COVID-19 pandemic?	It is a bivariate variable. It equals 1 when a respondent has anxiety; otherwise, it takes 0 value. (No= 0; Yes= 1)
Mental Disorder Index	It is a combination of four mental disorders, including boredom, loneliness, insomnia, and anxiety.	It is a continuous variable showing the overall state of mental illness for each respondent. I use a factor analysis method provided in Appendix C to create this index.
Job loss	Have you lost your job, or has your activity (as self-employed) been stopped as a consequence of the COVID-19 pandemic?	It is a bivariate variable. It equals 1 when a respondent has lost his or her job; otherwise, it takes 0 value. (No= 0; Yes= 1)
Mortgage	Do you currently have a mortgage on your house?	It is a bivariate variable. It equals 1 when a respondent is in debt to housing; otherwise, it takes 0 value. (No= 0; Yes= 1)
Gender	What is your gender?	It is a bivariate variable. It equals 1 when a respondent

		is women; otherwise, it takes 0 value for men. (No= 0; Yes= 1)
Age group	How old are you?	It is a multinomial variable defining the age group of each respondent as follows, Between 18 and 25 =1; Between 26 and 35=2; Between 36 and 45=3; Between 46 and 55=4 ; Between 56 and 65=5 ; Above 65=0
Income Group	In what range is the gross annual income of your household? *Respondents chose among income ranges that were determined using the latest available data from the Luxembourg Income Study.	It is a multinomial variable defining the income group of each respondent as follows, First quintile =0 *; Second quintile=1; Third quintile=2; Fourth quintile=3; Fifth quintile=4
Smoker	Are you a smoker?	It is a bivariate variable. It equals 1 when a respondent smokes cigarettes; otherwise, it takes 0 value for men. (No= 0; Yes= 1)
Current living area	In what type of area are you currently living?	It is a multinomial variable defining the current living place of each respondent as follows, Countryside=0; Urban area=1; Semi-urban=2
Religious services	With what weekly frequency have you done any of the following activities (attended religious services)since the COVID 19 outbreak in your country?	It is a bivariate variable. It equals 1 when a respondent attending religious activities at least once a week; otherwise, it takes 0 value for men. (No= 0; Yes= 1)

Appendix 3B. Estimates with LASSO method

Variable	Anxiety	Boredom	Insomnia	Loneliness
Job loss	0.091	0.113	0.149	0.112
Mortgage	0.042	0.023	0.022	0.023
Gender	0.194	0.078	0.092	0.077
Age	0.029	0.000	0.009	0.000
Income	0.013	0.030	0.008	0.030
Living area	0.072	0.107	0.029	0.107
Smoker	0.070	0.066	0.051	0.065
Religious services	-0.115	-0.059	-0.005	-0.058
Region Fixed Effects	0.004	0.002	-0.003	0.002
Country Fixed Effects	-0.033	0.012	0.058	0.011
Lambda	0.003	0.003	0.001	0.004
L1 Norm	0.663	0.490	0.426	0.485

Appendix 3C. Average government stringency and economic support indices

	China	Korea	Japan	Italy	UK	US
STN	59.43	41.11	26.49	50.17	29.33	29.95
GES	1.42	13.82	18.86	15.57	31.07	21.13

Notes: STN and GES indicate the average stringency and government economic support indices, respectively, covering 1 January to 23 April 2020. The former combines eight factors: school closures, business closures, cancelling public events, limitation on gatherings, stay-at-home restrictions, restrictions on internal movements, and finally, international travel controls. The latter includes income supports and debt relief. Both indices vary from 0 to 100.

Appendix 3D. Observed correlation matrix of mental wellbeing indices

Variable	Anxiety	Boredom	Insomnia	Loneliness
Anxiety	1			
Boredom	0.066	1		
Insomnia	0.217	0.094	1	
Loneliness	0.144	0.222	0.224	1

Appendix 3E. Anti-image covariance matrix of coefficients in the factor model

Variable	Anxiety	Boredom	Insomnia	Loneliness
Anxiety	1			
Boredom	-0.027	1		
Insomnia	-0.191	-0.040	1	
Loneliness	-0.092	-0.204	-0.187	1

Appendix 3F. Joint distribution between income and living locations

Living Environment	Households income classification					
	1st Quantile	2nd Quantile	3rd Quantile	4th Quantile	5th Quantile	Total
Rural	206	171	164	164	87	792
Semi-urban	451	447	524	464	348	2234
Urban	480	508	581	687	668	2924
Total	1137	1126	1269	1315	1103	5950

Chapter 4 Asymmetric effects of minimum wage policy on crime in the US: evidence from a Bayesian multi-kink model[18]

4.1. Introduction

The relationship between minimum wage and crime is always controversial in the US. Theoretically, an increase in minimum wage has two possible effects on crime rate: on the one hand, increasing minimum wage reduces the likelihood of committing crimes because the relative return of working increases compared to criminal activities (Becker, 1968; Gogger, 1998). On the other hand, raising the minimum wage leads to an increase in unemployment since labour costs increase and a firm's demand for labour decreases (Neumark and Wascher, 1992, Baker et al.,1999; Kabetek, 2021). Therefore, the probability of losing jobs surges for vulnerable labour forces, such as teens and young adults characterised as low-wage or low-skilled workers. As a result of increased unemployment, the crime rate increases. Since these two effects are opposite, it is theoretically unclear what the marginal effect of a minimum wage increase is on crime. A better approach would be to empirically examine the impact of minimum wage increases by utilising the asymmetric effects of minimum wage on crime.

In this regard, minimum wage can have a pull effect on crime rate when it is above a certain threshold, or it might have a push effect when it is below a tipping point[19]. Being aware of these asymmetric effects may give policymakers a more accurate guideline when minimum wage exceeds an unknown threshold. However, in crime research, investigating the asymmetric effects of economic variables on crime has not received much attention. There are some exceptions,Mocan and Bali (2010) analyse the asymmetric response of property and violent crime rates to unemployment variations in the US. The other notable research is Loureiro (2013). He evaluates the impact of positive and negative changes in real income of unskilled workers on both property and violent crime rates. These two studies consider positive and negative changes in economic

[18] A version of this chapter with the same title coauthored with Professors Marc K. Chan, my thesis external supervisor, is submitted to the 'Oxford Bulletin of Economics and Statistics' journal and is currently under review.

[19] A push effect causes people to attempt criminal activities due to crime incentives. However, a pull effect contributes more to preventing crime.

variables to find asymmetric effects of crime. However, more recent studies, Card et al. (2015) and Hansen (2017) show that asymmetric effects can be specified based on an unknown continuous threshold known as a regression kink technique. Being aware of such a threshold allows one to understand which level of a policy variable has a pull or push effect on an outcome variable. This study contributes to the literature by examining asymmetric effects of minimum wage on crime by employing a regression kink method. Compared to Mocan and Bali (2010) and Loureiro (2013), this approach allows us to find a critical threshold of minimum wage which is helpful for policymaking. In comparison with these studies, this current research finds unknown thresholds instead of segmenting variables based on positive or negative changes over time.

Further, there is an argument as to whether policy analysis should be considered in light of different segments of the conditional distribution of crime, since the outcomes of criminal behaviour differ in each quantile (Bresson et al., 2021). As another advantage of this research, using a quantile analysis helps to demonstrate how different parts of the distribution of crime rate heterogeneously react to minimum wage policy[20]. Koenker and Bassett (1978) highlight that employing a quantile method provides robust estimates even when data are skewed or include outliers. Su and Xu (2019) and Zhong et al. (2021) establish theoretical frameworks to specify a threshold effect for each segment of the distribution of an economic outcome. However, the asymmetric effects of minimum wage on different quantiles of the distribution of crime has not yet received any research attention. This paper fills this gap significantly and shows how the lower and above tipping point of minimum wage asymmetrically impacts each segment of the distribution of crime.

Moreover, several pieces of literature suggest that economic policies should be tailored based on regional characteristics (Katzaentine, 2000, Dube, 2014; Hoover and Giarratani, 2020). This aspect is vital in this research because more than two-thirds of local governments in the US adjust the local minimum wage after the federal government determines the national minimum wage. Loonam (2020) mentions that crime is a "localized phenomenon", so it should be analysed on a regional basis. Therefore, finding state-level thresholds of minimum wage allows local governments to implement suitable

[20] The quantile analysis examines the effect of explanatory variables on different levels of an outcome variable. For instance, it is shown how low or high crime rate reacts to minimum wage policy. However, regression kink analyses different levels of an explanatory variable, minimum wage on an outcome variable.

policies for controlling crime rates more effectively. Again, this approach has not yet received close scrutiny. There is only a handful of research, Okui and Wang (2021), that bases a framework for finding asymmetric effects of a policy variable over sections in a classical concept, however, it hasn't been applied in the crime literature yet. This study constructs a basis that each state has its own tipping points within a Bayesian framework.

This study differs from the previous literature on asymmetric effects of minimum wage on the following grounds. First, it investigates asymmetric effects below and above an unknown threshold of minimum wage on crime. Second, it analyses the effect of minimum wage policy across different parts of conditional distribution of crime. Third, it finds heterogenous thresholds of minimum wage for each state. Indeed, this paper fills a significant gap in the literature by answering the following question, "what is the threshold effect of the minimum wage over the conditional distribution of the crime rate in each state?". In this regard, a model is developed in which state-specific tipping points of minimum wages are identified across fifty US states. Since the state governments adjust their minimum wage heterogeneously after the federal decision, an unknown continuous threshold for each state is specified. The value of thresholds in each state determines what the critical value of minimum wage is across different regions. Accordingly, policymakers can learn how criminal behaviours are heterogeneously changed when minimum wage exceeds such critical thresholds. This aspect provides valuable information to both national and local governments about the consequences of the minimum wage policy on the perpetration of criminal activities.

The econometric model has been derived by marrying two recently introduced methods: a threshold quantile time-series model (Su and Xu, 2019; Zhong et al., 2021) and heterogeneous structural breaks in a panel data model (Okui and Wang, 2021). I construct the model based on a Bayesian approach for two reasons. Firstly, it avoids the nonstandard nature of error terms in the frequentist threshold methods (Hansen, 1999, 2017). Secondly, the Bayesian method overcomes the uncertain nature of parameters by employing prior distributions as the previous beliefs. Sims (2007) suggests that estimating coefficients in this framework is more efficient than the classical approach.

Most importantly, specifying the unknown continuous heterogenous tipping points, a regression kink design, in a panel model is a notable feature of this research. Finding state-level tipping points is more informative for policymaking, and it is more efficient than conventional panel threshold models. For instance, Hansen (1999, 2017)

investigates break points over time. In this context, this research provides a more informative technique compared to the existing literature because of specifying kink designs for each state within a panel data framework. This contribution makes the results more reliable for efficient policymaking because state-level governments can take appropriate actions to control crime in each state. This research adds to the literature via modelling the state-specific tipping points across the conditional distribution of the regression.

Both threshold and non-threshold methods are applied for evaluating the marginal effect of real minimum wage on different segments of the conditional distribution of property and violent crime rates. To do so, state-level data are employed from 1976 to 2014. Findings support an asymmetric effect of minimum wage on crime rates in the US.

In this regard, results illustrate that an increase in the below-threshold real minimum wage decreases the probability of property crime being committed at all quantiles. This relationship exists at 10 and 30 percentiles. However, when minimum wage is less than a threshold, violent crime increases in the median to upper quantiles. Also, the evidence confirms a negative correlation between the above threshold minimum wage and each segment of the conditional distribution of property crime rate in the US. On the other hand, the above threshold of minimum wage is positively associated with the lower median of the distribution of violent crime. Raising the minimum wage in the non-threshold model has negatively impacted the entire distribution of violent and property crime rates. The other findings support a negative relationship between the state of the business cycle and different quantiles of property and violent crime rates. Further, a growth in college attainment rate leads to an insignificant effect on the distribution of property crime in the US. However, this variable has negatively influenced the upper median of the distribution of violent crime. As a result of this finding, encouraging people to engage in college education can have a preventative effect on crime when society faces a high violent crime rate. Finally, accumulating human capital via the growth of schooling attainment rate negatively affects the property crime rate when the crime rate is not high.

This chapter proceeds as follows. Section 4.2 reviews literature connecting economic variables with criminal outcomes. In this Section, particular attention is paid to the US based studies. Section 4.3 introduces the empirical model and estimation strategy.

Section 4.4 provides data description and estimates. Finally, Section 4.5 concludes and discusses the findings.

4.2. Literature Review

Several studies specify the relationship between economic conditions and crime. Becker (1968) presents a model relying on a cost-benefit approach. His approach rests on the usual analysis of the expected utility function. Individuals commit crimes when their marginal utilities are more than the time allocated to lawful activities. According to Ehrlich (1973), the chance of finding a job in the legal sector diminishes as unemployment increases. It implies that unemployed individuals tend to be more involved in criminal activities. Grogger (1998) shows how market wages affect delinquency based on a time-allocation model. In this direction, people commit crimes when their earnings from criminal activities exceed market wages. His findings show that falling wages may lead to a rise in crime. Further, he mentions that education can indirectly reduce crime via increased wage rates. Raphael and Winter-Ember (2001) analyse the nexus between unemployment and crime in the US. They estimate the effect of unemployment on several types of felony offenses by applying a panel data method. Their specification includes state-specific time trends for the period from 1971 to 1997. Their results confirm a positive impact of unemployment on different types of property crime. They suggest that a considerable segment of the crime reduction during the 1990s is ascribable to the decreased unemployment rate. However, they cannot find strong evidence for the effect of the unemployment rate on violent crime.

Lochner (2004) underlines the role of education on crime. In the US, he investigates how the average schooling years can control a great deal of white-collar crime such as forgery, fraud, and embezzlement. His findings show that years of schooling are positively correlated with white-collar arrest rates. He finally suggests that if human capital raises the marginal returns from working more than those from attending to crime, education can reduce these types of crime. Lochner and Moretti (2004) employ incarceration microdata to examine the effect of educational attainment on crimes of adults. More precisely, they investigate the impact of education on the probability of incarceration for men using US Census data. Their findings show that the high school graduation rate and the average education rate have negatively affected the arrest rate. Additionally, the results indicate that the increase in schooling years considerably decreases property and

violent crime. Machin and Meghir (2004) investigate the effects of economic incentives on various types of crime. They consider the 25th percentile of real hourly wage as one of the significant determinants of property crime in England and Wales. Then, the lower quantile of real wages variation is examined by using regional data from the mid-1970s to the mid-1990s. Their findings indicate that reducing the wages of unskilled workers leads to an increased crime rate.

Lee and Holoviak (2006) investigate how the labour market conditions are associated with different types of crime in three Asia-Pacific countries; Australia, Japan, and South Korea. Using annual data from 1972 to 2001 and applying the Johansen method they confirm long-run relationships between the unemployment of young males and various types of crime. Buonanno and Leonida (2006) analyse the effects of educational attainment on crimes in Italy. They mention that education can reduce crime via increasing labour market opportunities. Accordingly, they measure university education by the proportion of university degree holders in the population. Then, they employ regional data from 1980 to 1995 and apply a panel data technique to estimate the effect of education on crime. Their findings suggest that an increased high school graduation rate leads to a plunge in the crime rate. In this regard, their results demonstrate no significant evidence for linking crime and university completion. Machin et al. (2012) investigate the impact of compulsory school leaving age on violent and property crime rates in England and Wales. They mention the crime rate will be decreased when the ratio of people with no educational qualification is reduced, or the age of leaving school increases. Speziale (2014) analyses the relationship between total and unemployment rates with four different types of crime in Italy. He employs local data from 2000 to 2005 and the panel data method. The results suggest that unemployment is positively associated with all types of crime rates, including theft, fraud, and robbery, as well as total crime. The study concludes that youth unemployment rate affects these crime rates less than the overall unemployment rate.

In an examination of the effect of minimum wage on crime, Beauchamp and Chan (2014) assess the probability of committing crimes for different groups of ages, genders, and races in the US from 1997 to 2010. Their findings indicate that a hike in the minimum wage leads to increased criminal activities. They argue that the likelihood of leaving the labour market or transferring from full-time to part-time jobs increases for low-wage workers when the minimum wage surges.

Bell et al. (2018) investigate the impact of economic recession on property and violent crime in the US and the UK. They show that the probability of involvement in criminal activities for school dropouts during a recession is higher than others entering a buoyant labour market.

Andrews and Deza (2018) show how oil price fluctuation affects the value of oil reserves and the crime rate in Texas. They argue that when the value of oil reserves jumps, the number of immigrants, especially young males, increases. Therefore, the increased ratio of young males to the population influences criminal activities in Texas. They demonstrate that a hike in the reserve value has positively increased murder, robbery, and larceny by 0.16, 0.55, and 0.18 percent, respectively. Sameem and Sylwester (2018) examine the association between business cycles and crime rates in the US. They use the employment rate as the proxy of the business cycle performances. Also, they consider the ratio of various races as a percentage of total population – African Americans, Hispanics, and Whites – and different age categories – 15-19, 20-24, 25-34, 35-44, and 45-54 – to understand how these variables affect crime rates. Using county-level data from 1990 to 2013, they apply a panel data method in which both time and county fixed effects capture the unobserved heterogeneities over time and across counties. Their results support the existence of a positive relationship between the unemployment rate and property crime. However, the association between different types of violent crime and the unemployment rate is variable.

Braun (2019) investigates how the minimum wage affects criminal behaviour in the US. In this scenario, she models various types of property crime by considering different ratios of the minimum wage to median wage in each quantile. Also, some demographic controls such as poverty rate and average household income are supposed to capture the variation in crime rates. The findings indicate a "U-shaped" relationship between the minimum-to-median wage ratio and crime rates across quantiles. In this regard, minimum-to-median wage ratio and crime rates are associated negatively across quantiles and the highest negative association observed at the fourth quantile.

Fone et al. (2019) examine the relationship between the minimum wage and criminal behaviour in the US. They use National Longitudinal Survey of Youth 1997 (NLSY97) information from 1998 to 2016. Besides minimum wage, the effects of some controls such as share of races, males, and college-educated people are evaluated on the property, drug, and violent crime rate. They use county-level data and apply a fixed-effect Poisson

panel data model. The findings indicate a ten-percent hike in the minimum wage from 1998 to 2016 leads to 80000 additional property crimes. As they mentioned, this phenomena was happened due to adverse labour demand effect of minimum wage.

Chalfin and Deza (2019) investigate the nexus between parental education and delinquent behaviour of teenagers in the US. They discuss how a higher education level of parents correlates with a lower crime rate of children. To examine the impact of intergenerational education on crime, they gathered more than twelve thousand observations from the National Longitudinal Survey of Youth in 1979. As a function of compulsory schooling laws, a combined parental education year is modelled. This estimated amount of parental education is considered as a determinant of various types of delinquency in the US. The results indicate an additional year of parental education diminishes the likelihood of damaging property, committing assault, and shoplifting by 22, 11, and 12 percent, respectively.

As it was reviewed, education and state of business cycle are amongst the most important factors that impact the criminal behaviours trend in the US. The existing literature confirms a crime-minimum wage nexus. Also, the literature clearly shows the relationship varies across regions and different groups. Further, the relationship is not consistent across different types of crimes in the US. As a result of this fact, it is still important for policymakers to understand what the heterogenous effect of minimum wage policy is across different states and regions in the US.

4.3. Model Strategy

In order to examine asymmetric effects of minimum wage on crime rates, a mixed effects panel regression kink model with heterogeneous time trends[21] is set up as follows:

$$LCR_{st}^{(k)} = \mathrm{M.W.}'_{st}\, I\left(q_{st} \le \gamma_s^{(k)}\right)\beta_1^{(k)} + \mathrm{M.W.}'_{st}\, I\left(q_{st} > \gamma_s^{(k)}\right)\beta_2^{(k)} + W'_{st}\,\Lambda^{(k)} + \delta_s^{(k)}\mathrm{t} + b_s^{(k)} + \varepsilon_{st}^{(k)}, \quad (4.1)$$

where LCR is the logarithm of the crime rate. k indicates the different types of crime (i.e., for violent Crime, k=1, and property crime, k=2. M. W. denotes the hourly minimum wage.

[21] Wansbeek and Knaap (1999), Phillips and Sul (2007), Hayakawa et al. (2019), and Cao et al. (2021) show that using heterogeneous time trends leads to more efficient estimates in the panel data analysis.

I(.) is an indicator function. q is a threshold variables and γ_s are threshold parameters varying across states[22]. β_1 and β_2 are the coefficients of regression corresponding to the below and above threshold minimum wages. Based on Lochner and Moretti (2004), Lochner (2004), Buonanno and Leonida (2006), Sameem and Sylwester (2018), I use schooling and college attainments and business cycle as control variables in the model[23]. Accordingly, the control variables are $W' = [1, \mathrm{ScHC}, \mathrm{CoHU}, \mathrm{BCycl}]$ in which ScHC and CoHC indicate growth rates in schooling and college attainments, respectively. BCycl is the lagged output gap to illustrate how previous economic conditions affect criminal behaviour. This variable is interpreted as the business cycle. Indeed, it allows us to examine whether having a better or worse economic circumstance leads to committing more or less crime. Λ and β indicates the regression slopes. β_1 and β_2 are asymmetrical and flexibly take different values. γ_s takes into account unobserved heterogeneity of crime rate over time based on each state's trend. b_s indicate state-level random effects, and ε_{st} are measurement errors. b and ε are independent of each other. Subscripts t and s (t= 1, …, T; s= 1, …, n) indicate time and state, respectively.

This approach provides more flexible specifications than conventional econometric approaches regarding determining thresholds introduced by Hansen (1999, 2017) and Zhang et al. (2017). Identifying a certain threshold for each state instead of finding a tipping point for the cohort leads to a more precise regional evaluation of policy. This feature is one of the innovative aspects of this research in comparison with alternative approaches.

Following Zhong et al. (2021), the multi-kink quantile regression within Bayesian mixed-effect panel data is specified below:

[22] As described before, the minimum wage variation in most states differs from what the federal government determines nationally because local governments adjust the amount of hourly minimum wage by their state-level living costs after enacting the country-level minimum wage determined by the federal government. This issue leads to heterogeneous variations of the minimum wage across states.

