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Thesis

WORKPLACE WELLNESS: AN ANALYSIS OF FIRM AND INDIVIDUAL FACTORS IN THE LEAST HEALTHY SECTORS

ANDRÉ LUIZ RIBEIRO COUTINHO BERARDO DE MORAES COÊLHO

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Thesis presented to the Graduate Program in Economics (Programa de Pós-Graduação em Economia – Pimes) at the Federal University of Pernambuco (Universidade Federal de Pernambuco – UFPE) as a requirement for obtaining the doctorate degree in economics.

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Tese apresentada ao Programa de Pós-Graduação em Economia da Universidade Federal de Pernambuco, como requisito parcial para a obtenção do título de doutor em Teoria Econômica.

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BANCA EXAMINADORA

____
Profª. Dra. Tatiane Almeida de Menezes (Orientadora)
Universidade Federal de Pernambuco

____
Profº. Dr. Raul da Mota Silveira Neto (Examinador Interno)
Universidade Federal de Pernambuco

____
Profº. Dr. André Matos Magalhães (Examinador Interno)
Universidade Federal de Pernambuco

____
Profº. Dr. André Luis Squarize Chagas (Examinador Externo)
Universidade Estadual de São Paulo

____
Profª. Dra. Roberta de Moraes Rocha (Examinador Externo)
Universidade Federal de Pernambuco

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ABSTRACT

This thesis aims to analyze how individual and firm factors influence a person to work in the least healthy sectors using firms' and workers' observed and non-observed characteristics through a Discrete Choice Model. The main idea is to understand how individual and firm factors impact a person to work in the least healthy sector conditional on individuals' and firms' characteristics using unique combined data through individual CPF (Individual Taxpayer Registry) from the SES-PE 2020 (Pernambuco State Health Department) and RAIS 2019 (Annual List of Social), containing latitude and longitude where each person lives and works. The State of Pernambuco was one of the states with the most cases in Brazil, fifth in the nation, with 25,760 cases as of May 24, 2020, and the model is estimated for its capital, Recife. The model is first estimated for the essential sectors. Thus, men present a higher chance of working in the essential sectors, and there is a lower incidence of an older or non-white individual being employed in these sectors. A higher minimum wage attracts more workers, and there is also a higher incidence of working hours and job tenure among employees in the essential sectors. The model is then estimated by dividing the economic sectors into two groups, the Least Healthy and Other Sectors. First, the least healthy group is defined by the highest number of people who tested positive for COVID-19 among all economic sectors. Second, it is defined by the economic sectors that are considered the essential sectors, the ones that did not experience lockdown. The model estimated with the latter definition best fits the data. The current thesis's importance is to contribute to how the workers' and firms' characteristics affect an individual working in the least healthy sectors. The research advances because COVID-19 is an exogenous factor that helps expose which economic sectors the individuals work in are the least healthy. Public policies can be directed to promote equal opportunities through racial quotas, gender equality, income distribution, investment in the health system and education, public transportation, and sanitation. The informal sector is not considered.

Keywords: Discrete Choice; Economic Sectors; COVID-19; Recife.

RESUMO

Esta tese tem o objetivo de analisar como fatores do indivíduo e da firma influenciam uma pessoa trabalhar no setor menos saudável utilizando caraterísticas observáveis e não observáveis dos trabalhadores e da firma através do modelo de *Discrete Choice*. A ideia principal é entender como fatores do indivíduo e da firma impactam uma pessoa trabalhar num setor menos saudável condicional a características do indivíduo e da firma usando dados únicos combinados por meio do CPF individual (Cadastro Pessoa Física) da SES-PE 2020 (Secretaria do Estado de Saúde) e RAIS 2019 (Relação Anual de Informações Sociais), contendo latitude e longitude onde cada pessoa mora e trabalha. O estado de Pernambuco era um dos estados com mais casos no Brasil, quinto do país, 25.760 casos em 24 de maio de 2020, e o modelo é estimado para sua capital, Recife. O model é primeiramente estimado para os setores essenciais. Então homens apresentam uma maior chance de trabalhar nos setores essenciais, e há uma incidência menor de indivíduos mais velhos ou não brancos sendo empregados nesses setores. Um maior salário mínimo atrai mais trabalhadores, e há também uma maior incidência de horas trabalhadas e tempo de trabalho no mesmo emprego entre os empregados nos setores essenciais. O model é depois estimado dividindo os setores da economia em dois grupos, o *Least Healthy*, menos saudável, e *Other Sectors*, outros setores. Primeiro o grupo do setor não saudável é definido pelo maior número de pessoas que testaram positivo para Covid-19 entre todos os setores da economia. Segundo, é definido pelos setores da economia quais são considerados setores essenciais, os que não entraram em lockdown. O model estimado pela segunda definição é o que melhor se ajusta aos dados. A importância da tese atual é contribuir no como as características dos trabalhadores e da firma tem efeito em um indivíduo trabalhar nos setores menos saudáveis. A pesquisa avança porque COVID-19 é um fator exógeno que ajuda a expor quais setores econômicos os indivíduos trabalham são menos saudáveis. Políticas públicas podem ser direcionadas para promover oportunidades iguais através de quotas raciais, igualdade de gênero e distribuição de renda, investimento no sistema de saúde e educação, transporte público e saneamento. O setor informal não é considerado.