[23] Based on the existing literature other controls, such as race type, unemployment ratio, consumer demand/inflation at the state level etc. could be considered in the model but due to data limitations or missing variables, I could not control their effects. To overcome this issue, the empirical model applies a mixed effect technique to capture unobserved heterogeneities in the model.

$$Q_{LCR_{st}^{(k)}}(\tau \mid MW_{st}, W_{st})$$
$$= \left(MW_{st} - \gamma_{s\tau}^{(k)}\right) I\left(MW_{st} \leq \gamma_{s\tau}^{(k)}\right) \beta_{1\tau}^{(k)}$$
$$+ \left(MW_{st} - \gamma_{s\tau}^{(k)}\right) I\left(MW_{st} > \gamma_{s\tau}^{(k)}\right) \beta_{2\tau}^{(k)} + W_{st}' \Lambda_{\tau}^{(k)} + \delta_{s\tau}^{(k)} \mathrm{t} + b_{s\tau}^{(k)}$$
$$+ \varepsilon_{st}^{(k)}, \tag{4.2}$$

$$b_{s\tau}^{(k)} \sim N(0, \xi^{2(k)}). \tag{4.3}$$

In equation (4.2), τ reflects regression quantiles. Also, in equation (4.2), the left part equals the inversed function of the cumulative distribution of the logarithm of crime rate given the random effects, $b_{s\tau}^{(k)}$, $Q_{LCR_{st}^{(k)}}(\cdot) \equiv F^{-1}_{LCR_{st}^{(k)}}(\cdot)$. Compared to Zhong et al.[24] (2021), this model is developed based on a panel setting. Further, based on Geraci and Bottai (2007), Luo et al. (2012) and Zamanzadeh et al. (2020), the error term has asymmetric Laplace distribution (ALD), which leads to more efficient estimates in comparison with Koenker and Bassett (1978).

This specification assists us in estimating how the conditional distributions of the property and violent crime rates at each quantile adjust across the different thresholds of income inequalities as well as other control variables. In equation (4.3), $\xi^{2(k)}$ is a variance of the random effects.

To simplify equation (4.2), it is assumed $X_{st}'(\gamma_{s\tau}^{(k)}) = [\left(MW_{st} - \gamma_{s\tau}^{(k)}\right) I\left(MW_{st} \leq \gamma_{s\tau}^{(k)}\right), \left(MW_{st} - \gamma_{s\tau}^{(k)}\right) I\left(MW_{st} > \gamma_{s\tau}^{(k)}\right)]$ and $\mathrm{B}_{\tau}^{(k)} = [\beta_{1\tau}^{(k)}, \beta_{1\tau}^{(k)}]$. So, equation (4.2) can be written as follows:

$$Q_{LCR_{st}^{(k)}}\left(\tau \mid X_{st}\left(\gamma_{s\tau}^{(k)}\right), W_{st}\right) = X_{st}'(\gamma_{s\tau}^{(k)})\mathrm{B}_{\tau}^{(k)} + W_{st}'\Lambda_{\tau}^{(k)} + \delta_{s\tau}^{(k)}\mathrm{t} + b_{s\tau}^{(k)} + \varepsilon_{st}^{(k)}, \tag{4.4}$$

As can be mentioned in equation (4.2), $\mathrm{B}_{\tau}^{(k)}$and $\Lambda_{\tau}^{(k)}$ are quantile specific. Also, the model has an additive error $\varepsilon_{st}^{(k)}$. In the quantile-based model, it is assumed that ε_{st} follows an

[24] They introduce a multi-kink quantile approach for a time series analysis.

ALD with iid across s and t. The density distribution for the LCR, relying on ALD, is written below:

$$f\left(LCR_{st}^{(k)}\right) = \frac{\tau(1-\tau)}{\sigma^{(k)}} exp\left\{-\rho_\tau\left(\frac{LCR_{st}^{(k)}-\mu_{st}^{(k)}}{\sigma^{(k)}}\right)\right\}, LCR_{st}^{(k)} \in (-\infty.+\infty). \quad (4.5)$$

In the above function $LCR_{st}^{(k)} \sim ALD\left(\mu_{st}^{(k)}, \sigma^{(k)}, \tau\right)$, where $-\infty < \mu_{st}^{(k)} < +\infty$, $0 < \tau < 1$ and $\sigma^{(k)} > 0$ are the indicators of location, skew, and scale parameters, respectively. Further, it shows the weighted sums of absolute deviations by $\rho_\tau(.)$ which is known as a check or tick function.

$$\rho_\tau(\vartheta) = \vartheta\left(\tau - l_{(-\infty.0)}(\vartheta)\right) = \ |\vartheta|\left((1-\tau)l_{(-\infty.0)}(\vartheta) + \tau\, l_{[0.+\infty)}(\vartheta)\right), \vartheta \in R, \quad (4.6)$$

where l(.) is a representative of an indicator function. The weights of deviations can take a negative or positive value when $(1-\tau)$ or τ, respectively. Additionally, the cumulative density function (CDF) relying on the ALD satisfies the following condition for different quantiles when it is centred at $\mu_{st}^{(k)}$:

$$F_{LCR_{st}^{(k)}}\left(\mu_{st}^{(k)} \mid \mu_{st}^{(k)}, \sigma^{(k)}, \tau\right) = P\left(LCR_{st}^{(k)} \le \mu_{st}^{(k)}\right) = \tau. \quad (4.7)$$

As far as the error terms follow ALD, i.e., $\varepsilon_{st}^{(k)} \sim ALD(0, \sigma^{(k)}, \tau)$, the LCR relies on ALD being given explanatory variables, i.e., $LCR_{st}^{(k)} \sim ALD\left(\mu_{st}^{(k)}, \sigma^{(k)}, \tau\right)$. Then, the ALD representation of $LCR_{st}^{(k)}$ is defined as follows:

$$LCR_{st}^{(k)} = \sqrt{\frac{2\sigma^{(k)}E_{st}^{(k)}}{\tau(1-\tau)}} Z_{st}^{(k)} + \frac{1-2\tau}{\tau(1-\tau)} E_{st}^{(k)} + \mu_{st}^{(k)}, \quad (4.8)$$

Taking Z and E as standard normal and exponential random variables, respectively, they are mutually independent. Considering equation (4.5), the density function of the LCR model – given the parameters, covariates, and random effects – is shown below:

$$f\left(LCR_{st}^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, b_{s\tau}^{(k)}\right) =$$

$$\frac{\tau(1-\tau)}{\sigma^{(k)}} \exp\left\{-\rho_{\tau}\left(\frac{LCR_{st}^{(k)} - \left(X_{st}'\left(\gamma_{s\tau}^{(k)}\right)\mathrm{B}_{\tau}^{(k)} + W_{st}'\Lambda_{\tau}^{(k)} + \delta_{s\tau}^{(k)}\mathrm{t} + b_{s\tau}^{(k)}\right)}{\sigma^{(k)}}\right)\right\}. \quad (4.9)$$

Defining $LCR_{s}^{(k)} = (LCR_{s1}^{(k)}, \cdots, LCR_{sT}^{(k)})'$, the density for the s-th state is:

$$f\left(LCR_{s}^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, b_{s\tau}^{(k)}\right) =$$

$$\prod_{t=1}^{T} f(\, LCR_{st}^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, b_{s\tau}^{(k)}). \quad (4.10)$$

Then, it enables one to measure the joint density of $(LCR_{s}^{(k)}, b_{s}^{(k)})$ as follows:

$$f\left(LCR_{s}^{(k)}, b_{s}^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)}\right) =$$

$$f\left(LCR_{s}^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, b_{s\tau}^{(k)}\right) \times f(b_{s}^{(k)} \mid \xi^{2(k)}), \quad (4.11)$$

Letting $LCR^{(k)} = ((LCR_{1}^{(k)}, \cdots, LCR_{n}^{(k)})$ and $b^{(k)} = (b_{1}^{(k)}, \cdots, b_{n}^{(k)})$, so, the likelihood function for all states is shown as,

$$\left(LCR^{(k)}, b^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)}\right) =$$

$$\prod_{s=1}^{n} \prod_{t=1}^{T} f(\, LCR_{s}^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, b_{s\tau}^{(k)}) \times f(b_{s\tau}^{(k)} \mid \xi^{2(k)}), \quad (4.12)$$

In order to estimate coefficients in a Bayesian framework, one needs to calculate the posterior distribution relying on priors of the parameters (Christensen et al., 2010), i.e., $\mathrm{B}_{\tau}^{(k)}$, $\lambda_{\tau}^{(k)}$, $\gamma_{s\tau}^{(k)}$, $\sigma^{(k)}$, $\delta_{s\tau}^{(k)}$ and $\xi^{2(k)}$. Multiplying the likelihood function by priors provides the posterior distribution as:

$$\pi\left(\mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \xi^{2(k)}, \delta_{s\tau}^{(k)}, b^{(k)} \mid LCR^{(k)}\right) \propto f\left(LCR^{(k)} \mid \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \sigma^{(k)}, \delta_{s\tau}^{(k)}, b^{(k)}\right) \times f(b^{(k)} \mid \xi^{(k)}) \times \pi\left(\mathrm{B}_{\tau}^{(k)}\right) \times \pi\left(\Lambda_{\tau}^{(k)}\right) \times \pi(\gamma_{s\tau}^{(k)}) \times \pi\left(\sigma^{(k)}\right) \times \pi\left(\delta_{s\tau}^{(k)}\right) \times \pi\left(\xi^{2(k)}\right), \quad (4.13)$$

where $\pi\left(\mathrm{B}_{\tau}^{(k)}\right)$, $\pi\left(\Lambda_{\tau}^{(k)}\right)$, $\pi(\gamma_{s\tau}^{(k)})$, $\pi\left(\sigma^{(k)}\right)$, $\pi\left(\delta_{s\tau}^{(k)}\right)$ and $\pi\left(\xi^{2(k)}\right)$ indicate priors for parameters. They allow us to calculate the marginal posterior distribution of the specified parameters.

It is assumed that the priors of coefficients, $\pi\left(\mathrm{B}_{\tau}^{(k)}\right)$, $\pi\left(\Lambda_{\tau}^{(k)}\right)$, $\pi\left(\sigma^{(k)}\right)$ and $\pi\left(\delta_{s\tau}^{(k)}\right)$ follow a multivariate normal distribution:

$$\pi\left(\mathrm{B}_{\tau}^{(k)}\right) \sim N(\mathrm{B}_{0\tau}^{(k)}, \Psi_{\mathrm{B}_{\tau}}^{(k)}), \tag{4.14}$$

$$\pi\left(\Lambda_{\tau}^{(k)}\right) \sim N(\Lambda_{0\tau}^{(k)}, \Psi_{\Lambda_{\tau}}^{(k)}), \tag{4.15}$$

$$\pi(\gamma_{s\tau}^{(k)}) \sim N(\gamma_{s_0\tau}^{(k)}, \Psi_{\gamma_{s\tau}}^{(k)}), \tag{4.16}$$

$$\pi(\delta_{s\tau}^{(k)}) \sim N(\delta_{s_0\tau}^{(k)}, \Psi_{\delta_{s\tau}}^{(k)}), \tag{4.17}$$

in which the means of prior distributions for $\mathrm{B}_{\tau}^{(k)}$, $\Lambda_{\tau}^{(k)}$, $\gamma_{s\tau}^{(k)}$ and $\delta_{s\tau}^{(k)}$ are demonstrated by $\beta_{0\tau}^{(k)} = 0$, $\Lambda_{0\tau}^{(k)} = 0$, $\gamma_{s_0\tau}^{(k)} = 0$ and $\delta_{s_0\tau}^{(k)} = 0$, respectively. Consequently, the variances related to these prior distributions are $\Psi_{\mathrm{B}_{\tau}}^{(k)}$, $\Psi_{\Lambda_{\tau}}^{(k)}$, $\Psi_{\gamma_{s\tau}}^{(k)}$, and $\Psi_{\delta_{s\tau}}^{(k)}$, respectively (discussed below). Also, to obtain exact values of thresholds across states, I constrain $\pi(\gamma_{s\tau}^{(k)})$ between the minimum and maximum amount of the minimum wage in each state. It is assumed that priors of $\sigma^{(k)}$ and $\xi^{(k)}$ follow an inverse gamma (I.G.) distribution (Zamanzadeh et al., 2020).

$$\pi\left(\sigma^{(k)}\right) \sim IG(\varphi_0, \theta_0), \tag{4.18}$$

$$\pi\left(\xi^{2(k)}\right) \sim IG(\varphi_{00}, \theta_{00}), \tag{4.19}$$

In all the distributions above, $\mathrm{B}_{0\tau}^{(k)}$, $\Psi_{\mathrm{B}_{\tau}}^{(k)}$, $\Lambda_{0\tau}^{(k)}$, $\Psi_{\Lambda_{\tau}}^{(k)}$, $\gamma_{s_0\tau}^{(k)}$, $\Psi_{\gamma_{s\tau}}^{(k)}$, $\delta_{s_0\tau}^{(k)}$, $\Psi_{\delta_{s\tau}}^{(k)}$, φ_0, θ_0, φ_{00} and θ_{00} are hyperparameters. φ_0 and φ_{00} reflect shape hyperparameters. θ_0 and θ_{00} represent scale hyperparameters. The posterior joint distribution and full conditions are documented in Appendix 4A at the end of this chapter.

Following Spiegelhalter et al. (2002), this paper applies the Deviance Information Criterion (DIC) to compare models in a Bayesian framework. Accordingly, I test whether the threshold-based model is more efficient and has a better fit compared to non-threshold models. Several researchers van der Linde (2005), Shriner and Yi (2009) and Spiegelhalter et al. (2014) indicate that it is a powerful tool for testing hypotheses, comparing models, and selecting variables in complicated Bayesian models.

The DIC is defined for threshold and non-threshold models over quantiles as follows,

$$DIC_{\tau}^{Thr} = 2\overline{D(\theta_{\tau}^{Thr})} - D(\bar{\theta}_{\tau}^{Thr}),$$

$$DIC_{\tau}^{non} = 2\overline{D(\theta_{\tau}^{non})} - D(\bar{\theta}_{\tau}^{non}).$$

Where θ_{τ}^{Thr} and θ_{τ}^{non} indicate the coefficients included in the threshold and non-threshold models across quantiles. $D(\theta_{\tau})$ measures as the usual deviance over quantiles and it is defined as $D(\theta_{\tau}) = -2\log\left(f(LCR_{st} \mid \theta_{\tau})\right)$. $\overline{D(\theta_{\tau})}$ and $\bar{\theta}_{\tau}$ are the posterior means of the deviance and parameters. It should be noted that the smaller value of the DIC presents a better fit.

4.4. Data and Estimates

4.4.1. Data

The data covers fifty states of the US from 1976 to 2014[25]. The sample includes 1,950 observations for property crime, and the same number of observations are available for violent crime. The crime data are collected from the *Uniform Crime Reporting* (UCR) Statistics of the Federal Bureau of Investigation (FBI). Based on the UCR, "property crime is defined as offenses of burglary, larceny-theft, motor vehicle theft, and arson". The UCR mentions that "violent crime includes offences of murder and nonnegligent manslaughter, rape, robbery, and aggravated assault". The output gap is employed as a measure of the state of business cycles. Essentially, it is the difference between current and potential real GDP, divided by potential real GDP, presented in percentage value. This variable was obtained from the *Federal Reserve Bank of St. Louis*. Also, college

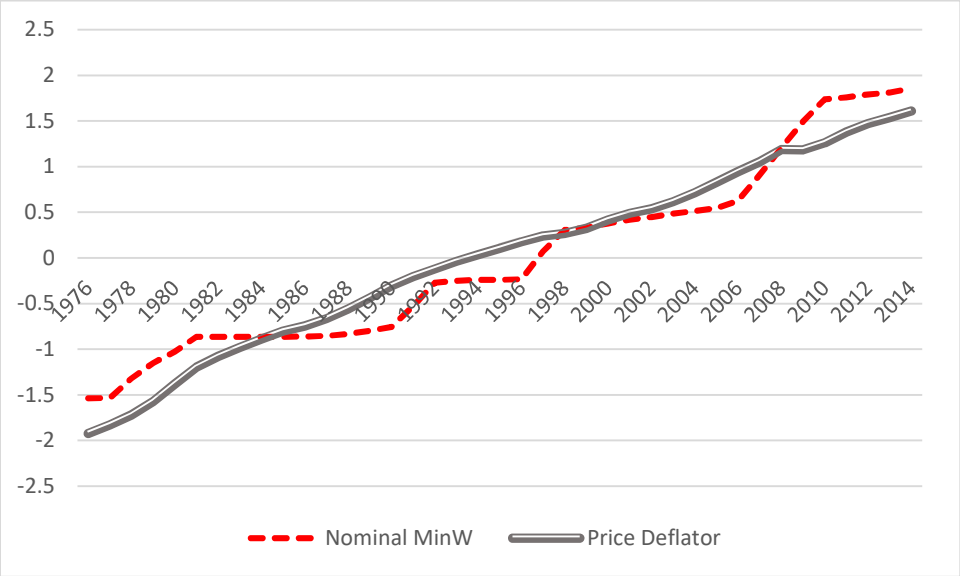
[25] 2014 is the end of sample for collection of this data set because there is no availability beyond this period.

attainment is defined as the proportion of the total number of college graduates to each state population[26]. The minimum wage data are gathered from the "*Washington Center for Equitable Growth*". This nominal variable is changed to real by adjusting the implicit price deflator based on personal consumption expenditures (2012=100). This price deflator is also obtained from the *Federal Reserve Bank of St. Louis*.

4.4.2. Descriptive Statistics

Studying how the central tendency of two main variables alters across states can help to understand how state-level minimum wage policies affect crime rates in the US. To get a precise picture of how minimum wages vary across states, one needs to analyse the central tendency of nominal and real minimum wages. Real minimum wage variations are used to explore how an increase in minimum wage impacts the average purchasing power of "in-poverty workers" in each state. Initially, the main characteristics of the nominal and real minimum wages are examined across the fifty States in the US. I then compare the normalised minimum wage changes and normalised consumer price deflator (CPD). Figure 4.1 depicts the trend of both variables over the sample period.

Figure 4.1: Normalised nominal minimum wage and consumer price deflator



[26] Both the high school and college attainment rates are gathered from Professor Mark Frank database (https://www.shsu.edu/eco_mwf/inequality.html).

Source Author's calculation.

As seen from the Figure, the standardised value of the nominal minimum wage (dashed line), for 18 periods out of 39 years (1976-1984, 1998-1999, and 2008-2014) is higher than the normalised consumer price deflators (solid line). This implies consumers could afford necessary goods and services in these 18 periods. However, for the remaining 21 periods, employees with a minimum wage income cannot cover their living expenses[27].

Consequently, implementing a minimum wage policy based on nominal rate will be misleading due to neglecting the living cost. The minimum wage is adjusted with the average consumer price index, and the analysis is constructed relying on the real minimum wage to avoid the effect of price accumulation (inflation). This approach allows the understanding of the policy effect when the real purchasing power of low-wage workers is targeted.

To show the values of the central tendency of the state-level real and nominal minimum wages, Table 4.1 provides values of the mean (average), median, and standard deviation of these variables as follows,

[27] Multiplying nominal minimum wage to 8, 36 or 144 hours to obtain the daily, weekly or monthly earnings of minimum wage workers does not change the normalised minimum wage values in the sample.

Table 4.1. Descriptive statistics of nominal and real minimum wage

	Hourly nominal Minimum Wage				Hourly real Minimum Wage (chained in 2012 dollars)			
	Mean	*Minimum*	*Maximum*	*S.D.*	*Mean*	*Minimum*	*Maximum*	*S.D.*
Alabama	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Alaska[I]	5.24	2.80	7.75	1.63	7.57	6.08	9.32	0.79
Arizona	4.66	2.30	7.90	1.61	6.69	5.29	7.79	0.74
Arkansas	4.57	2.30	7.25	1.46	6.59	5.29	7.79	0.66
California[V]	5.11	2.30	8.00	1.90	7.24	5.76	8.50	0.85
Colorado	4.67	2.30	8.00	1.62	6.69	5.29	7.79	0.75
Connecticut[IV]	5.21	2.30	8.70	1.99	7.35	5.82	8.62	0.89
Delaware	4.79	2.30	7.25	1.63	6.85	5.29	7.79	0.70
Florida	4.68	2.30	7.93	1.62	6.71	5.29	7.79	0.73
Georgia	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Hawaii	4.95	2.40	7.25	1.61	7.09	5.88	7.99	0.57
Idaho	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Illinois	4.84	2.30	8.25	1.83	6.88	5.29	8.41	0.87
Indiana	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Iowa	4.66	2.30	7.25	1.49	6.72	5.52	7.79	0.64
Kansas	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Kentucky	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Louisiana	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Maine	4.84	2.30	7.50	1.64	6.92	5.79	7.84	0.62
Maryland	4.56	2.30	7.25	1.46	6.59	5.29	7.79	0.66
Massachusetts	5.11	2.30	8.00	1.92	7.23	5.80	8.50	0.86
Michigan	4.65	2.30	7.40	1.59	6.68	5.29	7.86	0.74
Minnesota	4.63	2.30	7.25	1.45	6.69	5.79	7.79	0.56
Mississippi	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Missouri	4.61	2.30	7.50	1.52	6.63	5.29	7.79	0.69
Montana	4.62	2.30	7.90	1.56	6.64	5.29	7.79	0.72
Nebraska	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Nevada	4.69	2.30	8.25	1.69	6.71	5.29	8.41	0.82
New Hampshire	4.59	2.30	7.25	1.46	6.63	5.63	7.79	0.64
New Jersey	4.77	2.30	8.25	1.61	6.84	5.29	8.02	0.69
New Mexico	4.60	2.30	7.50	1.55	6.63	5.29	7.97	0.75
New York	4.71	2.30	8.00	1.63	6.75	5.29	7.82	0.72
North Carolina	4.56	2.30	7.25	1.46	6.59	5.29	7.79	0.66
North Dakota	4.53	2.30	7.25	1.43	6.55	5.37	7.79	0.67
Ohio	4.67	2.30	7.95	1.63	6.70	5.29	7.79	0.76
Oklahoma	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Oregon[II]	5.39	2.30	9.10	2.12	7.56	5.52	8.93	0.96
Pennsylvania	4.62	2.30	7.25	1.51	6.65	5.52	7.79	0.67
Rhode Island	5.01	2.30	8.00	1.73	7.13	6.07	8.09	0.61
South Carolina	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
South Dakota	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Tennessee	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Texas	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Utah	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Vermont	5.11	2.30	8.73	1.99	7.20	5.88	8.57	0.91
Virginia	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Washington[III]	5.38	2.30	9.32	2.19	7.54	5.76	9.09	1.04
West Virginia	4.58	2.30	7.25	1.49	6.61	5.29	7.79	0.68
Wisconsin	4.60	2.30	7.25	1.48	6.63	5.52	7.79	0.63
Wyoming	4.53	2.30	7.25	1.43	6.55	5.29	7.79	0.68
Average								

Notes: up scripts “I” to “V” show the highest average real minimum wage in the first five states during 1976-2014.

Table 4.1 reveals interesting information regarding minimum wage distribution from several aspects. Firstly, there are 18 states following the federal minimum wage. The

values of central tendency of real and nominal minimum wages for these states are the same. However, the magnitudes of the state-specific minimum wage tipping points in these regions are unequal because the variation of criminal activities is not the same across these states.

Secondly, the highest values for average nominal and real minimum wages were utilised by Alaska, Washington, Oregon, Connecticut, and Vermont from 1976 to 2014. The highest standard deviation is also found in the mentioned states except for Alaska. In this case, Alaska is the most active state regarding the implementation of minimum wage policy constantly over time. However, during the last decade of the sample period, others are more active regarding minimum wage policymaking.

On the other hand, it is worth investigating the distribution of violent and property crime to understand the variation of state-level crime rates over time. Exploring the distributional criteria provides enough information regarding the heterogeneity of the two types of crime. For this purpose, Table 4.2 shows the descriptive statistics of violent and property crime across fifty states from 1976 to 2014.

Table 4.2. Descriptive statistics of violent and property crime

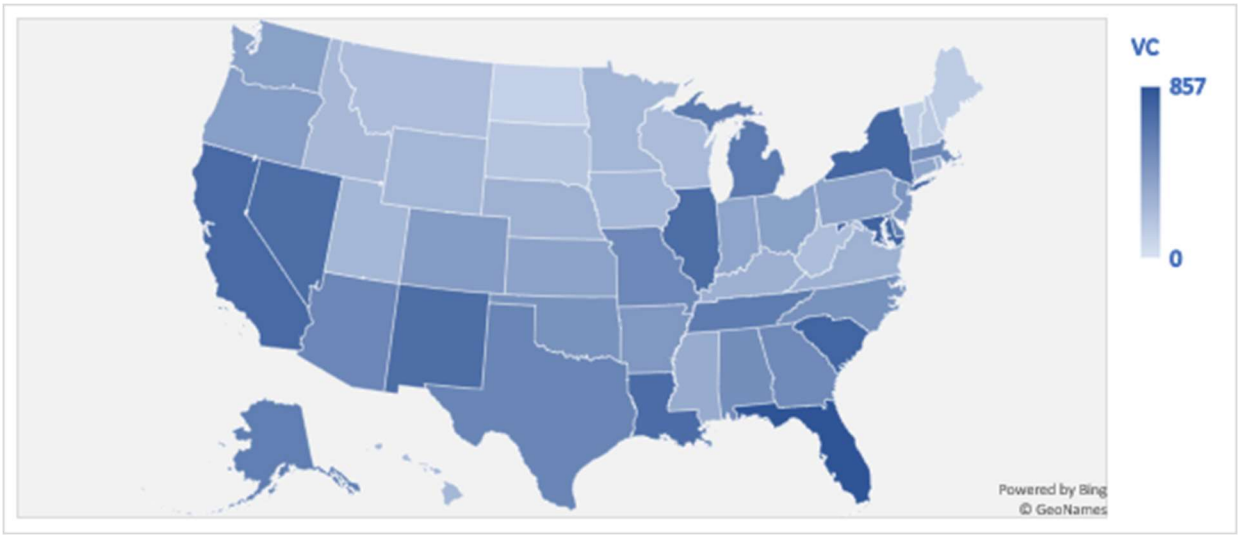
	Rate of Violent Crime					Rate of Property Crime				
	Mean	*Median*	*Maximum*	*Minimum*	*S.D.*	*Mean*	*Median*	*Maximum*	*Minimum*	*S.D.*
Alabama	506.6	450.1	871.7	383.7	123.4	3912.1	3971.6	4521.4	3177.6	345.8
Alaska	604.4	613.9	770.9	436.0	85.3	4352.7	4571.4	5979.1	2637.8	1031.1
Arizona	552.6	551.1	715.0	399.9	90.5	5849.4*	6357.8	7519.9	3197.5	1362.0
Arkansas	453.3	469.6	595.1	297.7	90.0	3729.9	3738.4	4581.7	3018.1	388.1
California	728.7	742.9	1119.7	396.1	215.2	4580.7	4865.1	6939.5	2441.1	1492.5
Colorado	427.6	417.0	578.8	291.2	85.6	4738.7	4808.8	6821.4	2530.1	1431.7
Connecticut	366.0	366.3	553.7	236.9	84.6	3681.8	4092.5	5469.2	1920.4	1120.8
Delaware	578.3	611.1	762.4	321.6	113.6	4315.6	4227.3	6301.8	2982.0	972.8
Florida	857.4*	833.9	1244.3	460.0	219.2	5696.6**	6051.8	7819.9	3105.3	1496.3
Georgia	531.0	495.7	756.3	359.7	113.2	4585.0	4386.4	6337.3	3281.2	798.4
Hawaii	259.0	258.4	299.5	219.4	18.7	5249.0***	5554.7	7182.8	3050.0	1175.7
Idaho	251.0	246.2	322.0	202.2	28.7	3246.1	3627.1	4468.8	1854.8	775.5
Illinois	706.3	724.9	1039.2	370.0	186.7	4069.8	4459.6	5461.1	2075.9	972.2
Indiana	375.0	344.8	537.0	283.8	75.4	3696.6	3738.4	4552.5	2649.4	453.2
Iowa	255.9	268.5	354.4	132.9	52.6	3315.5	3505.8	4546.4	2093.8	660.7
Kansas	386.8	382.8	510.8	282.6	50.9	4100.8	4203.2	5034.9	2735.2	592.0
Kentucky	302.1	289.5	535.5	198.8	72.9	2757.9	2757.8	3253.4	2246.9	229.4
Louisiana	709.7	678.0	1061.7	472.8	151.1	4641.6	4642.1	5909.7	3458.8	738.9
Maine	141.2†††	127.8	224.7	103.7	33.1	3077.9	3142.8	4174.2	1986.4	599.6
Maryland	761.0**	786.6	1000.1	446.1	149.0	4357.9	4569.1	5777.7	2507.5	906.2
Massachusetts	546.5	531.3	804.9	391.4	114.4	3541.1	3654.4	5477.8	1857.1	1140.6
Michigan	620.6	614.2	803.9	427.3	115.3	4335.7	4495.0	6212.2	2043.9	1261.2
Minnesota	267.7	267.2	359.0	189.0	48.0	3606.4	3877.8	4571.7	2297.5	656.7
Mississippi	332.1	304.6	502.8	260.1	68.5	3295.6	3208.8	4343.3	2172.9	546.9
Missouri	543.3	525.7	763.0	422.0	92.8	4071.6	4083.9	4878.6	2906.5	462.3
Montana	226.7	224.8	365.0	116.0	67.0	3704.0	3887.3	4841.7	2394.1	776.2
Nebraska	294.1	281.8	451.4	181.5	70.9	3547.0	3721.2	4162.5	2523.5	472.9
Nevada	708.4	691.0	1001.9	524.2	113.5	5075.5	5304.9	7996.0	2576.3	1582.5
New Hampshire	144.9	139.5	217.3	86.3	30.7	2809.4	2624.2	4499.8	1838.9	746.7
New Jersey	464.3	440.1	647.6	261.2	125.2	3660.7	4046.8	5797.0	1734.1	1230.2
New Mexico	703.9	686.8	961.4	500.9	117.9	4945.2	5298.5	6053.2	3425.9	890.9
New York	744.5	831.8	1180.9	381.8	280.9	3669.5	3718.3	5882.0	1718.2	1456.9
North Carolina	484.2	466.4	681.0	329.5	98.8	4154.3	4120.8	5230.3	2873.1	599.9
North Dakota	105.8†	80.2	266.4	47.0	68.6	2413.5†††	2497.7	2923.6	1780.2	326.9
Ohio	398.8	388.7	561.8	275.7	74.1	3915.1	3937.8	4950.8	2799.1	497.7
Oklahoma	484.6	497.4	664.1	286.6	85.2	4334.5	4312.3	5608.0	2990.7	667.1
Oregon	410.6	457.4	551.1	232.3	114.5	5001.8	5262.5	6558.2	2879.0	1146.0
Pennsylvania	383.2	382.3	480.3	282.8	47.6	2704.7	2793.9	3372.4	1931.7	357.2
Rhode Island	324.5	333.5	462.0	219.2	66.4	3838.7	3743.5	5524.1	2173.6	1034.2
South Carolina	756.9***	741.2	1030.5	494.8	151.3	4468.0	4477.6	5217.2	3460.3	434.9
South Dakota	183.0	171.4	326.5	99.0	56.7	2371.8††	2467.3	3116.3	1619.6	427.7
Tennessee	615.6	666.0	789.7	382.6	136.6	4011.1	4031.7	4722.1	3060.6	424.4
Texas	560.6	550.0	840.1	355.7	115.4	5080.1	5020.5	7365.1	3019.4	1148.1
Utah	259.5	255.7	334.0	197.1	38.3	4545.5	4757.2	5762.0	2878.5	897.4
Vermont	129.0††	126.9	184.2	96.9	19.9	3229.6	3073.9	5115.0	1524.4	886.9
Virginia	294.0	295.0	374.9	187.9	49.5	3277.1	3530.9	4349.1	1930.3	701.8
Washington	400.2	405.3	534.5	277.9	70.8	5199.3	5438.9	6646.6	3579.1	924.8
West Virginia	224.9	211.5	350.7	131.4	61.4	2294.0†	2281.3	2632.6	2034.7	162.4
Wisconsin	234.3	248.9	290.9	131.5	44.2	3408.9	3604.6	4616.0	2088.3	681.2
Wyoming	264.3	255.2	430.1	195.5	50.1	3509.7	3653.1	4701.8	1964.7	704.0

Notes: The symbols "*", "**", and "***" refer to the first three states with the highest crime rate. The notations "†", "††" and "†††" indicate the first three states with the lowest crime rate.

Table 4.2 shows the average rates for violent and property crimes across states. For instance, the lowest and highest average violent crime rates belong to North Dakota and Florida, respectively. These average rates equal 105.8 and 857.4 respectively per 100,000 population from 1976 to 2014. Comparing these rates with the average crime rate in the US, 437.3, reveals that the probability of crime occurring in North Dakota and Florida is approximately 25% and 200% respectively of the likelihood of violent crime in the US overall. It refers to the heterogeneous criminal behaviour across states.

Additionally, the violent crime rate's standard deviation (S.D.) across states varies from 18.7 to 280.9. In this regard, states with high crime rates have a higher variation over time as compared to those that have relatively low crime rates. Figure 4.2 reveals this issue by depicting the average violent crime rates across states as follows,

Figure 4.2: State-level Violent Crime



Source: Author's calculation.

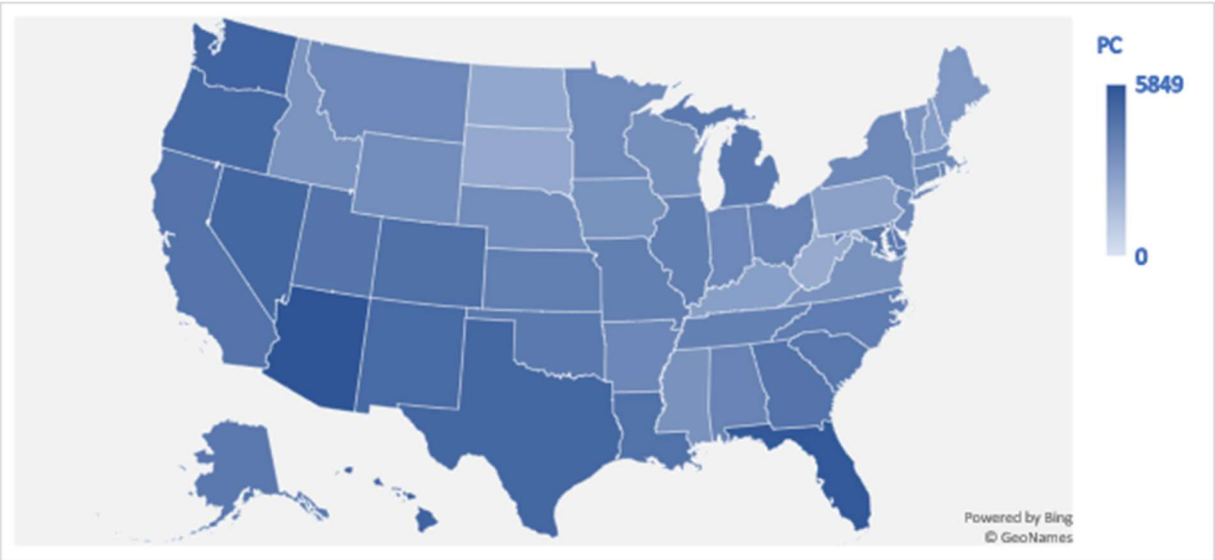
As seen from Figure 4.2, the average violent crime rate with bright blue corresponds to the low violent crime rate. In contrast, the dark blue represents states with high crime rates. The figure illustrates that the probability of violent crime occurring in the West North Central, New England, and Mountain divisions is less than in the other states in the US.

On the other hand, based on Table 4.2, the lowest and highest average rate of property crime occurred in West Virginia and Arizona at 2,294 and 5,849.4 per 100,000 population, respectively, from 1976 to 2014. Comparing these rates implies that the probability of property crime occurring in Arizona as the most unsafe state is 250% more than the likelihood of crime occurring in the safest State, West Virginia.

Additionally, the median and average rates of property crime are close in West Virginia. The standard deviation of property crime in this state equals 164.2, the lowest in the US. It implies that West Virginia is constantly the safest place for property owners in the US. In contrast, Arizona's median and average property crime rates have deviated from each other more than other states. In this regard, the median of property crime is 6,357.8, and its standard deviation equals 1,362. Based on this data, it appears that property crime distribution in Arizona from 1976 to 2014 is skewed to the left tail.

Figure 4.3 illustrates the average of property crime across 50 states of the US as follows:

Figure 4.3: State-level Property Crime



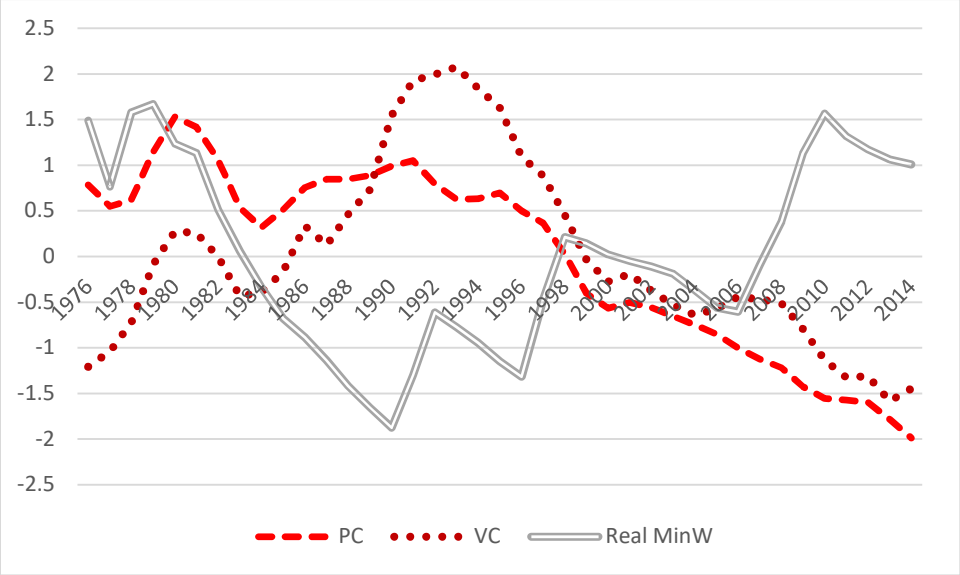
Source: Author's calculation.

As shown in Figure 4.3, the states with the highest average property crime rates are illustrated in dark blue. It mainly covers the South and West Coasts and the South Atlantic division. In contrast, the states with shaded light blue exhibited a lower property crime rate over time. Therefore, states located in the West North Central, and Northeast divisions enjoy a lower property crime rate than other parts of the US.

These examples depict how the distribution of crime is highly heterogeneous in the US. This variation is potentially related to differences in real minimum wages across states.

In order to understand how crime rates impact unlawful behaviour over time, the co-movements of crime incentives and both property and violent crime rates are illustrated. To accomplish this, first, the variation of the normalised real minimum wage and crime rates is demonstrated below,

Figure 4.4: Co-movement between real MinW and crime rate

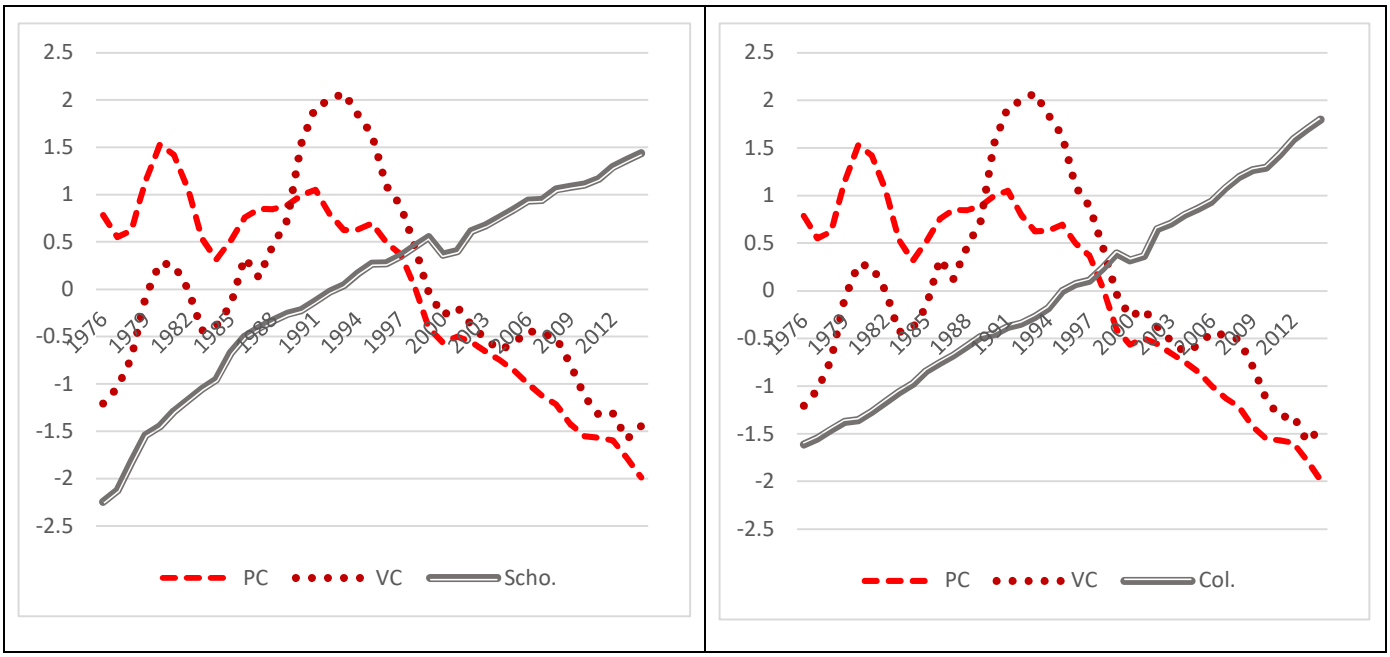


Source: Author's calculation.

Notes: P.C. and V.C. refer to the normalised values of the property and violent crime rates.

Figure 4.4 illustrates the co-movement between real minimum wage and criminal activities in the US. The dotted and dashed lines demonstrate the variations of the normalised violent and property crime rates over time. The figure reveals that the normalised real minimum wage has a negative association with violent and property crime. However, this movement for violent crime is much greater than for property crime. In this instance, the correlation coefficient between the real minimum wage and violent crime is approximately twice as much as that for property crime, -0.70 compared to -0.34. The example indicates that the marginal effect of minimum wage policies on violent crimes is higher than its marginal effect on property crimes. Further, the co-movement between crime and educational attainment provides valuable information with regard to the possible marginal impacts of school and college education on the criminal activities in the US. Figure 4.5 depicts these co-movements.

Figure 4.4: Co-movement between the school and college attainment with crime



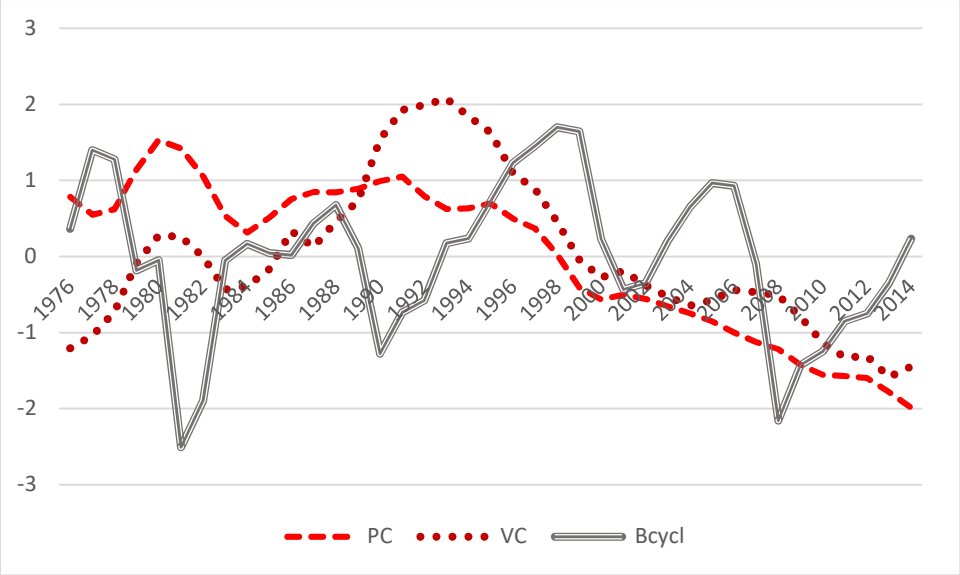
Source: Author's calculation.

Notes: Scho. and Col. denote the high school and college attainment rates, respectively. P.C. and V.C. refer to the normalised values of the property and violent crime rates, respectively.