Palavras-chaves: Escolha Discreta; Setores Econômicos; COVID-19; Recife.

List of Figures

List of Tables

Table of contents

1 Introduction

A healthy population is crucial for sustained economic growth, and good health is a significant determinant of human capital, which leads to increased productivity (ZON; MUYSKEN, 2001). However, identifying the least healthy sector and the types of individuals who work in them can be challenging. An exogenous factor may help identify which economic sectors are the least healthy. The occupational choice not only determines income but also contributes to social networks and affects socioeconomic position (LANDBERGIS et al., 2018).

Worker characteristics affect occupational choice, with work being associated with health and health disparities for individuals and societies (BROWN et al., 2019). Therefore, occupational safety and health are crucial when workers are deciding where to be employed, as it affects the labor market. Furthermore, exposure to airborne substances harmful to health at work can negatively impact the worker's health, affecting productivity.

In this work, the objective is to identify how individual and firm factors influence a person to work in the least healthy sectors using firms and workers' observed and non-observed characteristics using a Discrete Choice Model. The model uses a unique matched individual dataset for Recife from RAIS 2019 and SES-PE 2020 containing CPF. The research advances because of an exogenous factor that helps expose which economic sectors are the least healthy. This research can help create new public policies or improve existing ones.

In this study, the econometric framework of the discrete choice model is not used to define individual preferences concerning a set of consumption alternatives. Instead, it helps identify which individuals work in the least healthy sector given their observed and non-observed characteristics, as well as their firms. The economic sectors with higher airborne exposure transmission are the least healthy, and the pandemic is an exogenous shock that allows identifying which sectors are the least healthy. Workers in the least healthy sectors of the economy put themselves at greater risk of contracting viral diseases. Commuting distance also poses a risk, as exposure to an airborne virus increases with increasing commuting distance (ANDO et al., 2021).

The current thesis aims to evaluate how individual and firm factors impact individuals to work in the least healthy sectors, based on their individual and firm characteristics, including salary and commuting distance. This information can guide future public policies during similar pandemics and aid in determining which economic sectors should be shut down (LEWIS, 2022).

The data used in this study is unique and rich, combining information from SES-PE 2020 and RAIS 2019, including CPF, latitude, and longitude of individuals' residences and workplaces. The results are considered exogenous as the labor data was collected from RAIS 2019, not influenced by the pandemic, while COVID-19 data was obtained from SES-PE 2020.

The thesis's main objective is to identify how individual and firm factors influence a person to work in the least healthy sectors using firms' and workers' observed and non-observed characteristics through a Discrete Choice Model. The least healthy firms are identified by the number of positive COVID-19 cases in a particular economic sector. If the least healthy sector is an essential sector that did not shut down during the lockdown in 2020, their workers were more vulnerable to virus exposure, contraction, and transmission, and the dummy variable lockdown captures this effect. And individual characteristics such as age, sex, wage, and commuting distance are also taken into account. The specific objectives include constructing the dataset, georeferencing individual coordinates, mapping COVID-19 distribution among economic sectors, identifying the individuals' characteristics who work in the least healthy sector, as well as the firms, and making public policy suggestions.

The study focuses on Recife, the capital of Pernambuco, and the results may be used to develop policies promoting health equity, controlling future pandemics, and avoiding the development of respiratory diseases, particularly among vulnerable people living in poor communities. Future research is needed to analyze which economic sectors are the least healthy, considering vulnerable people living in poor communities. Additionally, the study can be extended to evaluate if the results persist in other similar cities in the country. Future research should also consider people who work in the informal economic sector. This first section is the introduction, the second section presents the literature review, the third section displays the methodology, the fourth section presents the results and discussion, and the fifth section concludes the thesis.