Figure 4.5 illustrates that education is negatively associated with committing crime over time. In this regard, the correlation coefficients between the school attainment rate and violent and property crimes equal -0.15 and -0.8, respectively. These values for college education and violent and property crimes are equal to -0.35 and -0.92, respectively. The magnitude of the correlation coefficients implies two notable points. First, educational attainment prevents violent crime less than property crime. Moreover, college education has a greater impact on committing crimes than schooling. The figure sheds light on an important issue, i.e., the normalised values of both the high school and college attainment rates increase over time. Estimating regression with trending variables probably leads to misleading results. Therefore, the growth of the educational variables is used to avoid the spurious regression trap. This approach is informative for policy implications because it allows the government to influence criminal activities by implementing suitable educational policies.

In order to understand how business cycles and criminal activities are linked, Figure 4.6 demonstrates the co-movement between the output gap – as the state of the business cycle – and different crime rates over time,

Figure 4.5: Co-movement between output gap and crime rate



Source: Author's calculation.

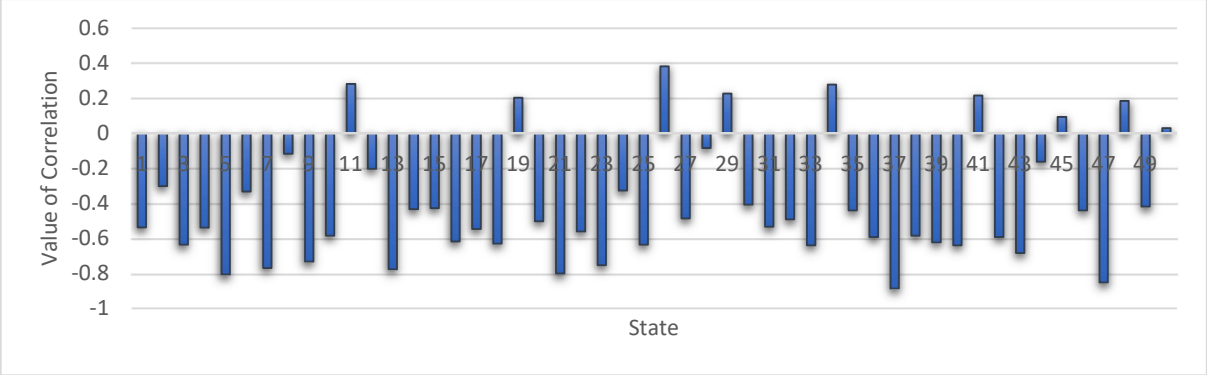
Notes: BCycl refers to the output gap as the state of the business cycle. P.C. and V.C. refer to the normalised values of the property and violent crime rates, respectively.

According to Figure 4.6, there is a mixed relationship between the state of the business cycle and violent and property crime over time. For example, output gap and violent crime have a positive co-movement during 21 periods. These numbers for property crime are 24. However, the number of positive co-movements between the business cycle and crime rates is more considerable than negative associations. The correlation coefficients for violent and property crime are minimal, e.g., 0.06 and 0.08, respectively. This point highlights the likelihood of existing quantile correlations between a better or worse economic condition and crime instead of a conditional mean relationship.

The correlation between crime rates and minimum wage across states has been measured to understand the possible effect of a minimum wage on the crime rate. This method can assist in adopting the right expectation about the reaction of crime rates to minimum wage policy. Figures 4.7 to 4.10 depict this relationship in each state from 1976 to 2014 as follows[28].

[28] Also, two scatter plots of average crime incidence and real minimum wage from 1976 to 2014 haven reported in Appendix 4B.

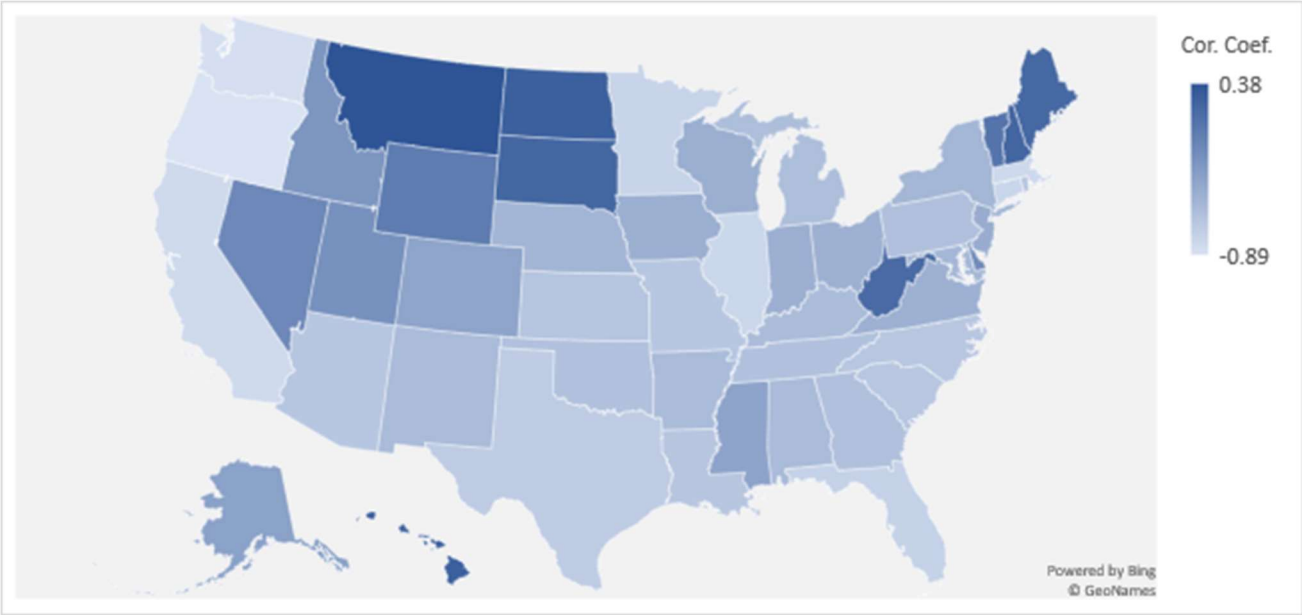
Figure 4.6: Correlation between Violent Crime Rate and real Minimum Wage across states (A)



Source: Author's calculation.

Notes: the numbers in horizontal axis indicate the name of states based on alphabetic order i.e., state 1 is Alabama and state 50 is Wyoming. Authors' calculation

Figure 4.7: Correlation between Violent Crime Rate and real Minimum Wage across states (B)



Source: Author's calculation.

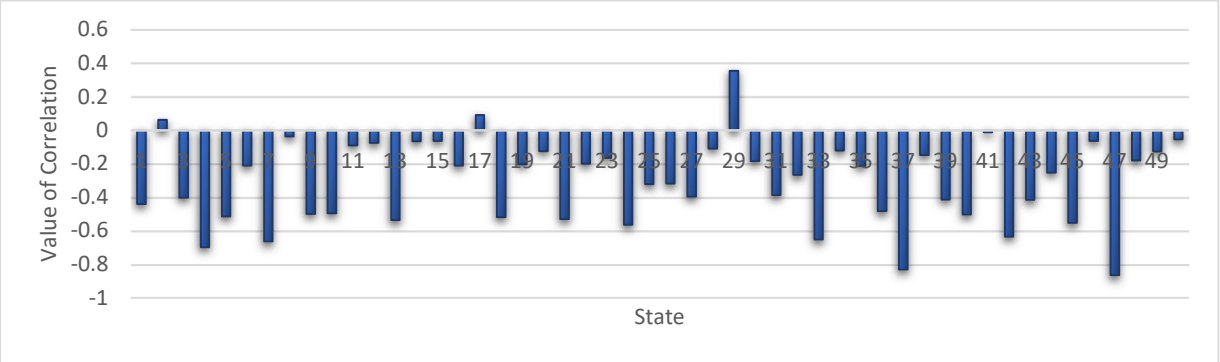
Figure 4.7 illustrates that the relationship between minimum wage and violent crime rates across 41 states is negative. This fact sheds light on how a hike in minimum wage changed the behaviour of committing a violent crime in the US. As a result, the expected marginal effect of real minimum wage on violent crime is negative. Figure 4.8 exhibits another

important point regarding the existence of highly heterogeneous relationships between violent crime rate and state-level real minimum wages. For instance, the most positive correlations occurred in Montana (34), Hawaii (11), and North Dakota (34), with the corresponding values equal to 0.383, 0.282, and 0.279, respectively. The highest negative correlation happened in Oregon (37), Washington (47), and California (5), with the quantities equal to -0.886, -0.852, and -0.806, respectively.

Note that the dissimilar correlation coefficients in the states, with equal amounts of federal minimum wage, illustrate the possibility of different (real minimum wage) thresholds across these states.

To point out what the possible marginal effect of real minimum wage is on the property crime rate in the US, the correlation coefficients of these variables are presented in Figures 4.11 and 4.12.

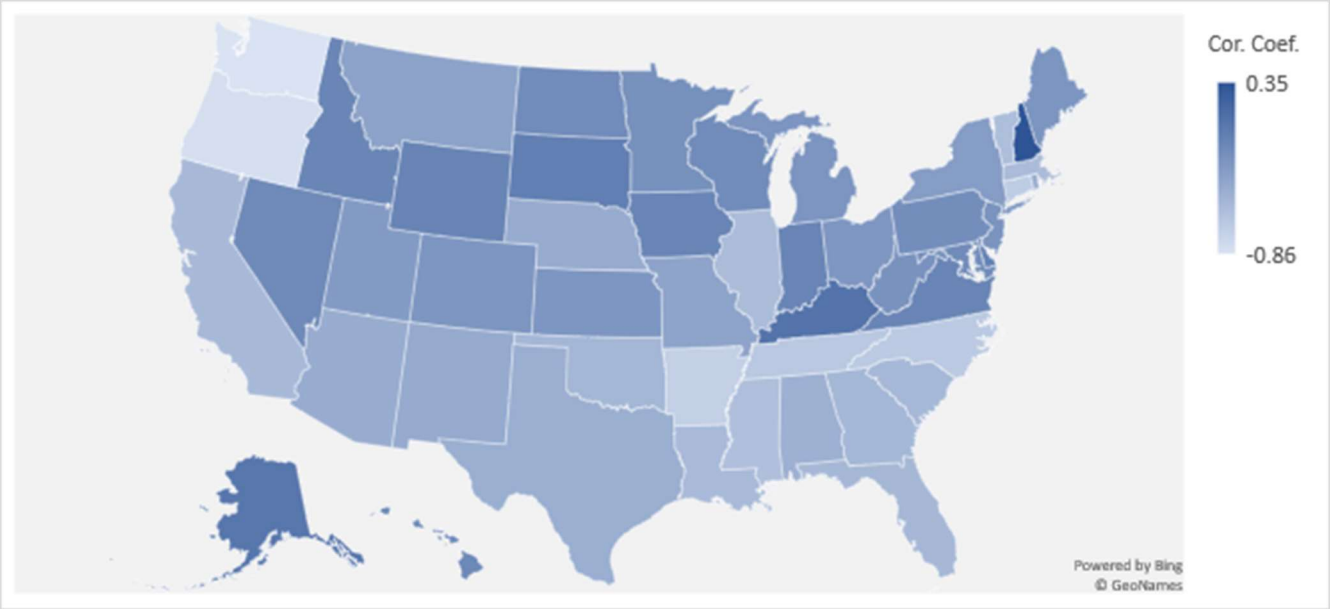
Figure 4.8: Correlation between Property Crime Rate and real Minimum Wage across states (A)



Source: Author's calculation.

Notes: the numbers in horizontal axis indicate the name of states based on alphabetic order, i.e., State 1 is Alabama, and State 50 is Wyoming.

Figure 4.9: Correlation between Property Crime Rate and real Minimum Wage across states (B)



Source: Author's calculation.

As observed from Figure 4.8-1, crime rates and state-level minimum wage are negatively correlated in 47 states. Figure 4.9 reveals which type of crime is more sensitive to minimum wage policy. Since the average value of state-level correlation between real minimum wage and violent and property crime rates equals -0.404 and -0.306, respectively, one can infer that violent crime is more sensitive to minimum wage policy. An interesting heterogeneous relationship between minimum wage and property crime reveals those states like Washington (47), Oregon (37), and Arkansas (4) – with a correlation coefficient equal to -0.864, -0.831, and -0.698, respectively – are more responsive to minimum wage policy. It shows how state-level wage policy negatively affects crime rate and may have a pull effect. However, an increase in minimum wage does not seem to be an efficient instrument in New Hampshire (29), Kentucky (17), and Alaska (2), with positive correlation coefficients equalling 0.355, 0.091, and 0.062, respectively. It illustrates there is potentially a push effect of minimum wage in some states.

Although these correlation coefficients provide valuable information to expect possible signs of the marginal effect of minimum wage on violent crime, they cannot show the threshold effect of minimum wage on crime. Also, they cannot reveal how the below and above minimum wage threshold affects the (different segments of the) distribution of

violent crime. Therefore, using a multi-kink regression technique is crucial to find the state-level tipping points of minimum wage and evaluate the impact of below and above the threshold of this variable on each quantile of crime.

4.4.3. Estimations and Results

To evaluate the effect of minimum wage on the conditional distribution of crime rates, I estimate two different equations for each crime rate. One equation shows how the various segments of property and violent crime rates react to variations of low and high levels of minimum wages. Based on threshold effects, the impact of the low and high levels of minimum wages on the two types of crime rates is evaluated. The other equation just evaluates the total effect of minimum wage on different quantiles of the crime rate. Therefore, to have comprehensive coverage, the estimation results cover the impact of three types of minimum wages – namely low, high, and total – on the conditional distribution of crime rates.

The Open BUGS software is employed for the Bayesian Estimation of the threshold quantile regression model[29]. The non-informative priors relaxed over coefficients with zero means and the precision parameters – inverse of the variance – equal 0.1. The Gibbs sampling method with 10,000 iterations is applied. The initial 5000 iterations are burnt out and discarded, and the remaining 5000 iterations are used for measuring the posterior marginal distributions.

The estimated coefficients for each non-threshold crime equation at each quantile are equal to 55 =50 (state-specific time trends) + 4 (explanatory variable) + 1 (intercept). This number for threshold model equals 106 =50 (state-specific time trends) + 50 (state-specific minimum wage thresholds) + 5(explanatory variable) + 1 (intercept). Therefore, for five different quantiles, namely τ=10, 30, 50(median), 70, and 90, I estimate 225 and 530 coefficients for non-threshold and with-threshold models for each property and violent crime. The 1000 coefficients of state-specific time trends are not reported since the specific-time trends are just applied to take into account state-level unobserved heterogeneity over time. However, they are statistically significant, and all diagnostic tests support their validities.

[29] The codes and data are available upon request.

Graphical diagnostic tests, such as the history of simulation and posterior distribution of coefficients, are applied to show the validity of the results. Appendix 4C reports these diagnostics for the below threshold minimum wage (*MinW-BeT*), the above threshold minimum wage (*MinW-AbT*) and the minimum wage (*MinW*). The results of these Graphical tests from Appendix B1 to B4 confirm the validity of the estimates.

Geweke's (1992) diagnostic test is employed for all coefficients and 250 state-level thresholds of each crime rate to ensure that the simulations of coefficients are suitably converged to specific values. Results from the Geweke test are presented in Appendix 4D and does not reject the convergence of coefficients.

4.4.3.1. Results of Violent Crime Model

In this part, the estimated values of B_τ, Λ_τ, and $\gamma_{s\tau}$ are presented. In an attempt to make policy recommendations, the main determinants of crime are discussed with respect to different segments in the conditional distribution of violent crime. Table 4.3 reports the estimated coefficients for the violent crime rate as follows.

Table 4.3. The effect of minimum wage on the conditional distribution of violent crime rate

	Model without threshold					**Model with (state-level) threshold**				
	τ=0.1	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***	***τ =0.1***	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***
Intercept	**21.890*****	**4.968*****	**6.191*****	**1.211*****	**-29.540*****	**18.30*****	**7.394*****	**-4.733*****	**-7.760*****	**-18.430*****
	(0.1030)	(1.1290)	(0.6962)	(0.5194)	(0.4000)	(0.0244)	(0.0390)	(0.0417)	(0.0529)	(0.0446)
ScHC	**0.0007**	**-0.0012**	**-0.0027***	**-0.0015**	**0.0007**	**0.0010**	**-0.0004**	**-0.0018**	**0.0001**	**0.0008**
	(0.0013)	(0.0015)	(0.0015)	(0.0016)	(0.0014)	(0.0012)	(0.0013)	(0.0015)	(0.0015)	(0.0013)
CoHC	**0.0007**	**0.0002**	**-0.0002**	**-0.0007**	**-0.0012*****	**0.0005**	**0.0003**	**-0.0005**	**-0.0008***	**-0.0010****
	(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
BCycl	**-0.0188*****	**-0.0119*****	**-0.0069*****	**-0.0021*****	**-0.0005**	**-0.0186*****	**-0.0124*****	**-0.0098*****	**-0.0061*****	**-0.0036*****
	(0.0015)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0014)	(0.0015)	(0.0015)	(0.0017)	(0.0016)
MinW	**-0.1273*****	**-0.1099*****	**-0.1065*****	**-0.1166*****	**-0.1333*****					
	(0.0047)	(0.0044)	(0.0050)	(0.0060)	(0.0066)					
MinW-BeT						**-0.1872*****	**-0.1745*****	**0.0848*****	**0.0912*****	**0.1058*****
						(0.0071)	(0.0064)	(0.0151)	(0.0117)	(0.0093)
MinW-AbT						**0.0229****	**0.0677*****	**-0.1664*****	**-0.2087*****	**-0.2400*****
						(0.0129)	(0.0195)	(0.0071)	(0.0086)	(0.0082)
$\boldsymbol{\sigma^2}$	**0.0219*****	**0.0492*****	**0.0591*****	**0.0537*****	**0.0258*****	**0.0197*****	**0.0442*****	**0.0537*****	**0.0471*****	**0.0218*****
	(0.0005)	(0.0011)	(0.0014)	(0.0012)	(0.0006)	(0.0005)	(0.0010)	(0.0012)	(0.0011)	(0.0005)
DIC	**-3183**	**-2437**	**-2618**	**-2245**	**-2424**	**-3775**	**-3155**	**-2960**	**-2767**	**-3186**
No. of Coef.	55	55	55	55	55	106	106	106	106	106
Smpl. Size	1950	1950	1950	1950	1950	1950	1950	1950	1950	1950

Notes: The dependent variable is the log of (violent) crime rate, **ScHC**: growth of school attainment rate, **CoHC**: growth of college attainment rate, **BCycl**: lag of output gap, **MinW**: real minimum wage (chained in 2012 dollars), **MinW-BeT**: below threshold real minimum wage (chained in 2012 dollars), **MinW-AbT**: above threshold real minimum wage(chained in 2012 dollars), $\boldsymbol{\sigma^2}$: variance of regression and **DIC**: deviance information criterion presented by Spiegelhalter et al. (2002) as a model selection criteria in a Bayesian framework. The values in the parentheses indicate the standard deviations (sd) of coefficients calculated based on a Bayesian framework.

The upper scripts "***", "**", and "*" demonstrate the significance of each coefficient at 99, 95, and 90 percent of credible intervals, respectively

As can be seen, the total minimum wage is negatively correlated with the conditional distribution of violent crime across different quantiles. In this case, the marginal effects of total minimum wage on violent crime rate at τ=0.1, 0.3, 0.5, 0.7, 0.9 equal -0.127, -0.110, -0.106, -0.116, -0.133, respectively.

On the other hand, the results illustrate interesting heterogeneous effects of the below and above minimum on different segments of the distribution of violent crime. For instance, the below threshold minimum wage increase leads to a diminished violent crime rate at τ=0.1, 0.3 by 0.187, 0.175 percent.

Further, the impact of the above threshold minimum wage on the conditional distribution of violent crime is positive at the median and higher quantiles.

It was found that the high school attainment rate growth has negatively affected the conditional distribution of violent crime rate at τ=0.3, 0.5.

Additionally, the growth of college attainment rate as a measure of the high level of education in the society has significantly affected the higher than median quantiles of the distribution of violent crime. In this way, based on the state-level threshold model, a one-percentage increase in the growth of college attainment rate decreases the violent crime rate at τ=0.7 and 0.9 by 0.0008 and 0.001 percent, respectively.

Finally, the estimated coefficients reveal interesting facts regarding the effect of the state of the business cycle on the conditional distribution of violent crime. The lag of the output gap is negatively correlated with all quantiles of violent crime. The magnitude of the marginal effect of the output gap decreases from the lowest towards the highest quantile. In this sense, the marginal effects of state of business cycle on violent crime rate at τ=0.1, 0.3, 0.5, 0.7, 0.9 equal -0.019, -0.012, -0.010, -0.006, -0.004, respectively.