2 Literature Review

2.1 Occupational Health Inequities

Occupational health inequities have been an important factor in many kinds of research, the work done by the people is highly segregated by race, gender, and age, besides it being influenced by their geographic location and educational attainment, and income (AHONEN, 2018). Occupational health risk perception affects negatively job satisfaction, where work stress and organizational commitment mediate the role between occupational health risk perception and job satisfaction. Reducing occupation health risk perception improves employees' job satisfaction (SHAN et al., 2022).

Work supports and promotes health while carrying the risk of injury, illness, and death. Job security, work-life balance, and workplace culture contribute to employees' well-being, benefiting employers through increased productivity, reduced healthcare costs, and improved retention rates (MCLELLAN, 2017).

Occupation largely determines income, contributes to social networks, influences socioeconomic position, a fundamental cause of disease. Moreover, social determinants of health such as race or gender, affect the types of jobs people can attain, also the hazards they encounter. Black, Hispanic, or Asian women are more susceptible to low wages, work hazards, job insecurity, and harassment. Standard socioeconomic statuses measures, such as education and income influence what type of job an individual is more likely to be employed (LANDBERGIS et al., 2018).

The workers' and firms' characteristics influence where the individuals work. Occupational Safety and Health is an important subject for the labor market. There are 2.78 million fatal work-related injuries and illnesses each year, with 2.4 million due to work-related diseases, which amounts to 3.94 percent of the global GDP in 2017. Improving occupational safety and health and also creating a culture of prevention is an urgent need (ILO, 2017).

Job strain and job insecurity are associated with negative health outcomes such as cardiovascular disease, mental health problems, and musculoskeletal disorders.

Understanding the relationship between job strain, job insecurity, and health can help to identify effective interventions to promote health and well-being in the workplace, leading to more effective strategies for improving workplace health and well-being (STRAZDINS et al. 2004).

Workers in lower socioeconomic or social class positions are exposed to greater job insecurity and other work organization hazards when compared to workers in higher socioeconomic positions. Moreover, racial minorities are also exposed to greater job insecurity. To reduce these hazards and disparities, employment and workplace policies and programs are potentially needed (LANDSBERGIS et al., 2014). Contemporary work environments are characterized by high demands, low control, and job insecurity, which can have negative effects on workers' health, physical and mental (SOUZA, RENNIE et al., 2003).

Employment in high-injury or illness occupations is independently associated with workers who are male, Black and have a high school degree, low wages, and foreign births. Fatal occupational injury rate ratios are elevated for males, older workers, and some specific occupations, such as agriculture, forestry, fishing and mining industries, and transportation (STEEGE et al., 2014). An increase in education induces individuals to have a healthy lifestyle by exercising and getting health checkups regularly. Higher levels of education are associated with better health outcomes, but there is influence by other factors such as income, access to healthcare, and cultural norms (PARK; KANG, 2008).

International migrant workers are at considerable risk of work-related ill health and injury. They often subject migrant workers to higher risks of poor occupational health outcomes, such as work-related injuries, illness, and stress. Working conditions, low levels of job security, and limited access to health care and social protection influence these mentioned health outcomes. There is a need to address the occupational health needs of international migrant workers, to improve their health and well-being, preventing negative impacts on the health of their communities (HARGREAVES et al., 2019).

Health inequalities are not just the result of individual lifestyle choices, but it is rooted in social, economic, and political factors. Social factors can be often hidden leading to a lack of action to address health inequalities. To develop more effective policies and programs to improve health outcomes for all, there is a need to address health inequality, bringing these hidden assumptions into the open (KLEIN, 2000).

Workplace health promotion programs can have a positive impact on various measures of labor market performance, such as increased productivity, reduced absenteeism, and improved job satisfaction. Investing in workplace health promotion programs can be beneficial for work, besides improving health outcomes (HUBER et al, 2015). Labor market programs in aiding sick-listed workers to re-enter the workforce can have positive effects on employment outcomes. This type of program can be an important tool in promoting re-employment for sick-listed workers (HOLM et al., 2017).

Some programs such as Medicaid and Medicare helped reduce healthcare disparities improving access to care for vulnerable populations, and proving healthcare coverage to millions of low-income and elderly Americans (CHOWKWANYUN, 2018). Policy solutions such as job training programs and wage subsidies have helped people with disabilities to find jobs and have access to healthcare, contributing to fewer occupational health disparities (GILLIGAN, 2022).

Individual living in socioeconomically disadvantaged areas presents a lower healthy life expectancy than those in more affluent areas, with higher rates of chronic diseases and mortality. Factors such as limited access to health services, unhealthy living conditions, and higher levels of violence and crime have contributed to the disadvantaged population experiencing poor health. Policies to reduce social inequalities are necessary to improve the health outcomes and health disparities in Rio de Janeiro (SZWARCWALD, 2011).

Occupational health in the workplace needs improvement shifting from a reactive to a proactive and collaborative approach. With a focus on prevention, early intervention, and worker empowerment, creating a workplace that prioritizes the health and safety of its workers. By data collection and analysis to identify areas of concern and measure the effectiveness of interventions (PECKHAM et al, 2017).

To diminish occupational health disparities public health interventions are necessary to protect the health, although public health programs are often complex and involve social strategies, empowerment, capacity building, and knowledge across sectors. In many low-income and middle-income countries, public health is mostly preventive health care and primary health. Some public health programs' outcome measures are not captured in these countries, but new well-being measures have been developed to fix it (GRECO et al., 2016). A greater risk for diseases and shorter lifespans is one of the poorer health outcomes people with low incomes living in poverty can face. Income support programs can alleviate those who are in need if they participate in these programs, although there is unequal access to them (FINKELSTEIN et al., 2022).

2.2 Occupational Respiratory Diseases

Inhaling materials in the workplace can cause respiratory diseases in the workplace, and these diseases can lead to chronic lung conditions. The inhalation of these workplace materials can affect different parts of the respiratory tract and cause symptoms such as rhinitis, laryngitis, and asthma. This work-related illness affects workers' livelihood and health (BECKET, 2000). The increasing use of nanomaterials in the workplace can lead to unique respiratory toxicities, and the global nature of the workforce, which can result in a lack of uniformity in workplace exposure standards and difficulty in tracking occupational lung diseases (MATTEIS, 2017).

The presence of airborne pollutants in indoor environments has been associated with individuals' discomfort or adverse health effects (RIM; NOVOSELAC, 2010). High exposure to biological dust is associated with higher odds of developing respiratory symptoms and airway obstruction (FARUQUE et al., 2021a). Airborne occupational exposures are associated with lower lung function levels, with effects more pronounced among males and smokers (FARUQUE et al., 2021b).

Occupational airborne exposure to quartz, asbestos, and dust or fumes increases the incidence of respiratory symptoms and asthma, independent of sex, age, educational level, smoking habits, and even pack-years, the latter being the amount a person has smoked over a long period (TOMAS; GULSVIK; BAKKE, 2002). While traditional occupational exposures such as asbestos and coal dust are still a concern, new exposures such as nanomaterials are increasingly emerging as a threat to respiratory health. Occupational respiratory diseases are preventable through approaches such as hazard substitution and local ventilation (CULLINAN et al., 2017).

Chronic respiratory diseases, including chronic obstructive pulmonary disease and asthma, are major contributors to the global disease burden, with an increase in prevalence over time. Chronic respiratory diseases accounted for 3.9 million deaths in 2017, an increase of 18.0% compared to 1990. Risk factors such as smoking, indoor and outdoor air pollution, and occupation-related exposure to dust and chemicals, are significant contributors to the burden of chronic respiratory diseases. Addressing these risk factors and implementing effective prevention can help reduce the burden of chronic respiratory diseases globally (SORAINO et al. 2020).

Various allergens can cause respiratory allergies, such as natural rubber latex, enzymes, cleaning agents, and pharmaceuticals. Some effects of these allergens are respiratory symptoms, skin rashes, and asthma. All these affect negatively healthcare workers, thus there is a need for proper diagnosis and recommendations for reducing exposure to allergens in the workplace, increasing awareness and action to protect healthcare workers from occupational respiratory allergies (MAZUREK; WEISSMAN 2016).

Work is linked to health and health disparities for individuals and societies. Psychological factors such as the benefits of a high-status job or the burden of perceived job insecurity, besides physical exposures to dangerous working conditions such as asbestos or rotating shift work, can generate health differences (BURGARD; KATHERINE, 2013). The prevalence of respiratory health symptoms and conditions is an important factor when choosing where to work.

Children who live in afro-descendant neighborhoods present a higher incidence of asthma rates, making noticeable health inequalities between African American and other children. It is due to disparities in environmental exposures, healthcare access, and socio-economic factors that are often associated with segregation (ALEXANDER; CURRIE, 2017) Ambient environmental pollution, pollution in the air outside of work, and occupational pollution, pollution in the workplace, can lead to an increased risk of respiratory diseases such as asthma, bronchitis, and lung cancer. Better monitoring and regulation of air pollution might help reduce the negative impact on public health (NISHIDA; YATERA, 2022).

Factors for a sustainable approach to occupational disease surveillance to protect workers from occupational respiratory diseases are needed. Adequate funding, collaboration with healthcare providers, and ongoing data quality assurance are important, besides the collection of high-quality data, the development of targeted prevention strategies, and the evaluation of the effectiveness of these strategies (HOY; BRIMS, 2022).