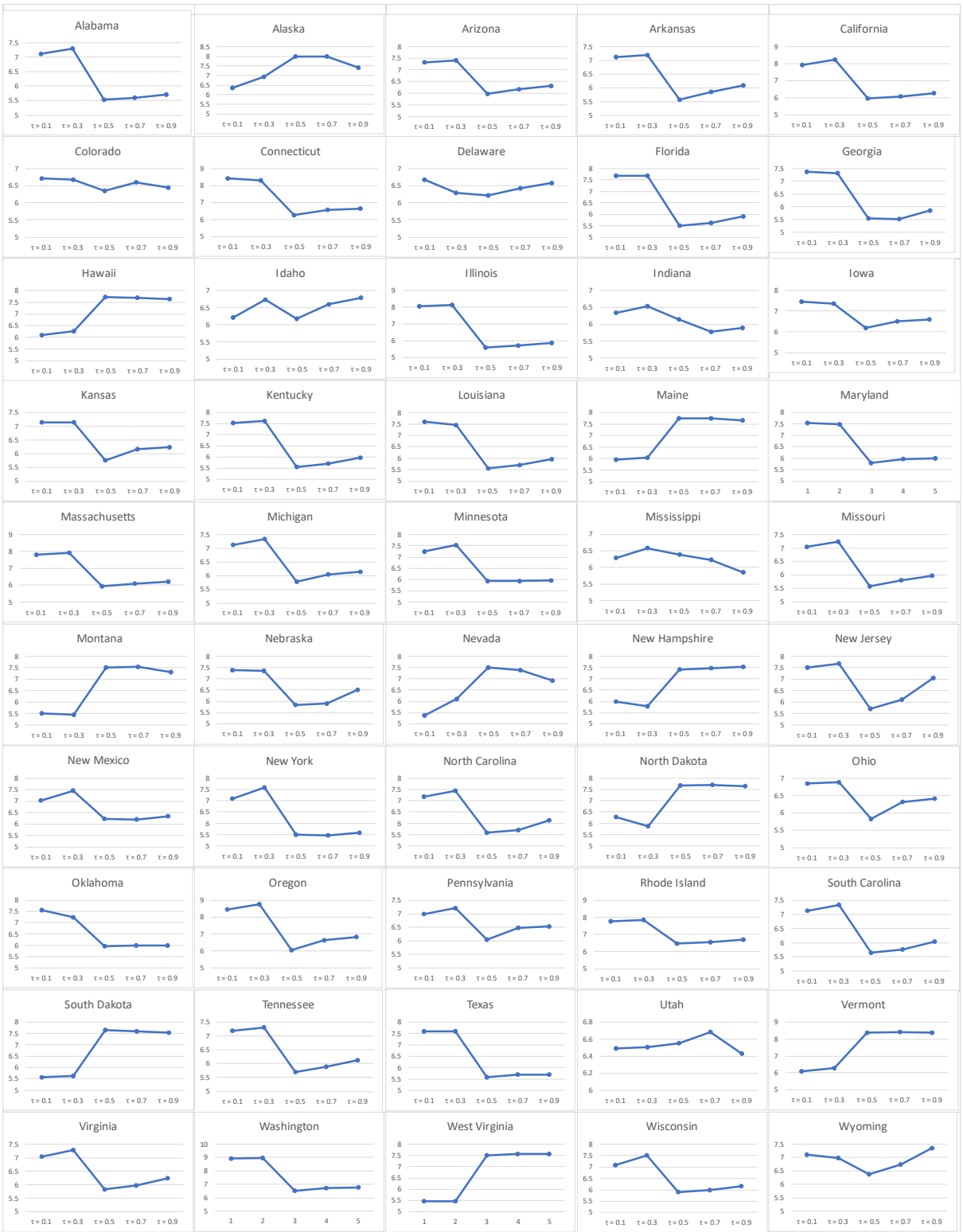
4.4.3.2. Estimates of Thresholds for Violent Crime Model

It is worthwhile to see how thresholds vary across states in the US to have a comprehensive outlook to reducing crime via implementing a minimum wage policy. According to Table 4.3, I obtained 250 = 5(quantiles)×50(states) different tipping points for real minimum wage corresponding to each segment of the distribution of violent crime and across fifty

states in the US. The estimated thresholds of the real minimum wage are reported in Figure 4.9[30].

[30] In Appendix D1, I report the numerical values of the thresholds of the real minimum wage for violent crime.

Figure 4.10: Thresholds of the State-level real MinW for violent crime over quantiles



This Figure provides valuable information regarding the thresholds of minimum wage across the distribution of violent crime. It is noteworthy that the thresholds for each state and each quantile represent the tipping points of minimum wages in each state over time and in terms of different segments of crime distribution. In Florida, Maryland, and South Carolina, the states with the highest violent crime levels, the thresholds of the real minimum wage all follow the same trajectory. Thresholds are high in lower quantiles and vice a versa. In this case, the thresholds of hourly real minimum wage at the lower part of the distribution of violent crime, [τ=0.1 and τ=0.3], equal [7.69$ and 7.67$] for Florida, [7.55$ and 7.48$] for Maryland and finally [7.14$ and 7.34$] for South Carolina. However, the value of thresholds at the median and higher parts of the distribution of violent crime is considerably lower than the first two quantiles. Accordingly, the thresholds of hourly real minimum wage at τ=0.5, 0.7 and 0.9 are equal to [5.50$, 5.62$ and 5.90$] for Florida, [5.79$, 5.95$ and 5.99$] for Maryland and finally [5.66$, 5.76$ and 6.04$] for South Carolina.

Conversely, the real minimum wage thresholds have a similar trajectory across the distribution of violent crime in the states with the lowest level of violent crime, such as North Dakota, Vermont, and Main. Thresholds are low in lower quantiles and vice a versa. In these states, the values of real minimum wage thresholds at the lower quantiles, τ=0.1 and 0.3, are much less than these quantities at the median and the higher parts of the distribution of violent crime. For instance, the thresholds of hourly real minimum wage at the lower part of the distribution of violent crime, [τ=0.1 and τ=0.3] equal [6.28$ and 5.87$] for North Dakota, [6.10$ and 6.28$] for Vermont and finally [5.96$ and 6.05$] for Main. However, the value of thresholds at the median and higher parts of the distribution of violent crime is noticeably higher than the first two quantiles. For example, the thresholds of hourly real minimum wage at τ=0.5, 0.7 and 0.9 are equal to [7.67$, 7.70$ and 7.66$] for North Dakota, [8.37$, 8.41$ and 8.39$] for Vermont and finally [7.73$, 7.74$ and 7.67$] for Main.

The average value of the state-level thresholds of the minimum wage is 7.02$, 7.12$, 6.27$, 6.41$ and 6.51$ per hour for τ=0.1 to τ=0.9, respectively. It reveals that lower thresholds have a larger tipping point than the median and higher quantiles. It means critical thresholds of real minimum wage are higher when violent crime rate is low compared to a high crime rate.

4.4.3.3. Results of Property Crime Model

The results regarding the quantile effects of three types of minimum wages – total, below the threshold, and above threshold minimum wages-- on the property crime rate in the US are presented in Table 4.4 as follows,

Table 4.4. The effect of minimum wage on the conditional distribution of property crime rate

	Model without threshold					**Model with (state-level) threshold**				
	τ=0.1	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***	***τ =0.1***	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***
Intercept	**3.816*****	**3.287*****	**0.364*****	**-7.738*****	**-25.98*****	**11.220*****	**4.192*****	**2.124*****	**4.106*****	**4.118*****
	(0.1056)	(0.1022)	(0.1636)	(0.0854)	(0.1962)	(0.0185)	(0.0319)	(0.0159)	(0.0280)	(0.0277)
ScHC	**-0.0017****	**-0.0013**	**-0.0003**	**0.0002**	**-0.0009**	**-0.0016****	**-0.0013**	**-0.0005**	**0.0000**	**0.0000**
	(0.0009)	(0.0010)	(0.0010)	(0.0010)	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0009)	(0.0009)
CoHC	**0.0006***	**0.0002**	**0.0000**	**-0.0001**	**0.0000**	**0.0005***	**0.0004**	**0.0001**	**0.0000**	**0.0000**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
BCycl	**-0.0154*****	**-0.010*****	**-0.0062*****	**-0.0032*****	**0.0010**	**-0.0144*****	**-0.0095*****	**-0.0075*****	**-0.0037*****	**-0.0036*****
	(0.0012)	(0.0012)	(0.0011)	(0.0011)	(0.0009)	(0.0011)	(0.0011)	(0.0010)	(0.0010)	(0.0010)
MinW	**-0.0831*****	**-0.0827*****	**-0.0805*****	**-0.0774*****	**-0.0654*****					
	(0.0030)	(0.0026)	(0.0030)	(0.0032)	(0.0030)					
MinW-BeT						**-0.1205*****	**-0.1165*****	**-0.0273*****	**-0.0223****	**-0.0241*****
						(0.0044)	(0.0048)	(0.0067)	(0.0137)	(0.0055)
MinW-AbT						**-0.0135*****	**-0.0283*****	**-0.1261*****	**-0.1434*****	**-0.1451****
						(0.0065)	(0.0086)	(0.0058)	(0.0102	(0.0074)
σ^2	**0.0144*****	**0.0308*****	**0.0368*****	**0.0319*****	**0.0146*****	**0.0135*****	**0.0296*****	**0.0351*****	**0.0298*****	**0.0297*****
	(0.0003)	(0.0007)	(0.0009)	(0.0007)	(0.0003)	(0.0003)	(0.0007)	(0.0008)	(0.0008)	(0.0007)
DIC	**-3786**	**-4468**	**-4367**	**-4246**	**-3478**	**-5259**	**-4626**	**-4576**	**-4586**	**-7860**
No. of Coef.	55	55	55	55	55	106	106	106	106	106
Smpl. Size	1950	1950	1950	1950	1950	1950	1950	1950	1950	1950

Notes: The dependent variable is the log of (property) crime rate, **ScHC**: growth of school attainment rate, **CoHC**: growth of college attainment rate, **BCycl**: lag of output gap, **MinW**: real minimum wage(chained in 2012 dollars), **MinW-BeT**: below threshold real minimum wage(chained in 2012 dollars), **MinW-AbT**: above threshold real minimum wage(chained in 2012 dollars), σ^2: variance of regression and **DIC**: deviance information criterion presented by Spiegelhalter et al.(2002) as a model selection criteria in a Bayesian framework. The values in the parentheses indicate the standard deviations (sd) of coefficients calculated based on a Bayesian framework.

The upper scripts "***", "**", and "*" demonstrate the significance of each coefficient at 99, 95, and 90 percent of credible intervals, respectively.

The findings confirm that the below and above thresholds of the minimum wage have negatively affected the distribution of property crime rates at all quantiles.

However, the negative effect of the below tipping point of real minimum wage at the lower median parts of the distribution of property crime is much bigger than the effect of the above threshold and vice versa. For example, a hike in the below tipping point of real minimum wage decreases the likelihood of property crime at $\tau=0.1$ and $\tau=0.3$ by 0.12 and 0.116 percent, respectively. However, increasing the above tipping point of real minimum wage reduces the probability of criminal behaviour at the same segments by 0.013 and 0.028 percent, respectively.

Comparing the magnitude of the marginal effect of total minimum wage on the conditional distribution of violent and property crime rates reveals another significant aspect of this research. All segments of distribution of violent crime are more elastic – in absolute values – to minimum wage policy than property crime. It suggests that anti-social behaviours like rape and sexual assault, robbery, assault and murder are more sensitive to minimum wage policy.

Further, the growth of the school attainment rate has negatively and significantly affected the lowest quantile of the distribution of the property crime rate in the US. In this sense, a hike in the growth of school attainment rate lowers the likelihood of committing property crime at $\tau=0.1$ by 0.002 percent. Moreover, the effect of the growth of the college attainment rate is only significant at $\tau=0.1$.

Finally, the state of the business cycle has negatively impacted all quantiles of property crime. From this perspective, the two lowest quantiles, $\tau=0.10$ and $\tau=0.3$, of property crime are more highly affected by the lag of output gap than others. From this point of view, a one-percentage-point hike in the output gap leads to a descent of the property crime rate by 0.015 and 0.01 percent, respectively. Comparing the marginal effect of the state of the business cycle on different parts of the distribution of violent and property crime exposes that violent crime is more sensitive to economic ups and downs than property crime. As a result of this finding, the business cycle affects more property crime when it is low compared to a higher one.

4.4.3.4. Estimates of Thresholds for Property Crime Model

Based on the conditional distribution of property crimes in each state, Table 4.6 presents the estimated tipping points for the real minimum wage. Here, 250 = 5(quantiles)×50(states) thresholds are estimated[31].

[31] In Appendix 4E2, the numerical values of the thresholds are reported for the real minimum wage for property crime.

Figure 4.11: Thresholds of the State-level real MinW for property crime over quantiles

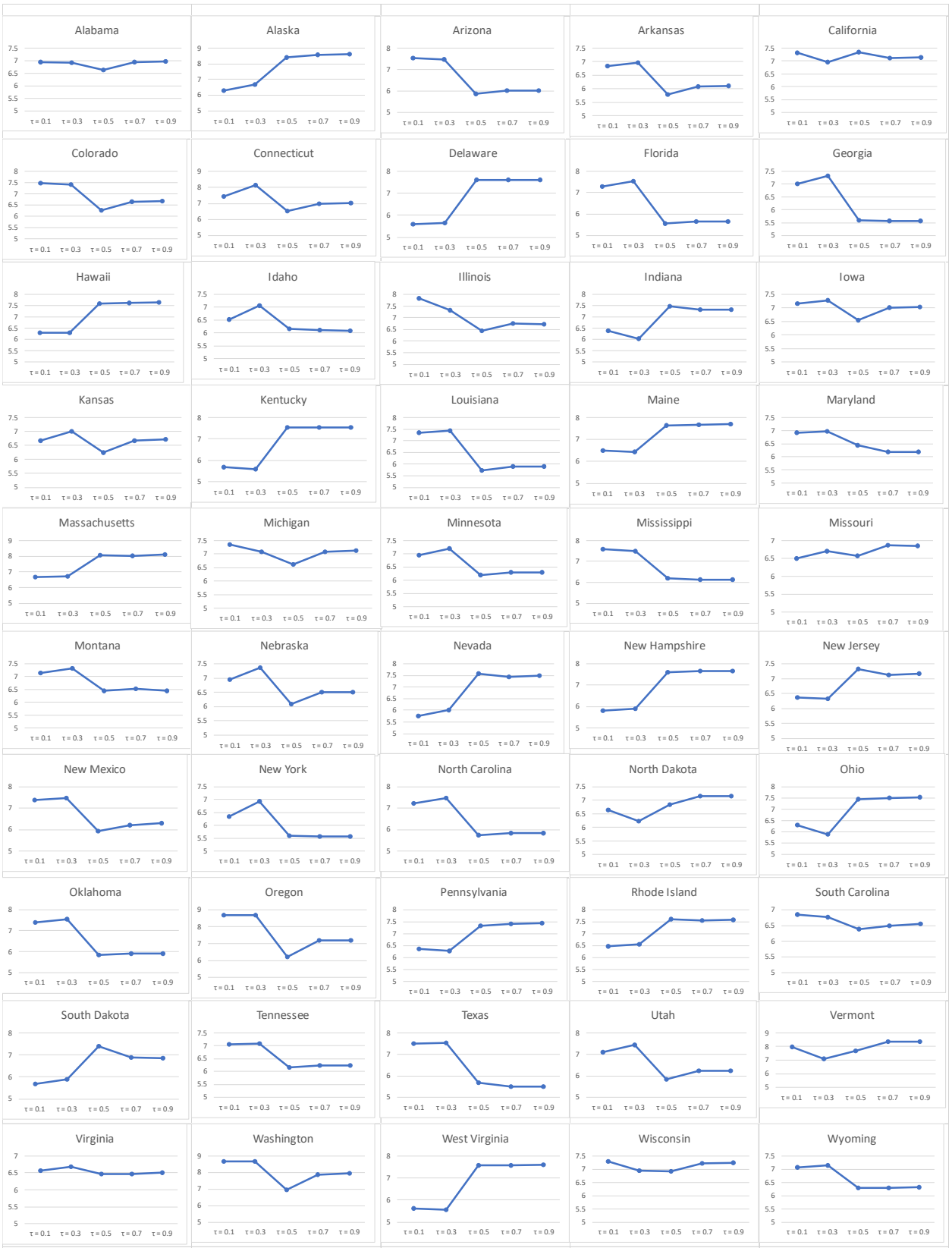


Figure 4.12 shows that the variation of the threshold of real minimum wage is quite heterogeneous across the conditional distribution of property crime, especially in states with high crime rates. In this regard, it is seen that Florida, Oregon and Washington have the same pattern in which the value of thresholds at the first two quantiles (τ=0.1 and 0.3) is higher than the other segments. Conversely, the pattern of real minimum wage thresholds is opposite in Hawaii and Nevada, the states ranked with third and sixth highest property crime rates.

On the other hand, the variation of the thresholds across the distribution of property crime is nearly the same in the states with the lowest levels of property crime, such as West Virginia, South Dakota, North Dakota, Pennsylvania, Kentucky, and New Hampshire. In these cases, the values of real minimum wage thresholds at τ=0.1 and 0.3 are much less than those at the median and the higher parts of the distribution of property crime. For example, the thresholds of hourly real minimum wage at the lower segment of the distribution of property crime, [τ=0.1 and τ=0.3] equal [$5.63 and $5.57] for West Virginia, [$5.67 and $5.90] for South Dakota, [$6.65 and $6.23] for North Dakota, [$6.36 and $6.28] for Pennsylvania, [$5.67 and $5.58] for Kentucky and finally [$5.80 and $5.90] for New Hampshire. However, the value of thresholds at the median and higher parts of the distribution of property crime is conspicuously higher than the first two quantiles. For instance, the thresholds of hourly real minimum wage at τ=0.5, 0.7 and 0.9 are equal [$7.57, $7.58 and $7.60] for West Virginia, [$7.39, $6.89 and $6.86] for South Dakota, [$6.85, $7.15 and $7.16] for North Dakota, [$7.34, $7.42 and $7.45] for Pennsylvania, [$7.53, $7.54 and $7.55] for Kentucky and finally [$7.61, $7.65 and $7.66] for New Hampshire.

The average value of state-level thresholds equal $6.89, $6.93 $6.68, $6.82 and $6.84 per hour at τ=0.1, 0.3, 0.5, 0.7 and 0.9. This shows that the variation of the average of state-level thresholds in the property crime model is less than those in the violent crime, $6.89, $6.93, $6.68, $6.82 and $6.84 per hour. However, the value of real minimum wage thresholds in both models is not too far from each other. It reveals that the critical threshold of real minimum wage is low when property crime is in its median compared to the cases with low and high crime rates.

4.4.3.5. Model with National Minimum Wage Threshold

Estimating regressions with national-level thresholds can allow one to compare the results with a heterogeneous threshold model. Following Spiegelhalter et al. (2002), this study applies the Deviance Information Criterion (DIC) to test which model is more efficient in a Bayesian framework. Hence, a national-level threshold model is estimated for each violent and property crime to understand whether the average value of the state-level real minimum wage thresholds equals the national-level threshold. In addition, estimating regression with a national-level tipping point allows the comparison of two different types of threshold models, state-level and national, to understand which method is more efficient. For this purpose, the Gibbs sampling method is employed with 10,000 iterations and burning out the initial 5000 iterations. The estimated coefficients at each quantile are equal to 57 = 50 (state-specific time trends) + 1 (national minimum wage thresholds) + 5 (explanatory variable) + 1 (intercept). Therefore, for five different quantiles, namely τ=10, 30, 50, 70, 90, I estimate 235 coefficients for each property and violent crime rates. The results of the national-level threshold model are presented in Table 4.5 as follows.

Table 4.5. The effect of minimum wage with (national-level) threshold on the conditional distribution of violent property crime

	Violent crime					**Property crime**				
	τ=0.1	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***	***τ =0.1***	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***
Intercept	**14.870*****	**-1.938*****	**0.3661*****	**-14.260*****	**-35.350*****	**13.480*****	**-3.887*****	**8.371*****	**-24.920*****	**-29.220*****
	(0.0314)	(0.1272)	(0.0271)	(0.0444)	(0.0280)	(0.0095)	(0.0384)	(0.0546)	(0.0386)	(0.0152)
ScHC	**0.0007**	**-0.0011**	**-0.0026***	**-0.0015**	**0.0002**	**-0.0018****	**-0.0015***	**-0.0003**	**0.0003**	**-0.0009**
	(0.0013)	(0.0016)	(0.0015)	(0.0018)	(0.0013)	(0.0009)	(0.0010)	(0.0010)	(0.0009)	(0.0008)
CoHC	**0.0007**	**0.0002**	**-0.0003**	**-0.0007**	**-0.0010****	**0.0006***	**0.0002**	**0.0000**	**-0.0001**	**0.0000**
	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
BCycl	**-0.0186*****	**-0.0111*****	**-0.0067*****	**-0.0035***	**-0.0032****	**-0.0157*****	**-0.0102*****	**-0.0063*****	**-0.0045*****	**0.0002**
	(0.0015)	(0.0018)	(0.0017)	(0.0019)	(0.0016)	(0.0013)	(0.0013)	(0.0011)	(0.0011)	(0.0008)
MinW-BeT	**-1.0930**	**-1.2900**	**-0.1041*****	**-0.0271**	**0.0899*****	**0.7093**	**0.3993**	**-0.0793*****	**0.0379***	**0.0419****
	(1.3950)	(1.3970)	(0.0053)	(0.0379)	(0.0272)	(1.3570)	(1.3650)	(0.0031)	(0.0255)	(0.0208)
MinW-AbT	**-0.1267*****	**-0.1077*****	**0.5401**	**-0.1266*****	**-0.1555*****	**-0.0836*****	**-0.0826*****	**-0.3047**	**-0.0843*****	**-0.0690*****
MinW- Trsh	*5.352****	*5.362****	*9.026****	*5.935****	*6.063****	*5.327****	*5.341****	*8.608****$^{}$	*5.834****	*5.824****
	(0.0615)	*(0.0680)*	*(0.2985)*	*(0.1051)*	*(0.0485)*	*(0.0386)*	*(0.0655)*	*(0.244)*	*(0.0449)*	*(0.0417)*
	(0.0048)	(0.0054)	(1.5910)	(0.0066)	(0.0067)	(0.0031)	(0.0028)	(0.6502)	(0.0037)	(0.0031)
σ^2	**0.0219*****	**0.0491*****	**0.0591*****	**0.0536*****	**0.0252*****	**0.0143**	**0.0308**	**0.0367**	**0.0317**	**0.0145**
	(0.0005)	(0.0011)	(0.0014)	(0.0012)	(0.0006)	(0.0003)	(0.0007)	(0.0008)	(0.0008)	(0.0003)
DIC	**-3268**	**-2756**	**-2620**	**-2256**	**-2474**	**-4657**	**-4482**	**-4381**	**-4322**	**-4749**
No. of Coef.	57	57	57	57	57	57	57	57	57	57
Smpl. Size	1950	1950	1950	1950	1950	1950	1950	1950	1950	1950

Notes: The dependent variable is the log of (violent and property) crime rate(s), **ScHC**: growth of school attainment rate, **CoHC**: growth of college attainment rate, **BCycl**: lag of output, **MinW- Trsh**: real minimum wage threshold, **MinW-BeT**: below threshold real minimum wage (chained in 2012 dollars), **MinW-AbT**: above threshold real minimum wage (chained in 2012 dollars), $\boldsymbol{\sigma^2}$: variance of regression and **DIC**: deviance information criterion presented by Spiegelhalter et al.(2002) as a model selection criteria in a Bayesian framework. The values in the parentheses indicate the standard deviations (sd) of coefficients calculated based on a Bayesian framework. The upper scripts "***", "**" and "*" demonstrate the significance of each coefficient at 99, 95, and 90 percent of credible intervals, respectively.

As shown in Table 4.5, the national-level model's estimated threshold values are quite different from those in the state-level model. For example, the values of the average state-level thresholds at τ= 0.1, 0.3, 0.5, 0.7, 0.9 for violent crime are equal to 7.02, 7.12, 6.27, 6.41, and 6.51 dollars per hour, respectively. These findings are in line with the estimates obtained from the state-level threshold models. However, the estimated values for the national-level threshold model at the same segments of the distribution of violent crime equal 5.35, 5.36, 9.03, 5.93, and 6.06 dollars per hour. To identify which model efficiently explains the association between criminal activities and minimum wage, the Deviance Information Criterion (DIC) and posterior variance of the model $\boldsymbol{\sigma^2}$ are considered. Consequently, the values of these measures at the state level are smaller than those at the national level. This feature shows that the state-level gives more efficient estimates compared to the model with national tipping points. Further, the Min and Max values of real minimum wage equal 5.29 and 9.32. However, the estimated thresholds from the lowest part to the median of the distribution of violent crime are very close to the lowest value real minimum wage (i.e., γ=5.35 for τ=0.1 and γ=5.3 for τ=0.536). The threshold value at the median (γ=9.03) is almost equal to the highest value of the minimum wage.