2.3 Least Healthy Sectors

Healthcare Workers are more exposed to airborne diseases such as influenza and tuberculosis because of close contact with infected individuals. Identifying specific hazards in a particular workplace and developing strategies to minimize exposure is important for risk assessment. The spread of airborne pathogens can be reduced through ventilation systems and air filtration, also safe work practices such as hand hygiene, disinfection, and proper handling of infectious materials protect the workers from airborne microbes leading to an improvement in occupational health (ÁLVAREZ, 2020). The high prevalence of burnout in healthcare workers can have a significant impact on patient care, healthcare costs, health and well-being of patients and workers. Factors such as long working hours, high workloads, and limited resources contribute to burnout (HERT, 2020).

A safe working environment is an important factor when choosing to work, some sectors such as construction, agriculture, and transportation emerged as the economic sectors with the highest mortality risk due to occupational accidents, followed by the fishing and forestry industries (MELCHIOR; ZANINI, 2019). Wholesale and retail trade sectors experience a high rate of nonfatal injuries and illnesses, overexertion being the most common cause, influencing lost productivity and medical expenses (ANDERSON et al., 2010). Workers in occupations such as construction and extractive trades reported wheezing and airway obstruction when compared to individuals in managerial and administrative jobs (MIRABELLI, 2012).

Workplace exposures have a significant impact on the development of nonmalignant respiratory diseases. About 15% of all adult-onset asthma cases in the United States are caused by workplace exposures, and many other respiratory diseases are also caused or worsened by workplace exposures, such as chronic obstructive pulmonary disease. Sectors like construction, manufacturing, agriculture, and health are associated with the highest risk of these respiratory diseases (BLANC et al., 2019).

Occupational asthma incidence has been attributed to cleaning agents, and it has not decreased over time, unlike the overall decline in asthma incidence for non-cleaning products. Occupations such as nurses present an increased risk of cleaning agent-attributed respiratory diseases. The use of safer cleaning products and the implementation of control measures might reduce exposure to harmful chemicals in the workplace (CARDER et al., 2019).

In the private industry employers from the U.S. reported 2.7 million nonfatal workplace injuries and illnesses in 2020, while in 2019 the number was higher, 2.8 million. Meanwhile reported respiratory illness cases in 2020 had a 4,000 percent increase, 428,700 cases compared to 10,800 cases in 2019. Looking at the economic sectors only health care and social assistance had an increase in total recordable cases for the number of nonfatal occupational injuries and illnesses when comparing 2019 with 2020. While cases with days away from work had increased for the same period for agriculture, forestry, fishing, and hunting, also manufacturing, wholesale trade, retail trade, transportation and warehousing, finance and insurance, real estate and rental and leasing, health care and social assistance, and other services (BLS, 2020a).

As for fatal work injuries, there were 4,764 in 2020, compared to 5,333 in 2019. The individuals were mostly white men between 45 and 54 years of age. Workers in transportation and material moving occupations and construction and extraction occupations accounted for almost half of all fatal occupational injuries. The administrative and support and waste management and remediation services also had a high number of fatal occupational injuries, 413 in 2020 and 498 in 2019. Accommodation and food services also had significant numbers 188 and 160, respectively in 2019 and 2020. Health care and social assistance, wholesale trade, retail trade, and other services also had several fatal injuries above a hundred for both years (BLS, 2020b).

Global occupational health and safety are associated with the dynamics of economic globalization. Millions of workers suffer from work-related illnesses and injuries worldwide. There is an unequal distribution of occupational health risks, with workers in low- and middle-income countries being particularly vulnerable to workplace hazards. Job sectors such as construction, agriculture, cleaning, and the restaurant industry attract more non-educated and poorly trained supervisors and workers who are migrants carrying unsafe behaviors across borders. The absence of global occupational health and safety infrastructure can amplify outcomes of infectious outbreaks like the Ebola pandemic and tuberculosis (LUCCHINI; LONDON, 2014).

2.4 Health and Work in the Context of the Pandemic

The exogenous factor to identify if an economic sector is the least healthy or not is an airborne disease. The novel coronavirus has made an economic impact without precedents, Great Depression in 1929 nor the 2008 recession together caused such economic collapse (FOSTER, 2020). The virus started spreading at Huanan Seafood Wholesale Market, in the city of Wuhan on December 2019 (ALANAGREH; ALZOUGHOOL; ATOUM, 2020). But recent studies have proven the first case happened in October or November 2019, meaning the virus did not emerge from the seafood market, but instead it was brought there, where the spread began significantly (HUANG et al., 2020). Until today most researchers in the field believe the novel coronavirus comes from bats, and these animals transmitted the disease to humans (ZHOU et al., 2020). It is alarming that the virus spreads contagiously passed on to others through saliva, coughing, sneezing, touching, or even by talking (NINGTHOUJAM, 2020).