Conversely, nearly the same condition exists for the property crime rate model with the national threshold. In this regard, the values of DIC and $\boldsymbol{\sigma^2}$ across all quantiles are higher than in the state-level model. It implies the state-level threshold model is more effective than the national one. In addition, the value of tipping points for property crime rate at τ= 0.1, 0.3 equal 5.33 and 5.34 per hour, respectively. This illustrates that these thresholds are too close to the lowest value of the minimum wage in the sample.

4.5. Conclusion

Crime is one of the most significant sources of insecurity and imposes many social and economic costs on individuals and societies. No doubt, controlling economic conditions or crime incentives such as minimum wage rate, educational levels, or recessions leads to reduced crime rates and better social and economic circumstances (Machin and Meghir, 2004 ; Sameem and Sylwester , 2018). For policymaking, it is essential to know how influential each factor is on crime rates. From this perspective, economists have generated controversy as to whether minimum wage affects crime positively or negatively. This paper provides a new approach which details a compromise between two radical views regarding the impact of minimum wage on crime in the US. This study disentangles the

state-level minimum wage to the below and above threshold of the real minimum wage in order to understand how the minimum wage policy positively or negatively triggers crime rates. The state-level regression kink method has greater flexibility to capture the heterogeneities among different states than conventional threshold techniques. Indeed, estimating the state-level tipping points for the minimum wage helps local state governments to enact more efficient, practical policy. A quantile method has been applied to analyse the effects of below and above threshold minimum wages on the conditional distribution of crime.

By applying the US crime data from 1976 to 2014, it was found that the overall effect of increase in minimum wage on each segment of violent and property crime rates is negative. It presents the pull effects of minimum wage on crime overall. Also, estimates support the asymmetric impact of minimum wage on crime rates in the US. In this regard, the marginal effects of the below threshold of the minimum wage have negatively affected violent crime when the rate is less than median in the sample. However, the marginal effect of this variable has positively influenced the conditional distribution of violent crime in the case the rate is high in the society. The finding supports the idea that the impact of the above threshold minimum wage on violent crime is positive when crime rate is considerably low in the society. Still, this variable impacted the upper segments of the distribution negatively. From a policy perspective, reducing real value of minimum wage below the threshold in the low-criminal areas leads to reduced violent crime.

Conversely, all segments of the distribution of property crime react negatively to both the below and the above threshold of actual minimum wage. However, the magnitude of the marginal effect of the above tipping point of the real minimum wage rises from the lowest (τ=0.1) to the highest (τ=0.9) parts of the distribution of property crime rate. On the other hand, the marginal effect of the below threshold of the real minimum wage weakens from the lowest to highest segments of the conditional distribution of property crime.

The findings also reveal that all segments of distribution of violent crime are more elastic – in absolute values – to minimum wage policy than property crime. It suggests that anti-social behaviours like rape and sexual assault, robbery, assault and murder are more sensitive to minimum wage policy.

Further, in the non-threshold and threshold models, the growth of high school attainment has negatively affected the conditional distribution of violent crime at τ=0.3, 0.5, and 0.7. This variable is more negatively correlated with the median and the lower than median

parts of the distribution of property crime. Additionally, the growth of the college attainment rate as a measure of the high level of education in the society has a significant and negative effect on the higher than median quantiles of the distribution of violent crime. However, in property crime, this variable influences the lowest segment of the distribution significantly but negatively.

Finally, the state of the business cycle has negatively impacted all segments of the conditional distribution of both violent and property crime rates. In this sense, in both threshold and non-threshold equations the output gap significantly lowers the probability of committing crimes in all quantiles of violent and property crime rates. In both criminal cases, the marginal effect of the state of the business cycle is more substantial in the lower quantiles than in the higher ones.

The estimated coefficients related to the tipping points of the minimum wages expose the average of state-level thresholds of property crime is smoother than those across the distribution of violent crime rate.

In future research work, one could employ multi-country data, particularly from European and other OECD countries, and compare the results with the US economy. Also, using microdata would clarify how changes in state-level minimum wages correlate with the different parts of the distribution of criminal activities. Due to data limitations, we could not consider this in the present study. Finally, the present study is a first step in defining the effects of below and above minimum wage tipping points on crime burdens. One can also evaluate the threshold effect of other variables, such as market wage, unemployment, income inequality, and so on, on the various segments of the distribution of crime.

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Appendix 4A. Posterior joint distribution and full conditions

The posterior joint distribution function is written as follows:

$$\pi\left(\mathrm{B}_{\tau}^{(k)},\Lambda_{\tau}^{(k)},\gamma_{s\tau}^{(k)},\sigma^{(k)},\xi^{2(k)},\delta_{s\tau}^{(k)},b^{(k)}\ \middle|\ LCR^{(k)}\right)\propto$$

$$\left(\frac{1}{\sigma^{(k)}}\right)^{T}\exp\left\{-\frac{1}{\sigma^{(k)}}\sum_{s=1}^{n}\sum_{t=1}^{T}\rho_{\tau}\left(LCR_{st}^{(k)}-\left(X_{st}'\left(\gamma_{s\tau}^{(k)}\right)\mathrm{B}_{\tau}^{(k)}+W_{st}'\Lambda_{\tau}^{(k)}+\delta_{s\tau}^{(k)}\mathrm{t}+\right.\right.\right.$$

$b_s^{(k)}\Big)\Big\} \times \left(\frac{1}{\xi^{2(k)}}\right)^{\frac{n}{2}} \exp\{-\frac{1}{2\xi^{2(k)}}\sum_{s=1}^{n}(b_s^{(k)})'(b_s^{(k)})\} \exp\left\{-\frac{1}{2}\left(\mathrm{B}_\tau^{(k)} - \mathrm{B}_{0\tau}^{(k)}\right)' \Psi_{\mathrm{B}_\tau}^{(k)^{-1}}\left(\mathrm{B}_\tau^{(k)} -\right.\right.$

$\left.\left.\mathrm{B}_{0\tau}^{(k)}\right)\right\} \times \left(\frac{1}{\xi^{2(k)}}\right)^{\frac{n}{2}} \exp\{-\frac{1}{2\xi^{2(k)}}\sum_{s=1}^{n}(b_s^{(k)})'(b_s^{(k)})\} \exp\left\{-\frac{1}{2}\left(\Lambda_\tau^{(k)} - \Lambda_{0\tau}^{(k)}\right)' \Psi_{\Lambda_\tau}^{(k)^{-1}}\left(\Lambda_\tau^{(k)} -\right.\right.$

$\left.\left.\Lambda_{0\tau}^{(k)}\right)\right\} \times \left(\frac{1}{\xi^{2(k)}}\right)^{\frac{n}{2}} \exp\{-\frac{1}{2\xi^{2(k)}}\sum_{s=1}^{n}(b_s^{(k)})'(b_s^{(k)})\} \exp\left\{-\frac{1}{2}\left(\gamma_{s\tau}^{(k)} - \gamma_{s_0\tau}^{(k)}\right)' \Psi_{\gamma_{s\tau}}^{(k)^{-1}}\left(\gamma_{s\tau}^{(k)} -\right.\right.$

$\left.\left.\gamma_{s_0\tau}^{(k)}\right)\right\} \times \left(\frac{1}{\xi^{2(k)}}\right)^{\frac{n}{2}} \exp\{-\frac{1}{2\xi^{2(k)}}\sum_{s=1}^{n}(b_s^{(k)})'(b_s^{(k)})\} \exp\left\{-\frac{1}{2}\left(\delta_{s\tau}^{(k)} - \delta_{s_0\tau}^{(k)}\right)' \Psi_{\delta_{s\tau}}^{(k)^{-1}}\left(\delta_{s\tau}^{(k)} -\right.\right.$

$\left.\left.\delta_{s_0\tau}^{(k)}\right)\right\} \times \left(\frac{1}{\sigma^{(k)}}\right)^{\varphi_0 - 1} \exp\{-\theta_0 \frac{1}{\sigma^{(k)}}\} \left(\frac{1}{\xi^{2(k)}}\right)^{\varphi_{00} - 1} \exp\{-\theta_{00} \frac{1}{\xi^{2(k)}}\}.$

(4.20)

Since posterior distribution with ALD prior is not conjugate, calculating both fixed and random effects parameters is quite sophisticated (Luo et al., 2012). In this direction, one can attempt to overcome this issue by using Marcov Chain Monte Carlo (MCMC) analysis. Therefore, the full condition of all the parameters can be written as follows,

$\mathrm{B}_\tau^{(k)} \mid LCR_{st}^{(k)}, \Lambda_\tau^{(k)}, \gamma_{s\tau}^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)}, \sigma^{(k)} \propto \exp\{-\frac{1}{2}\left(\mathrm{B}_\tau^{(k)} - \mathrm{B}_{0\tau}^{(k)}\right)' (\Psi_{\mathrm{B}_\tau}^{(k)})^{-1}\left(\mathrm{B}_\tau^{(k)} -\right.$

$\left.\mathrm{B}_{0\tau}^{(k)}\right) - \frac{1}{\sigma^{(k)}}\sum_{c=1}^{n}\sum_{t=1}^{T}\rho_\tau\left(LCR_{st}^{(k)} - \left(X_{st}'\left(\gamma_{s\tau}^{(k)}\right)\mathrm{B}_\tau^{(k)} + W_{st}'\Lambda_\tau^{(k)} + \delta_{s\tau}^{(k)}\mathrm{t} + b_{s\tau}^{(k)}\right)\right)\},$

(4.21)

$\Lambda_\tau^{(k)} \mid LCR_{st}^{(k)}, \mathrm{B}_\tau^{(k)}, \gamma_{s\tau}^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)}, \sigma^{(k)} \propto \exp\{-\frac{1}{2}\left(\Lambda_\tau^{(k)} - \Lambda_{0\tau}^{(G)(k)}\right)' (\Psi_{\Lambda_\tau}^{(k)})^{-1}\left(\Lambda_\tau^{(k)} -\right.$

$\left.\Lambda_{0\tau}^{(k)}\right) - \frac{1}{\sigma^{(k)}}\sum_{c=1}^{n}\sum_{t=1}^{T}\rho_\tau\left(LCR_{st}^{(k)} - \left(X_{st}'\left(\gamma_{s\tau}^{(k)}\right)\mathrm{B}_\tau^{(k)} + W_{st}'\Lambda_\tau^{(k)} + \delta_{s\tau}^{(k)}\mathrm{t} + b_{s\tau}^{(k)}\right)\right)\},$

(4.22)

$\gamma_{s\tau}^{(k)} \mid LCR_{st}^{(k)}, \mathrm{B}_\tau^{(k)}, \Lambda_\tau^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)}, \sigma^{(k)} \propto \exp\{-\frac{1}{2}\left(\gamma_{s\tau}^{(k)} - \gamma_{s_0\tau}^{(k)}\right)' \Psi_{\gamma_{s\tau}}^{(k)^{-1}}\left(\gamma_{s\tau}^{(k)} -\right.$

$\left.\gamma_{s_0\tau}^{(k)}\right) - \frac{1}{\sigma^{(k)}}\sum_{c=1}^{n}\sum_{t=1}^{T}\rho_\tau\left(LCR_{st}^{(k)} - \left(X_{st}'\left(\gamma_{s\tau}^{(k)}\right)\mathrm{B}_\tau^{(k)} + W_{st}'\Lambda_\tau^{(k)} + \delta_{s\tau}^{(k)}\mathrm{t} + b_{s\tau}^{(k)}\right)\right)\},$

(4.23)

$\delta_{s\tau}^{(k)} \mid LCR_{st}^{(k)}, \mathrm{B}_\tau^{(k)}, \Lambda_\tau^{(k)}, \gamma_{s\tau}^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)}, \sigma^{(k)} \propto \exp\{-\frac{1}{2}\left(\delta_{s\tau}^{(k)} - \delta_{s_0\tau}^{(k)}\right)' \Psi_{\delta_{s\tau}}^{(k)^{-1}}\left(\delta_{s\tau}^{(k)} -\right.$

$\left.\delta_{s_0\tau}^{(k)}\right) - \frac{1}{\sigma^{(k)}}\sum_{c=1}^{n}\sum_{t=1}^{T}\rho_\tau\left(LCR_{st}^{(k)} - \left(X_{st}'\left(\gamma_{s\tau}^{(k)}\right)\mathrm{B}_\tau^{(k)} + W_{st}'\Lambda_\tau^{(k)} + \delta_{s\tau}^{(k)}\mathrm{t} + b_{s\tau}^{(k)}\right)\right)\},$

(4.24)

$$\sigma^{(k)} \mid LCR_{st}^{(k)}, \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)} \sim IG(T + \varphi_0, \theta_0 + \rho_\tau \left(LCR_{st}^{(k)} - \left(X_{st}' \left(\gamma_{s\tau}^{(k)} \right) \mathrm{B}_{\tau}^{(k)} + W_{st}' \Lambda_{\tau}^{(k)} + \delta_{s\tau}^{(k)} \mathrm{t} + b_{s\tau}^{(k)} \right) \right)),$$

(4.25)

$$\xi^{2(k)} \mid LCR_{st}^{(k)}, \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \delta_{s\tau}^{(k)}, \sigma^{(k)} \sim IG(\frac{n}{2} + \varphi_{00}, \theta_{00} + \frac{1}{2} \sum_{c=1}^{n} (b_{s\tau}^{(k)})' (b_{s\tau}^{(k)})),$$

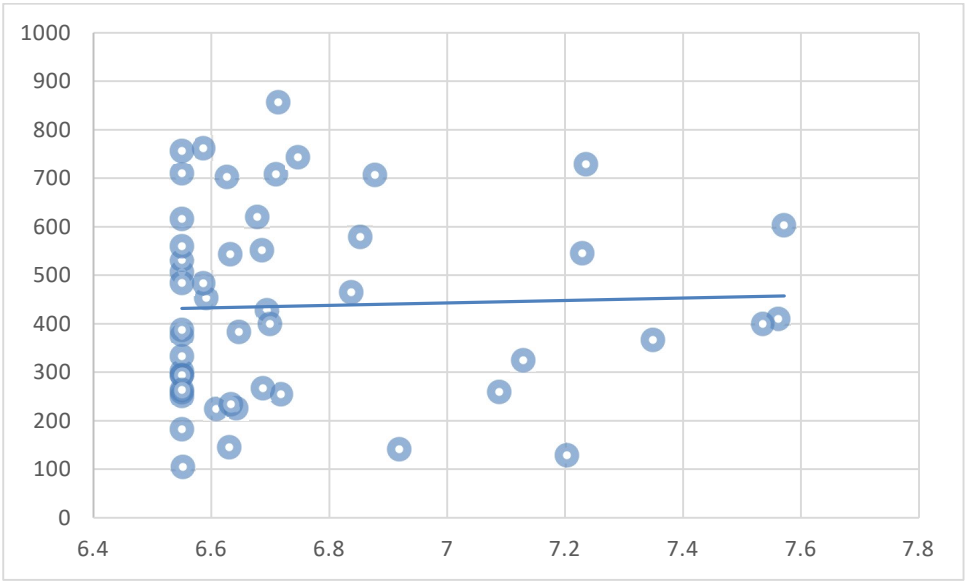
(4.26)

$$b^{(k)} \mid LCR_{st}^{(k)}, \mathrm{B}_{\tau}^{(k)}, \Lambda_{\tau}^{(k)}, \gamma_{s\tau}^{(k)}, \delta_{s\tau}^{(k)}, \xi^{2(k)}, \sigma^{(k)} \propto \exp \left\{ \frac{1}{\xi^{2(k)}} (b_s^{(k)})' (b_s^{(k)}) - \frac{1}{\sigma^{(k)}} \sum_{t=1}^{T} \rho_\tau \left(LCR_{st}^{(k)} - \left(X_{st}' \left(\gamma_{s\tau}^{(k)} \right) \mathrm{B}_{\tau}^{(k)} + W_{st}' \Lambda_{\tau}^{(k)} + \delta_{s\tau}^{(k)} \mathrm{t} + b_{s\tau}^{(k)} \right) \right) \right\}$$

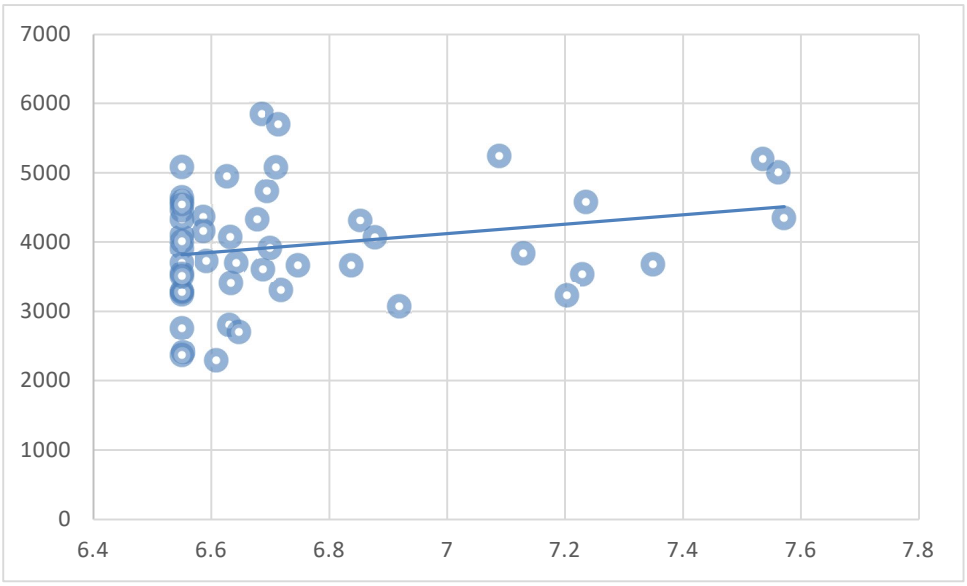
(4.27)

Appendix 4B. Scatter plot between crime and real minimum wage from 1976 to 2014

Scatter plot between average crime incidence and real minimum wage from 1976 to 2014



Scatter plot between average crime incidence and real minimum wage from 1976 to 2014



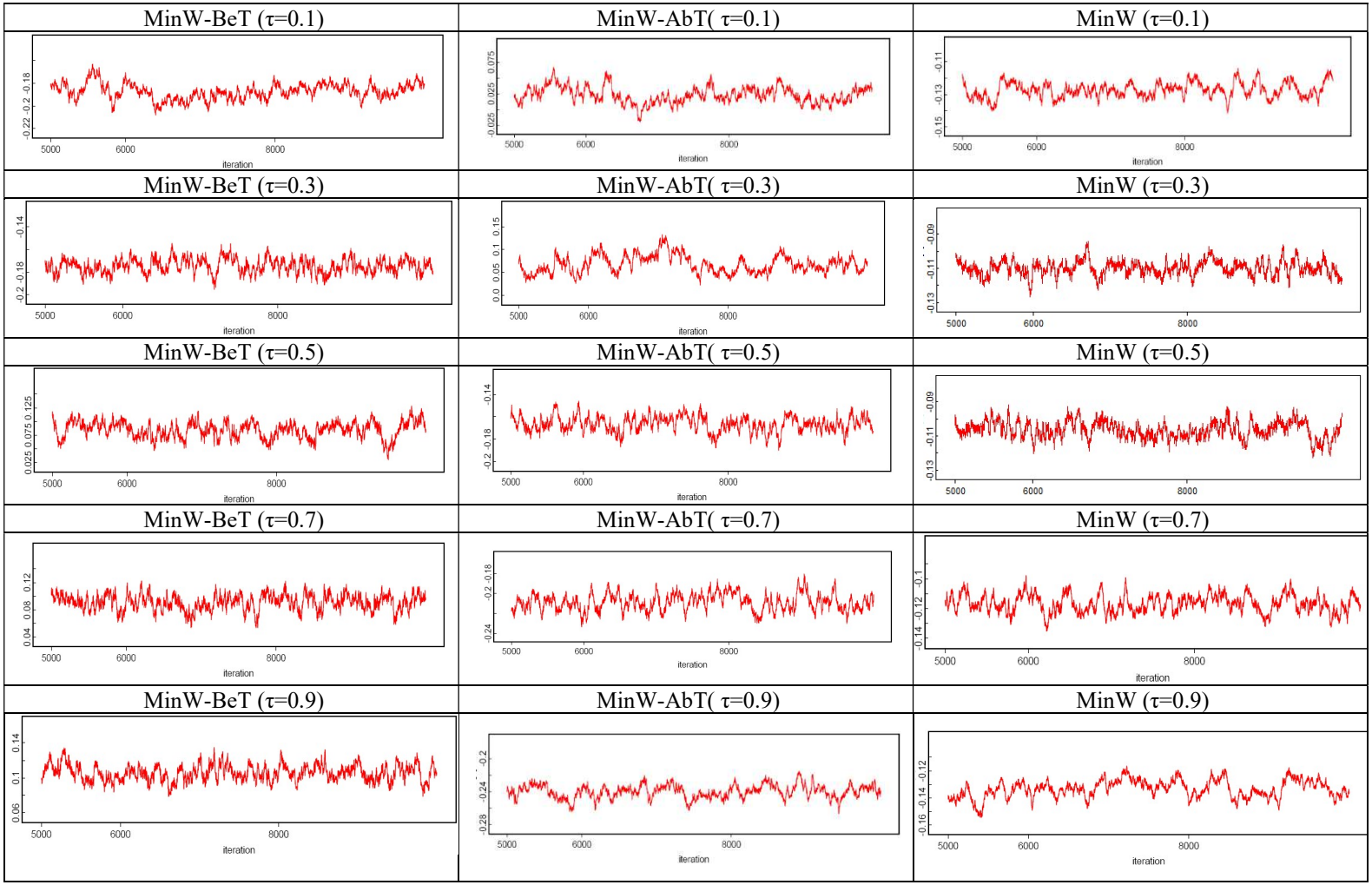
Appendix 4C. Graphical diagnostic tests

To assure that the MCMC simulation for each model coefficient fluctuates within a specific credible interval, I demonstrate the simulation history for each estimated coefficient. This type of diagnostic test reveals whether convergence is obtained over the iterations or not. In this sense, one can infer that the estimation is well-behaved when convergence happens. As can be visualised by Figures B1 and B3, estimated coefficients for real minimum wage and its values at below and above thresholds attain convergence (i.e., stationary within an interval) over simulation history. Note the horizontal and vertical axis in these graphs state the number of iterations and the value of simulation at each iteration, respectively.

Additionally, checking whether posterior density follows the prior pattern or not is another practical test to illustrate whether the results are reliable enough or not. From this perspective, drawing the approximate visual kernel of the (posterior) density function is suitable. Figures B2 and B4 depict the probability functions related to each coefficient.

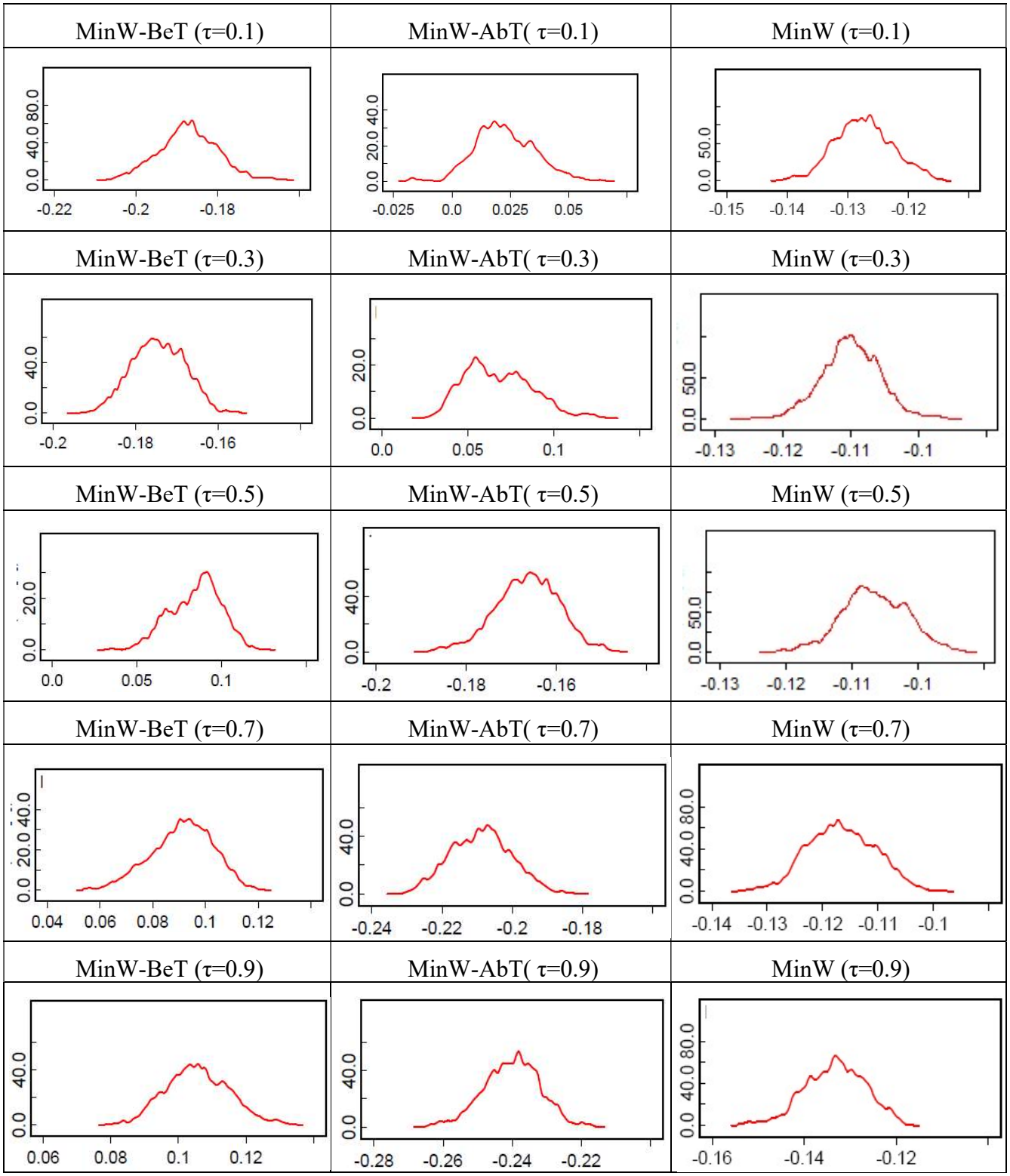
The centre of the density function shows the average (mean) of the posterior probability function. This value is presented as the magnitude of the estimated coefficient. Since all posterior functions are bell-shaped and their centre almost accord to the highest point (mode) of the density functions, one can be confident enough that the results are well behaved.

Appendix C1. History of Simulation for estimated coefficients of real minimum wage and its below and above thresholds across quantiles of violent crime



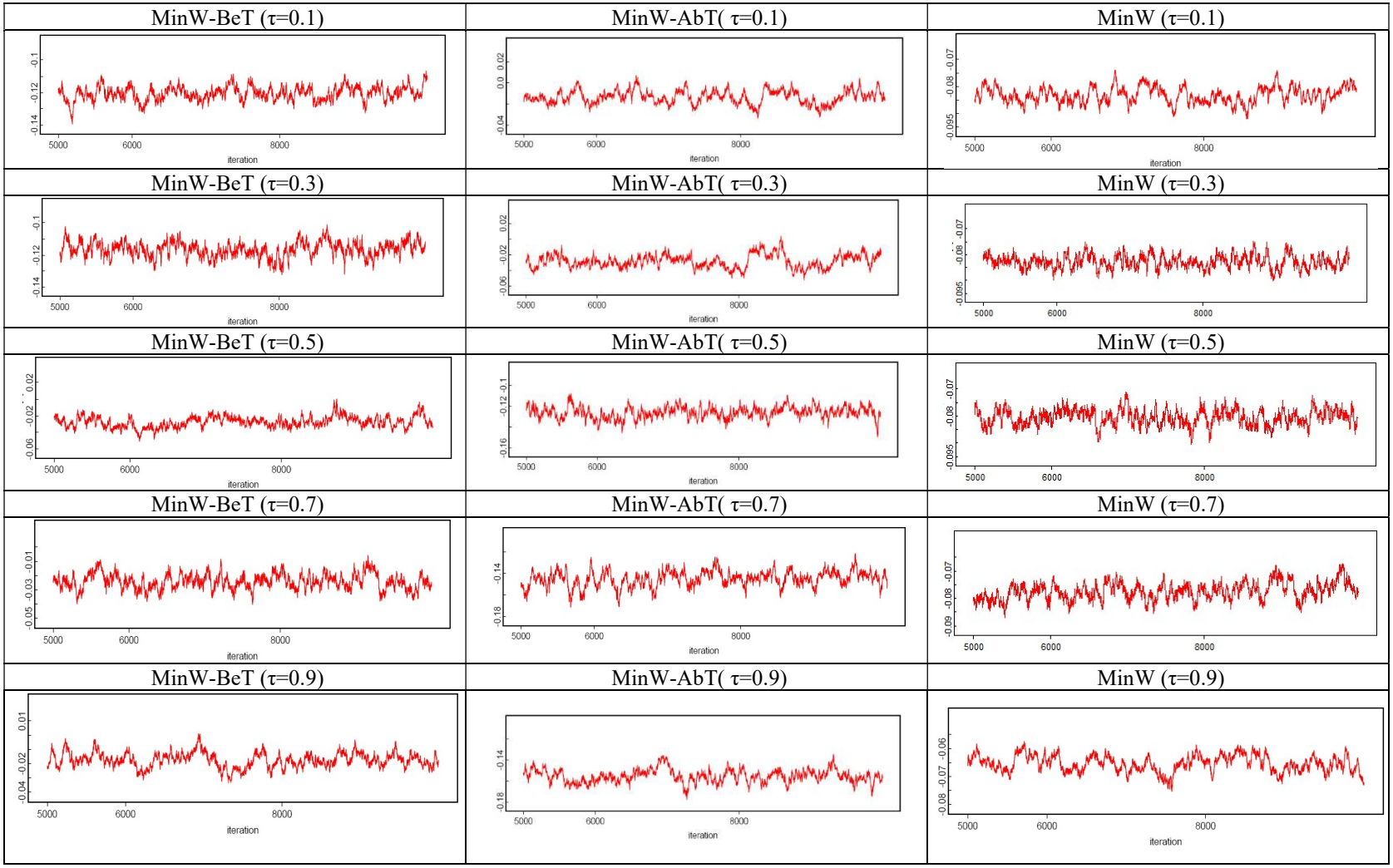
Notes: MinW-BeT: below threshold real minimum wage, MinW-AbT: above threshold real minimum wage, and MinW: real minimum wage

Appendix C2. The posterior distribution for estimated coefficients of real minimum wage and its below and above thresholds across quantiles of violent crime



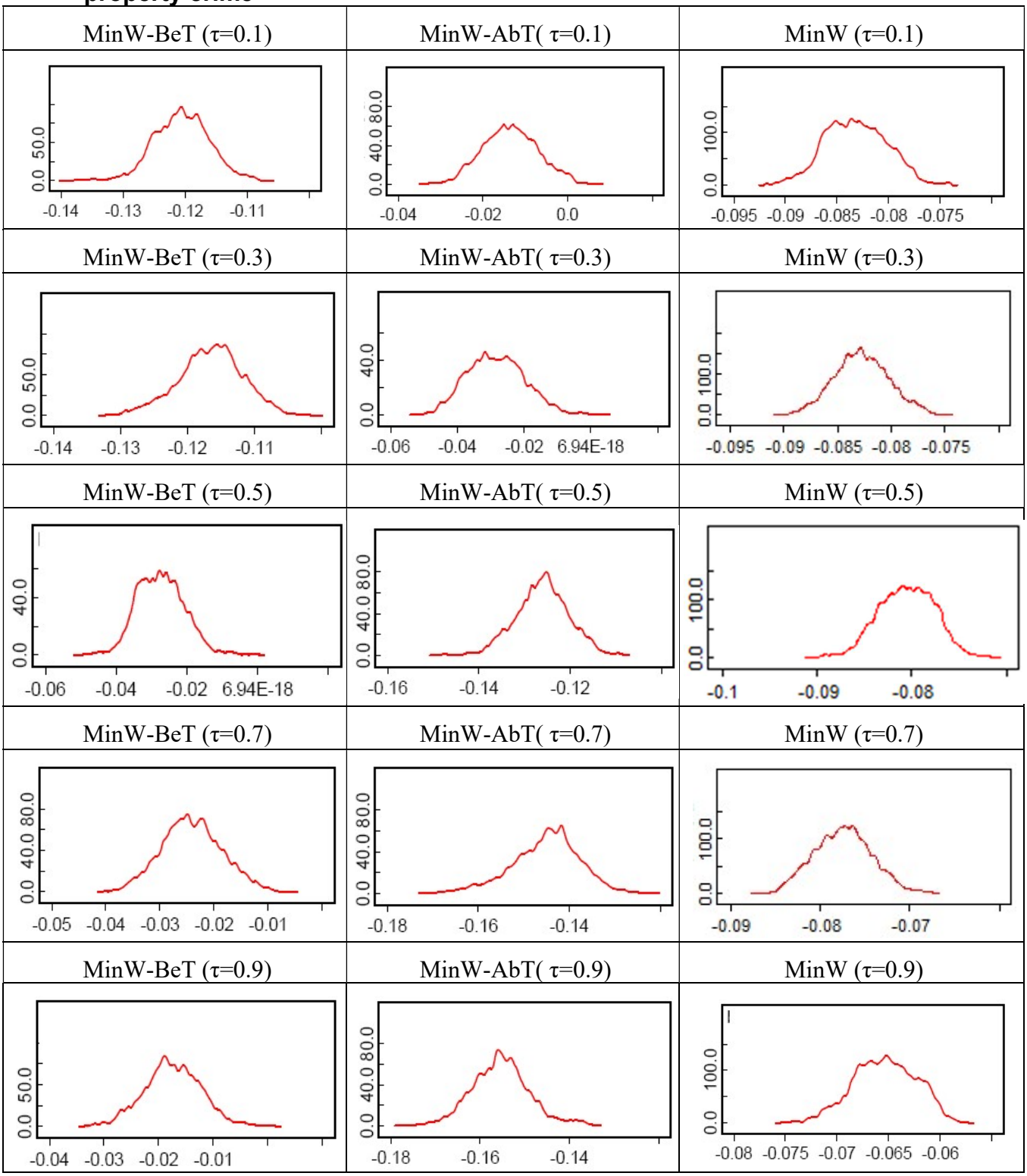
Notes: MinW-BeT: below threshold real minimum wage, MinW-AbT: above threshold real minimum wage, and MinW: real minimum wage

Appendix C3. History of Simulation for estimated coefficients of real minimum wage and its below and above thresholds across quantiles of property crime



Notes: inW-BeT: below threshold real minimum wage, MinW-AbT: above threshold real minimum wage and MinW: real minimum wage

Appendix C4. The posterior distribution for estimated coefficients of real minimum wage and its below and above thresholds across quantiles of property crime



Notes: MinW-BeT: below threshold real minimum wage, MinW-AbT: above threshold real minimum wage, and MinW: real minimum wage

Appendix 4D. Geweke diagnostic test

To assure that the MCMC simulation for each coefficient of the model fluctuates within a specific credible interval, I calculate the Geweke test as follows,

$$z = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}}}$$

where $\bar{x}_1$ and $\bar{x}_2$depict the average of simulation values at the first 10 and last 50 percentiles of a coefficient. S_1^2 and S_2^2 are the sum squared deviations from the means -- $\bar{x}_1$ and $\bar{x}_2$-- at the first 10 and last 50 percentiles of simulation. Also, n_1 and $n_2$shows the number of iterations at the first 10 and last 50 percentiles of the simulation. The amount of z is presented for the main coefficients of violent and property crime rates and the thresholds of real minimum wage in Tables C1 to C3 as follows,

Table D1. Geweke convergence test for violent crime equation across quantiles

	Without threshold					**With (state-level) threshold**				
	τ=0.1	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***	***τ=0.1***	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***
L-MinW						-0.09	0.02	-0.18	-0.19	-0.55
H-MinW						-0.14	0.65	-0.12	0.20	-0.24
MinW	0.79	0.17	-0.39	-0.25	0.95					
Sch-Hu	0.02	0.01	0.04	0.05	0.01	-0.38	-0.21	0.14	0.15	0.42
Col-Hu	-0.07	-0.05	0.00	-0.04	0.04	0.11	0.07	0.13	0.05	0.05
B-Cyc	0.13	0.03	-0.12	-0.06	0.16	0.33	0.17	0.11	-0.08	-0.15

Notes: the above values support the idea that there is no significant difference between the last 50% and the first 10% of the simulation history for each coefficient across various quantiles. Therefore, the null hypothesis cannot reject the equality of the two parts of the simulation.

Table D2. Geweke convergence test for property crime equation across quantiles

	Without threshold					**With (state-level) threshold**				
	τ=0.1	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***	***τ=0.1***	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***
L-MinW						0.47	-0.26	-0.02	0.20	-0.19
H-MinW						0.25	-0.02	0.04	0.43	-0.42
MinW	-0.29	-0.31	-0.10	1.01	-0.10					
Sch-Hu	-0.04	0.11	0.00	-0.09	0.01	0.02	0.07	0.00	-0.03	0.31
Col-Hu	0.01	-0.03	-0.04	0.06	-0.01	0.19	-0.08	0.03	0.00	-0.19
B-Cyc	-0.12	-0.04	0.07	0.31	-0.16	0.13	-0.05	0.10	0.09	0.32

Notes: the above values support the idea that there is no significant difference between the last 50% and the first 10% of the simulation history for each coefficient across various quantiles. Therefore, the null hypothesis cannot reject the equality of the two parts of the simulation.

Table D3. Geweke convergence test for state-level thresholds of minimum wage across quantiles

	Violent Crime					Property Crime				
	τ=0.1	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***	***τ =0.1***	***τ =0.3***	***τ =0.5***	***τ =0.7***	***τ =0.9***
Alabama	-0.09	0.10	-0.04	-0.11	0.14	0.39	0.15	0.05	-0.23	-0.40
Alaska	-0.21	0.26	0.04	-0.10	0.14	0.09	0.21	-0.16	0.00	0.20
Arizona	-0.41	-0.24	-0.23	-0.15	0.16	-0.12	-0.22	0.28	-0.17	0.29
Arkansas	-0.20	-0.02	-0.32	0.09	0.19	-0.11	-0.22	0.06	-0.13	0.84
California	-0.39	0.24	0.03	-0.12	-0.06	0.42	-0.08	-0.04	-0.08	0.04
Colorado	0.62	0.15	0.06	-0.15	0.29	-0.07	-0.15	-0.08	0.32	0.26
Connecticut	-0.08	0.33	-0.11	-0.06	0.05	-0.36	0.70	-0.44	-0.12	0.32
Delaware	-0.51	0.28	0.09	-0.17	0.13	0.12	-0.04	0.03	-0.02	0.07
Florida	0.08	0.08	-0.19	-0.24	-0.63	-0.01	0.04	0.12	-0.19	-0.19
Georgia	-0.45	0.19	0.15	-0.10	0.47	0.00	0.12	-0.34	-0.04	-0.17
Hawaii	-0.06	-0.07	0.20	0.04	0.47	-0.23	-0.18	-0.05	0.01	0.05
Idaho	-0.16	0.11	0.02	0.00	0.14	-0.03	-0.22	-0.20	-0.44	0.08
Illinois	-0.12	0.04	-0.17	0.21	0.00	-0.32	-0.28	0.23	-0.42	-0.01
Indiana	-0.11	0.28	0.31	-0.04	-0.10	0.18	0.25	0.07	-0.05	0.19
Iowa	0.50	0.04	0.18	-0.11	0.19	-0.53	0.27	-0.07	0.02	0.40
Kansas	-0.04	0.18	-0.31	-0.15	-0.01	-0.30	-0.44	-0.22	0.06	0.13
Kentucky	0.13	-0.02	0.15	-0.18	0.11	0.03	-0.10	-0.06	-0.12	0.02
Louisiana	0.12	0.03	-0.04	0.00	-0.02	-0.33	-0.17	0.02	0.50	0.19
Maine	-0.01	-0.07	-0.02	-0.09	0.15	0.04	0.01	-0.06	-0.08	-0.04
Maryland	0.25	-0.02	0.09	-0.04	0.21	-0.11	-0.28	0.05	-0.41	0.04
Massachusetts	0.21	-0.51	-0.04	-0.07	-0.02	-0.09	-0.15	0.13	-0.39	0.37
Michigan	0.17	-0.14	0.24	0.40	0.03	-0.03	-0.46	0.14	-0.02	0.24
Minnesota	-0.02	0.01	-0.03	0.07	-0.07	0.38	0.03	-0.02	0.06	-0.25
Mississippi	-0.19	0.31	0.10	-0.38	-0.25	-0.17	-0.08	-0.02	-0.26	0.15
Missouri	0.18	-0.09	-0.10	0.33	0.39	0.49	-0.56	-0.25	-0.07	0.10
Montana	0.08	-0.01	0.07	0.21	0.89	0.62	0.00	-0.01	-0.22	0.61
Nebraska	-0.32	0.05	-0.07	-0.10	0.06	0.10	-0.12	0.10	-0.14	-0.40
Nevada	0.07	0.42	-0.08	-0.11	-0.03	-0.03	-0.04	0.18	0.04	0.23
New Hampshire	0.49	0.02	0.11	0.04	0.02	0.02	-0.22	-0.08	-0.02	0.01
New Jersey	-0.05	0.00	-0.53	-0.22	0.15	0.25	0.31	-0.08	-0.09	0.14
New Mexico	-0.16	0.03	-0.17	0.13	0.03	-0.05	0.12	0.28	-0.42	-0.02
New York	0.07	-0.10	-0.14	0.01	0.09	-0.26	-0.03	-0.14	-0.08	0.37
North Carolina	-0.30	0.16	0.01	-0.08	0.31	0.24	-0.13	0.43	0.06	0.00
North Dakota	-0.09	-0.11	-0.05	0.01	-0.03	0.52	0.83	-0.06	-0.16	0.04
Ohio	-0.45	0.35	-0.02	-0.17	0.12	0.02	-0.37	0.14	-0.07	0.07
Oklahoma	0.21	0.27	-0.08	-0.11	-0.28	-0.19	-0.02	-0.27	0.26	-0.14
Oregon	-0.15	0.42	0.22	0.37	0.21	0.88	0.04	-0.17	0.06	0.04
Pennsylvania	-0.15	0.18	-0.08	-0.05	0.34	-0.09	0.25	-0.17	-0.02	0.24
Rhode Island	-0.49	0.00	-0.02	0.01	0.45	0.37	-0.25	0.16	0.05	0.10
South Carolina	0.04	-0.15	0.35	-0.10	-0.33	0.06	-0.40	-0.21	-0.04	-0.18
South Dakota	-0.03	0.03	0.03	-0.09	0.13	0.29	-0.14	0.01	-0.02	0.26
Tennessee	0.03	0.15	0.11	0.26	0.05	-0.11	-0.15	0.00	-0.05	0.47
Texas	0.03	0.00	0.16	-0.09	0.43	-0.01	-0.05	-0.48	0.12	0.01
Utah	0.37	0.28	-0.02	-0.07	0.33	-0.13	0.13	0.50	-0.48	-0.34
Vermont	0.06	0.34	-0.07	-0.17	-0.03	0.05	-0.29	-0.36	0.02	-0.25
Virginia	-0.62	0.00	0.03	-0.31	-0.08	0.05	-0.01	0.10	-0.20	0.50
Washington	0.64	0.21	-0.01	-0.07	-0.12	0.01	-0.60	0.53	-0.36	0.88
West Virginia	0.22	-0.11	0.04	0.16	0.00	0.16	0.02	-0.03	-0.05	-0.01
Wisconsin	0.34	0.10	0.18	-0.18	0.28	0.18	-0.02	-0.25	0.05	0.11
Wyoming	0.02	0.01	0.16	0.09	0.40	-0.11	0.11	0.34	-0.17	0.10

Notes: the above values support the idea that there is no significant difference between the last 50% and the first 10% of the simulation history for each coefficient across various quantiles. Therefore, the null hypothesis cannot reject the equality of the two parts of the simulation.