To investigate how COVID-19 influenced the economic sectors is essential for the government and companies to promote future strategies for dealing with COVID, which has a major impact on employment, output, growth, and competitiveness. The economic impact of COVID infection has affected labor productivity (AHUMADA, 2022), and establishing new policies to diminish its detrimental impact on the investments and activities of both private and public sectors is critical (PADHAN; PRABHEESH, 2021).

Workers in medical occupations and health services are most exposed to infections and diseases than any other sector, whereas the education industry and retail trade activities are one of the most exposed due to physical proximity. The education sector, continued to be operated remotely, decreasing exposure to the virus. Other sectors that had remote work such as finance and insurance and professional services, which employ mostly younger workers were less affected. Males above the age of 50 were the ones mainly at risk of complications from COVID-19. Sectors with a higher level of physical proximity and exposure to diseases are the ones with a higher risk of contagion, such as the health sector (BARBIERI et al, 2022)

COVID-19 affected tremendously all economic sectors influencing all jobs across the job market. Some companies took on average five years to recover their contribution to the GDP after the recession in 2008. The recession caused by the pandemic in 2020 resulted in an even worse scenario, in which small businesses would take even longer than five years, while many others would never reopen, especially in the most affected economic sectors such as arts, entertainment, and recreation, accommodation and food services, educational services, transportation and warehousing, and manufacturing (DUA et al., 2020).

The pandemic resulted in a reduced workforce across all economic sectors in which many people lost their jobs. Some of the reasons for this were social distancing, self-isolation, and travel restrictions. Many schools closed down, and the price of petroleum decreased, while the need for medical supplies and the demand in the food sector increased. The health system was vulnerable, and the workers in the health sector had to be exposed to a high risk of contracting the virus. The tourism sector was one of the hardest hits by the pandemic, and the sports industry had its schedules altered, besides having games without present spectators. In contrast, in the information technology industry, the pandemic accelerated the process of many companies having turned toward technological solutions. With rigorous lockdown measures, the online game experienced an emergence of record numbers of players, while domestic violence increased. Many countries announced packages of emergency loans, rescue packages, financial aid, decreasing interest rates, and other financial help in attempting to save businesses and alleviate poverty caused by the economic disaster the world was facing because of the virus (NICOLA et al., 2020).

Nations that were better equipped started to ease quarantine, and the economy started opening slowly during May 2020, such as China, Singapore, South Korea, Austria, Germany, New Zealand, and many others (KUPFERSCHMIDT, 2020). Most people would only be safe with the vaccines after many patients went into clinical trials hoping for an efficient new drug against the virus (CONTICINI et al., 2020).

The relief came when the U.S. Food and Drug Administration issued the first emergency use authorization for the COVID-19 vaccine, allowing the Pfizer-BioNTech Covid-19 Vaccine to be distributed in the United States on December 11th, 2020. (FDA, 2020). Moreover, the world’s first COVID-19 was administered on December 8th, 2020 by the nurse May Parsons at University Hospital Coventry in England, on a 91-year-old patient, Margaret Keenan, spreading hope that the pandemic could soon be over. (RCN, 2020). Thereafter, the world started racing against time to save human lives by vaccinating as many people as possible in the least amount of time (NGUYEN et al., 2021), especially after the COVID-19 vaccines have been proven to be efficient (KIM; MARKS; CLEMENS, 2021).

The economic sectors were affected differently during the pandemic, some were hit harder economically or took more time to recover. Individuals who were living in worse conditions were negatively affected in many aspects, including the lack of proper sanitation, clean drinking water, and a private bedroom for isolation when needed after contracting the virus, all these factors challenged the possibility of survival.

As in any adversity, countries with more resources have an advantage compared to others countries that lack them. In many countries, coronavirus cases were underreported, especially in countries without enough testing kits for the population, such as Brazil (REIS et al., 2020). This last country needs close attention because almost 50% of the population does not have water treated or sanitary sewage (DIAS et al., 2018). With agglomerated people living in the slums. It is very worrisome that the people living in these communities barely have what to eat and no soap. Buying hand sanitizers or wearing a mask is not feasible, and when someone is infected, it is almost impossible to be isolated because they have to share bedrooms with others at home (LANGLOIS, 2020). To take the ones who contracted the virus to the hospital is mainly not a choice because the hospitals are overloaded (MCCOY; TRAIANO, 2020).

The state of Pernambuco is part of the northeast region, where family wages inequality is very present, and the capital Recife has populated slums that are clustered in many areas, only about half the population has access to treated water and a sewage system, besides it was one of the states with most cases of the novel coronavirus in Brazil (FRAGA, 2020). Many studies show that people living in more vulnerable places, especially in the slums, are more prone to contracting the virus, than in places with good infrastructure (CORBURN, 2020).

The first person to be vaccinated in Brazil was a 54-year-old black nurse living in East São Paulo on January 17th, 2021. (PATRICIA, 2021). And in the state of Pernambuco, the first person to be vaccinated for COVID-19 was a 52-year-old nursing technician from Recife on January 18th, 2021. (ALVES, 2021). According to the World Health Organization (2022), as of today April 14th, 2022, there have been 30,183,929 cumulative cases, 661,493 cumulative confirmed deaths by COVID-19, 22,724 new cases in the last 24 hours, and 403,869,527 vaccine doses have been administered with 73.77% of Brazil's population fully vaccinated for COVID-19, that are 156,799,524 persons fully vaccinated over the whole population 212,6 million (WORLD BANK, 2020).

In Recife, the capital of the state of Pernambuco, 1,408,069 are fully vaccinated, approximately 90% (CONECTA REFICFE, 2022), and Recife's population is 1,661,017 (IBGE, 2021). In Pernambuco 7,051,299 are fully vaccinated, 79,45%, (SES-PE, 2022), and the state's population is 9,674,793 (IBGE, 2021). According to the World Health Organization (2022), there are no vaccines for children below 5 years old, as of March 2022. For children between 5 and 11, the percentage of people who received the first dose in Recife has been low in February 2022, at approximately 34% (G1 PE, 2022).

Agriculture was one of the ones least affected because of its low need for physical proximity and disease exposure. Meanwhile, hotels and restaurants require a high level of physical proximity, but most of them had to shut down during the pandemic, thus the disease exposure was low. The control the spread of the virus, the Italian Government adopted social distancing measures, including two lockdowns on March 11th and 25th of 2020. Sectors such as the health and food industries had to be kept open, increasing the workers' risk of contagion, although there were distancing measures (BARBIERI et al., 2022).

During the pandemic, according to the International Labour Organization (ILO), approximately 89 million jobs in the European Union are in high-risk sectors, while women are employed in 43 percent of these sectors. Meanwhile, the European Centre for the Development of Vocational Training (CEDEFOP), suggested that 44 million jobs are in high-risk sectors, but with women representing 51 percent of the workers, that is because manufacturing was not considered to be exposed to the crisis in Europe, increasing even more gender inequality (PAPADIMITRIOU; BLASKÓ, 2020).

The International Labour Organization classifies the economic sectors according to the impact of the crisis on economic output, the economic sectors with high impact are wholesale and retail trade; repair of motor vehicles and motorcycles, manufacturing, accommodation and food services, and real estate; business and administrative activities. The medium-high are arts, entertainment and recreation, and other services, transport, storage, and communication. For the medium, construction, financial and insurance services, mining, and quarrying. The agriculture, forestry, and fishing sector are considered low-medium, and finally, the low economic sectors are human health and social work activities, education, utilities, public administration, and defense; compulsory social security.

The total estimated economic cost of the COVID-19 Crisis is more than $16 trillion for the United States, which accounts for about 90% of the annual gross domestic product of the country. If a family is composed of four members, the estimated loss would be approximately 200 thousand dollars, making the pandemic the worst threat to the U.S. economy since the Great Depression. New unemployment claims reached 1 million per week for 20 weeks beginning at the end of March 2020, which is greater than the 695 thousand unemployment insurance claims in the week of October 2nd, 1982, which had been the greatest registered so far (CUTLER; SUMMERS, 2020).

Factors such as income, occupation, housing, and access to healthcare are important contributors to COVID-19 outcomes. Individuals from lower-income and minority communities were disproportionately affected by the pandemic due to difficult access to healthcare, higher rates of pre-existing conditions, and increased exposure to the virus due to employment in essential industries (BANERJEE et al., 2022). COVID-19 disparities are influenced by different job characteristics and house composition which increases the individuals' health risk. Afro-descendants at high risk of severe illness were 1.6 times to live in households containing health sector workers than white. And 56.5% of them lived in households with at least one worker who could not work from home, compared to 46.6% among whites. Afro-descendants also outnumbered white workers who were employed in the essential sector, increasing their risk of contagion (THOMAS; BERDAHL, 2020).