Appendix 4E: Threshold values over quantiles

Table D1. State-level real MinW thresholds and their normalised values for violent crime

	The real MinW thresholds					**Normalised values of the real MinW thresholds (S.D. from state's average real MinW)**				
	τ = 0.1	***τ = 0.3***	***τ = 0.5***	***τ = 0.7***	***τ = 0.9***	***τ = 0.1***	***τ = 0.3***	***τ = 0.5***	***τ = 0.7***	***τ = 0.9***
Alabama	7.12	7.30	5.53	5.59	5.72	0.84	1.10	-1.50	-1.41	-1.22
Alaska	6.34	6.93	7.97	7.98	7.39	-1.56	-0.81	0.51	0.52	-0.23
Arizona	7.33	7.40	5.98	6.18	6.32	0.86	0.96	-0.96	-0.69	-0.50
Arkansas	7.12	7.18	5.57	5.85	6.08	0.80	0.89	-1.55	-1.12	-0.77
California	7.93	8.21	5.93	6.07	6.25	0.81	1.14	-1.54	-1.38	-1.16
Colorado	6.72	6.67	6.35	6.60	6.45	0.04	-0.03	-0.45	-0.12	-0.32
Connecticut	8.40	8.31	6.24	6.58	6.66	1.18	1.08	-1.25	-0.87	-0.78
Delaware	6.67	6.30	6.22	6.42	6.58	-0.26	-0.79	-0.90	-0.61	-0.39
Florida*	7.69	7.67	5.50	5.62	5.90	1.34	1.32	-1.66	-1.49	-1.11
Georgia	7.38	7.33	5.53	5.52	5.84	1.22	1.15	-1.50	-1.51	-1.04
Hawaii	6.09	6.27	7.71	7.69	7.63	-1.75	-1.44	1.09	1.05	0.95
Idaho	6.22	6.73	6.17	6.59	6.79	-0.49	0.26	-0.56	0.06	0.35
Illinois	8.05	8.12	5.59	5.71	5.87	1.34	1.43	-1.48	-1.34	-1.16
Indiana	6.35	6.54	6.15	5.78	5.90	-0.29	-0.01	-0.59	-1.13	-0.96
Iowa	7.47	7.35	6.18	6.52	6.59	1.17	0.98	-0.84	-0.31	-0.20
Kansas	7.15	7.14	5.76	6.16	6.24	0.88	0.87	-1.16	-0.57	-0.46
Kentucky	7.54	7.61	5.56	5.71	5.96	1.46	1.56	-1.46	-1.24	-0.87
Louisiana	7.59	7.47	5.56	5.72	5.96	1.53	1.35	-1.46	-1.22	-0.87
Maine†††	5.96	6.05	7.73	7.74	7.67	-1.55	-1.40	1.31	1.32	1.21
Maryland**	7.55	7.48	5.79	5.95	5.99	1.45	1.35	-1.21	-0.97	-0.91
Massachusetts	7.81	7.93	5.94	6.10	6.22	0.67	0.81	-1.50	-1.31	-1.17
Michigan	7.11	7.32	5.78	6.04	6.14	0.58	0.86	-1.22	-0.86	-0.73
Minnesota	7.25	7.55	5.94	5.95	5.97	1.00	1.54	-1.34	-1.32	-1.29
Mississippi	6.28	6.57	6.39	6.23	5.85	-0.40	0.03	-0.24	-0.47	-1.03
Missouri	7.04	7.22	5.58	5.79	5.96	0.59	0.86	-1.52	-1.22	-0.97
Montana	5.50	5.45	7.52	7.54	7.30	-1.58	-1.65	1.22	1.25	0.92
Nebraska	7.39	7.35	5.83	5.90	6.52	1.24	1.18	-1.06	-0.96	-0.04
Nevada	5.39	6.11	7.51	7.38	6.92	-1.61	-0.73	0.98	0.82	0.26
New Hampshire	6.00	5.78	7.43	7.46	7.52	-0.98	-1.33	1.25	1.30	1.39
New Jersey	7.51	7.67	5.70	6.10	7.05	0.97	1.20	-1.65	-1.07	0.30
New Mexico	7.01	7.45	6.21	6.19	6.34	0.51	1.09	-0.56	-0.59	-0.39
New York	7.10	7.60	5.50	5.46	5.59	0.49	1.18	-1.74	-1.79	-1.61
North Carolina	7.18	7.44	5.57	5.69	6.14	0.89	1.29	-1.55	-1.36	-0.68
North Dakota†	6.28	5.87	7.67	7.70	7.66	-0.40	-1.01	1.67	1.72	1.66
Ohio	6.85	6.88	5.82	6.31	6.42	0.20	0.24	-1.16	-0.51	-0.37
Oklahoma	7.55	7.25	5.96	5.99	6.00	1.47	1.03	-0.87	-0.82	-0.81
Oregon	8.47	8.77	6.06	6.61	6.81	0.95	1.26	-1.56	-0.99	-0.78
Pennsylvania	6.98	7.21	6.04	6.47	6.53	0.49	0.84	-0.91	-0.27	-0.18
Rhode Island	7.76	7.86	6.46	6.57	6.70	1.03	1.20	-1.10	-0.92	-0.70
South Carolina***	7.14	7.34	5.66	5.76	6.04	0.87	1.16	-1.31	-1.16	-0.75
South Dakota	5.56	5.63	7.64	7.60	7.53	-1.46	-1.35	1.60	1.54	1.44
Tennessee	7.18	7.32	5.71	5.88	6.12	0.93	1.13	-1.24	-0.99	-0.63
Texas	7.60	7.59	5.59	5.69	5.70	1.54	1.53	-1.41	-1.26	-1.25
Utah	6.49	6.51	6.55	6.68	6.43	-0.09	-0.06	0.00	0.19	-0.18
Vermont††	6.10	6.28	8.37	8.41	8.39	-1.21	-1.01	1.29	1.33	1.31
Virginia	7.03	7.28	5.82	5.97	6.25	0.71	1.07	-1.07	-0.85	-0.44
Washington	8.93	8.97	6.53	6.69	6.74	1.34	1.38	-0.97	-0.82	-0.77
West Virginia	5.46	5.46	7.51	7.57	7.55	-1.69	-1.69	1.32	1.41	1.38
Wisconsin	7.07	7.52	5.89	5.99	6.17	0.70	1.41	-1.17	-1.02	-0.73
Wyoming	7.10	6.98	6.37	6.75	7.35	0.81	0.63	-0.26	0.29	1.18
Average	**7.02**	**7.12**	**6.27**	**6.41**	**6.51**	**0.35**	**0.50**	**-0.66**	**-0.48**	**-0.32**

Notes: the value of thresholds indicates the hourly minimum wage chained in 2012 US dollars ($).
The upper scripts "*", "**" and "***" demonstrate the most, second, and third most dangerous states in the US, respectively. The upper scripts "†", "††" and "†††" indicate the safest, second and third safest states in the US, respectively.

Table E2. State-level real MinW thresholds and their normalised values for property crime

	The real MinW thresholds					Normalised values of the real MinW thresholds (S.D. from state's average real MinW)				
	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$	$\tau = 0.1$	$\tau = 0.3$	$\tau = 0.5$	$\tau = 0.7$	$\tau = 0.9$
Alabama	6.94	6.91	6.64	6.95	6.97	0.57	0.53	0.13	0.59	0.62
Alaska	6.28	6.69	8.42	8.57	8.61	-1.63	-1.11	1.08	1.27	1.32
Arizona*	7.55	7.48	5.88	6.02	6.03	1.16	1.07	-1.09	-0.91	-0.89
Arkansas	6.85	6.96	5.79	6.08	6.11	0.39	0.56	-1.21	-0.77	-0.73
California	7.33	6.96	7.34	7.12	7.14	0.11	-0.33	0.12	-0.14	-0.12
Colorado	7.48	7.40	6.26	6.64	6.68	1.05	0.95	-0.57	-0.07	-0.01
Connecticut	7.45	8.15	6.51	6.99	7.03	0.11	0.90	-0.94	-0.40	-0.36
Delaware	5.58	5.65	7.60	7.62	7.62	-1.81	-1.71	1.07	1.10	1.10
Florida**	7.28	7.53	5.55	5.66	5.66	0.78	1.12	-1.59	-1.44	-1.44
Georgia	7.02	7.32	5.59	5.58	5.58	0.69	1.13	-1.41	-1.43	-1.43
Hawaii***	6.28	6.29	7.59	7.63	7.64	-1.42	-1.40	0.88	0.95	0.96
Idaho	6.53	7.07	6.15	6.10	6.09	-0.03	0.76	-0.59	-0.66	-0.68
Illinois	7.83	7.31	6.45	6.74	6.73	1.09	0.49	-0.49	-0.16	-0.17
Indiana	6.38	6.04	7.48	7.31	7.33	-0.25	-0.75	1.37	1.12	1.15
Iowa	7.15	7.27	6.55	7.01	7.04	0.67	0.86	-0.27	0.45	0.50
Kansas	6.68	6.99	6.24	6.67	6.71	0.19	0.65	-0.46	0.18	0.24
Kentucky	5.67	5.58	7.53	7.54	7.55	-1.29	-1.43	1.44	1.46	1.47
Louisiana	7.35	7.42	5.74	5.91	5.91	1.18	1.28	-1.19	-0.94	-0.94
Maine	6.49	6.44	7.65	7.68	7.70	-0.69	-0.77	1.18	1.23	1.26
Maryland	6.91	6.97	6.45	6.18	6.19	0.48	0.58	-0.21	-0.62	-0.61
Massachusetts	6.66	6.70	8.08	8.03	8.13	-0.66	-0.62	0.99	0.93	1.05
Michigan	7.36	7.09	6.61	7.09	7.14	0.92	0.55	-0.09	0.55	0.62
Minnesota	6.95	7.21	6.19	6.30	6.29	0.46	0.93	-0.89	-0.70	-0.71
Mississippi	7.59	7.48	6.19	6.13	6.13	1.53	1.37	-0.53	-0.62	-0.62
Missouri	6.50	6.70	6.58	6.86	6.85	-0.19	0.10	-0.07	0.33	0.32
Montana	7.14	7.31	6.44	6.52	6.44	0.69	0.93	-0.28	-0.17	-0.28
Nebraska	6.94	7.36	6.09	6.51	6.50	0.57	1.19	-0.68	-0.06	-0.07
Nevada	5.76	6.02	7.56	7.44	7.48	-1.16	-0.84	1.04	0.89	0.94
New Hampshire	5.80	5.90	7.61	7.65	7.66	-1.30	-1.14	1.53	1.59	1.61
New Jersey	6.37	6.32	7.32	7.13	7.17	-0.68	-0.75	0.70	0.42	0.48
New Mexico	7.37	7.48	5.92	6.20	6.29	0.99	1.13	-0.95	-0.57	-0.45
New York	6.35	6.92	5.59	5.56	5.56	-0.56	0.24	-1.61	-1.65	-1.65
North Carolina	7.23	7.46	5.74	5.85	5.84	0.97	1.32	-1.29	-1.12	-1.14
North Dakota†††	6.65	6.23	6.85	7.15	7.16	0.15	-0.48	0.45	0.90	0.91
Ohio	6.29	5.87	7.43	7.49	7.51	-0.54	-1.09	0.96	1.04	1.07
Oklahoma	7.39	7.54	5.84	5.91	5.92	1.24	1.46	-1.04	-0.94	-0.93
Oregon	8.70	8.70	6.21	7.19	7.18	1.19	1.19	-1.41	-0.39	-0.40
Pennsylvania	6.36	6.28	7.34	7.42	7.45	-0.43	-0.55	1.03	1.15	1.19
Rhode Island	6.46	6.56	7.61	7.55	7.58	-1.10	-0.93	0.79	0.69	0.74
South Carolina	6.86	6.76	6.38	6.50	6.56	0.46	0.31	-0.25	-0.07	0.01
South Dakota††	5.67	5.90	7.39	6.89	6.86	-1.29	-0.96	1.24	0.50	0.46
Tennessee	7.06	7.09	6.17	6.23	6.24	0.75	0.79	-0.56	-0.47	-0.46
Texas	7.49	7.53	5.68	5.49	5.50	1.38	1.44	-1.28	-1.56	-1.54
Utah	7.09	7.43	5.85	6.25	6.24	0.79	1.29	-1.03	-0.44	-0.46
Vermont	7.96	7.12	7.66	8.37	8.36	0.84	-0.09	0.51	1.29	1.27
Virginia	6.56	6.69	6.47	6.47	6.50	0.01	0.21	-0.12	-0.12	-0.07
Washington	8.68	8.66	6.95	7.87	7.94	1.10	1.08	-0.57	0.32	0.38
West Virginia†	5.63	5.57	7.57	7.58	7.60	-1.44	-1.53	1.41	1.43	1.46
Wisconsin	7.31	6.94	6.93	7.23	7.25	1.08	0.49	0.48	0.95	0.98
Wyoming	7.07	7.14	6.29	6.29	6.31	0.76	0.87	-0.38	-0.38	-0.35
Average	**6.89**	**6.93**	**6.68**	**6.82**	**6.84**	**0.16**	**0.23**	**-0.09**	**0.09**	**0.11**

Notes: the value of thresholds indicates the hourly minimum wage chained in 2012 US dollars ($). The upper scripts "*", "**" and "***" demonstrate the most, second, and third most dangerous states in the US, respectively. The upper scripts "†", "††" and "†††" demonstrate the safest, second and third safest states in the US, respectively.

Chapter 5 Conclusion

5.1. Introduction

This thesis reviewed the implications of different public policies related to health and labour economics. Chapter two analysed how performing government non-pharmaceutical policies can control the spread of coronavirus during the first 100 days of the pandemic. It answered important questions about the effectiveness of different policy instruments and showed how school and business closures, stay-at-home restrictions, testing policy and contact tracing contributed to the spread of the virus. This study also considers economic support to households, as another policy action, besides several socio-economic factors to control the variation of the infection rates. Following Zhang and Zhang (2014), Bühlmann and van de Geer (2015), van de Geer, S. (2017) and Dezeure et al. (2017), the study uses a novel method by considering high dimensionality, a debiased LASSO technique to overcome the problem of too many covariates in the model. Using the data of 37 lower and middle-income countries, the LASSO model was estimated, and different types of sensitivity tests were implemented to ensure the results' accuracy.

Chapter 3 connected both labour and health economics based public policies by investigating job loss's impact on individuals' mental wellbeing in six countries including China, South Korea, Japan, Italy, the UK and the US, during the first phase of the pandemic. The study evaluated the effects of unemployment on various measures of wellbeing loss such as anxiety, boredom, insomnia and loneliness. It showed how these wellbeing factors could be combined to obtain a unique index of mental wellbeing. Then, the association between job loss and the mental wellbeing index was evaluated. This study also examined the association between several socioeconomic and demographic factors on mental wellbeing loss such as gender, housing mortgage, age, income, living areas, smoking habits, and attending religious services. At the next step, the data clustered based on timing of the spread of the virus. Based on this approach, China and South Korea faced with the peak of infection prior to other countries in the sample. However, the other counties struggled with delayed infection peak when the survey gathered. Different estimates were applied for each cluster. Finally, reverse causality issue addressed in the chapter to show the results are not sensitive empirically.

Chapter 4 investigated the association between minimum wage policy and crime rates in the US. Using a US state-level data, a multi-kink quantile regression method within a Bayesian panel data framework applied on property and violent crime over three decades to provide reliable policy implications. It illustrated how minimum wage policy asymmetrically affects crime rates across different states in the US. To show how minimum wage policy can have pull or push effect on criminal activities, the study explored to find thresholds of minimum wages across different states in the US. In this regard a regression kink model developed to give a better understanding of the effect of minimum wage policy to both federal and local policymakers. This examination extended over each part of the distribution to realise how the policy works when crime is low (in low quantile) or it is high (in high quantile). As a result of these objectives, two different asymmetric effects were investigated in the research: (1) asymmetries across quantiles of an outcome variable and (2) asymmetries below or above a threshold of an explanatory variable.

5.2. Discussion of key findings

This thesis offers important policy implications in health and labour economics. Chapter 2's findings show that school closure, contact tracing and stay-at-home restrictions significantly mitigate the infection rate in LMCs. In this regard, school closure and contact tracing have the highest effect compared to other interventions. However, no significant correlation between business closures and infection rates has been found. Further, the results confirm that the testing and infection rates are positively correlated with each other during the early stages of the pandemic. The findings revealed that the economic support package to households is negatively associated with the infection rate. The estimated coefficients also suggested that infections become higher in countries with greater income inequality, higher tourist inflows, poorly educated adults, and weak governance quality. Therefore, closing schools and universities, limiting people to stay at home, and tracing the contacts of infected individuals are all effective policy interventions. Strengthening public institutions and increasing the number of health care workers are vital to assisting these countries in overcoming this health crisis. As such, benefiting from better socio-economic factors, the economic and institutional environment is also important in impacting the spread of infections.

Chapter 3 discussed how job loss induced by the COVID-19 pandemic leads to different types of mental illness, including anxiety, boredom, insomnia and loneliness. I found that job loss is an important factor affecting mental health during the pandemic. The results also showed that women are more prone to anxiety in China and South Korea, the countries faced an early peak of the pandemic. However, women severely suffer from anxiety, insomnia and loneliness in Italy, Japan, the UK and the US, the countries with delayed peak infection rates. This study showed that the risk of mental wellbeing loss is high for young people, residents of urban and semi-urban areas, as well as smokers. For policy implication, it is suggested that governments can take following actions to mitigate the side effects of job loss on wellbeing of people: performing effective labour market policies by increasing employment opportunities especially for young generation, providing mental health supports especially for people lost their jobs, implementing job retention schemes, paying job keepers employment benefits to retain their employees, establishing job training funds for people lost their jobs, allocating financial support by paying unemployment benefits to unemployed people until they find jobs, providing debt facilitator and postponing paying mortgages during the outbreak, and finally providing social supports to people lost their jobs, indebt households, women and youth.

Chapter 4 discusses how crime rates change asymmetrically across quantiles and over different states in response to minimum wage changes. The findings show that an increase in minimum wage on each segment of violent and property crime rates is negative. Also, results support the asymmetric impact of minimum wage on crime rates in the US. In this regard, all segments of the distribution of property crime react negatively to both the below and the above threshold of actual minimum wage. However, the magnitude of the marginal effect of the above tipping point of the real minimum wage rises from the lowest (τ=0.1) to the highest (τ=0.9) parts of the distribution of property crime rate. On the other hand, the marginal effect of the below threshold of the real minimum wage weakens from the lowest to highest segments of the conditional distribution of property crime. The findings show that the marginal effects of the below threshold of the minimum wage have negatively affected violent crime when the rate is less than median in the sample. However, the marginal effect of this variable has positively influenced the conditional distribution of violent crime in the case the rate is high in the society. The findings show that the impact of the above threshold minimum

wage on violent crime is positive when crime rate is considerably low in the society. Still, this variable impacted the upper segments of the distribution negatively.

5.3. Contributions

This thesis contributed in several ways to the existing knowledge in health and labour economics. Chapter 2 used a machine learning tool, a debiased LASSO estimator, in presence of too many factors to identify which policy actions are more effective in controlling COVID-19 infections in LMCs. This technique is applied in this context for the first time to bring insight to performing effective policy with regard to preventing one of the deadliest infectious diseases. It added to the literature first by considering several nonpharmaceutical interventions such as school and business closures, stay-at-home requirements, contact tracing, and testing policy. Secondly, it showed whether government economic support to households reduced the infection rate in LMCs. As another contribution of Chapter 2, a number of socioeconomic factors such as density of population, average years of adults' education, income inequality, international tourism arrivals, health care workers, and institutional quality affect the risk of infection were examined.

Chapter 3 filled several gaps in the literature: first, it showed how being unemployed because of pandemic is correlated with several policy mental wellbeing loss such as anxiety, boredom, insomnia and loneliness. Second, it aggregated these four aspects of mental disorders to create a mental disorder index using a factor analysis method. Then, the effect of this unique index of mental wellbeing loss is examined to understand how labour market changes deteriorates people's mental health. Another advantage of this study was to use a rich set of cross-country microdata instead of using one country information. To take advantage of this multi-country data asset, I examined that relationship not only for each country but also for groups of countries faced with peaks of pandemic in different phases of time. Splitting the dataset into two groups of countries based on early-peak vs delayed peak in the spread of the virus allowed me to differentiate the effect of a mental illness caused by the COVID-19 between countries experienced early peak of the pandemic in comparison with others faced the delayed peaks.

Chapter 4 contributed to the literature by developing a state-specific regression kink model. It developed methods introduced by Su and Xu (2019) and Zhong et al. (2021) within a Bayesian panel data framework. I investigated how minimum wage policy

heterogeneously impacted property and violent crime in the US. Accordingly, state-specific tipping points of minimum wages are identified across fifty US states. This analysis could help policymakers to learn how criminal behaviours are heterogeneously changed when minimum wage exceeds a critical value. This aspect provides valuable information to both national and local governments about the consequences of the minimum wage policy on the perpetration of criminal activities.

5.4. Scope for future research

I believe that this thesis can be extended in several ways. While Chapter 2 has employed a sample pertaining to infection rates for the recent COVID-19 pandemic, these results can be generalised to inform policy actions for other infectious diseases or future strains of COVID-19. One can consider the impact of the policy in different stage of the pandemic and compare the policy effectiveness. For example, it is evident that the COVID-19 restrictions in countries varied over time. Thus, estimating regressions for the first, second and third years of the pandemic and then compare the policy effectiveness over different time phases, would provide better intuitions whether the polices were effective at different stages. Additionally, I examined the trajectories of COVID-19 infections in the LMCs, but future studies can also investigate different datasets for high income countries. From a technical perspective, one can use the debiased LASSO method for analysing different aspects in economic research.

In Chapter 3, I evaluated the impact of the pandemic on wellbeing loss; however, COVID-19 has negatively affected both physical and mental health worldwide. One can evaluate the impact of job loss on physical health. Additionally, the COVID-19 crisis has been posing one of the most significant challenges in our recent memory, but it is not the last pandemic in life of societies. So, one can use the provided approach to analyse the impact of future pandemic on mental wellbeing of people. Also, this Chapter used the early stage of pandemic data, but one can use the data for later periods to understand whether impact of the pandemic on wellbeing of people changed over time or not. Further, the sample can be extended to other countries particularly in south Asia and Africa where infection rates were high.

Although Chapter 4 investigated the effects of minimum wage on crime, one can consider other applications of economic policies on crime or other socioeconomic outcomes. In

terms of the extension of this study, one can employ multi-country data to understand how policy variables heterogeneously impact the variation of macroeconomic variables. Utilising microdata can be helpful in understanding how individual behaviours react to policy changes over different parts of the distribution of an outcome.

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