Workers employed in the health and public safety sectors in Rio de Janeiro, Brazil were more vulnerable to the COVID-19 pandemic, especially non-white people and men (NEGRI et al., 2021). Also, the transport sector has been greatly affected due to restrictive measures on the mobility of the people to avoid public agglomerations and the spread of the virus (JUNIOR et al., 2021). Workers in economic sectors with a lower share of individuals working from home are exposed to a higher risk of contracting the virus, such as the food sector, agriculture, and health sector (CASTRO; MOREIRA, 2021).

Where people live influences how we can be protected from the virus. Even in times of lockdown, it is very hard to maintain social distance among residents inside the urban slums of India (WASDANI; PRASAD, 2020). In Brazil, it is not very different, the country faces challenges Europe doesn't, the agglomerations and poor living conditions inside the slums. Where social distance is almost impossible because the same room and bathroom must be shared with many other family members, besides the lack of basic sanitation, drinking water, or minimal hygiene. Hand sanitizers are a luxury for them because they can barely buy soap due to their socioeconomic conditions (PEREIRA, 2020). In this scenario, isolating someone who contracted the virus in the house is not an option, and if the symptoms evolve into something serious that needs assistance, most hospitals are overloaded with not enough intensive care unit (ICU) beds available (REQUIA, 2020).

The slums in Pernambuco are not different from this reality, there are over one thousand agglomerated slums, and 40% are in Recife, the state capital (MENEZES, 2013). Even worse, 72,3% of the state population does not have access to a sewage collection network, according to SNIS, *Serviço Nacional de Informações sobre Saneamento*, National Sanitation Information Service (BELFORT, 2019). The lack of access to water service and sewage collection by itself increases children's morbidity rates of certain diseases (MATTOS, 2019). When it comes to protecting from the novel coronavirus, all the hygiene precautions to control the spread cannot be easily taken by the population who does not have minimal decent standards of living. The social-economic factors of the population inside the slums are not favorable, and unfortunately, it will worsen with the pandemic, with an increase in unemployment, many people living in poverty, and extreme poverty (BUHEJI, 2020).

Health has always been an important factor in everyone's lives. But after COVID-19, health turned out to be a priority for many people. When choosing where to work, what sectors are most and least healthy is certainly an important element to consider. Over 70% of workers self-reported being in very good or excellent health in professional, scientific, and technical services, and also in education. Meanwhile, over 24% reported having fair or poor health working in the related sector of Human Health and Social Services. In Manufacturing, Food, accommodation, and transportation, over 15% self-reported fair or poor health. The average number of sick days over the course of a year is also important information. The Motor vehicles sector had the last sick days, 2.4, while the Finance sector had 2.2. While Health had 3.7, construction 3.8, public administration 3.8, and administrative activities 3.9. Health insurance coverage is also relevant when choosing where to work (ZEN, 2020).

Before the arrival of vaccines, lockdown measures were very relevant. While total shutdowns may be effective in reducing the spread of the virus, they come with significant economic and social costs. Targeted restrictions, such as closing certain types of businesses or limiting gatherings, may be more effective and less costly (CRONIN; EVANS, 2021). Mobility restrictions can be effective in reducing the spread of the virus, but disadvantaged communities face greater challenges in accessing healthcare and essential services during this period. Institutional inequalities must be taken into consideration to ensure a more equitable pandemic response (FAKIR; BHARATI, 2021).

Vaccination has been a crucial factor for labor recovery, by the beginning of October 34.5 percent of the people were fully vaccinated. Unfortunately, high-income and low-income countries presented a significant difference, 59.8 percent, and 1.6 percent, respectively. The hours worked and the downfall of productivity resulted in unprecedented unemployment affecting even more young people, especially young women. Fiscal stimulus packages have been indispensable for economic recovery, and low-income countries do not have the same options. On average, an increase in fiscal stimulus package of 1% of the annual Gross Domestic Product would have raised annual working hours by 0.3 percentage points by the first quarter of 2021 relative to the last quarter of 2019. As for economic recovery relative to vaccination, for every 14 persons fully vaccinated in the second quarter of 2021, 1 full-time equivalent job was added to the labor market globally. The recovery in low- and middle-income countries is even slower, because of slow vaccination, and fiscal constraints, besides risks of debt distress (ILO, 2021).

The Brazilian economy is recovering after COVID-19 with an unemployment level of 8.9%, and 9.7 million workers, in August 2022. Compared to the previous period closed in May, this is the lowest rate since the three months period ended in July 2015, 8.7%, and it is the lowest number of unemployed workers since November 2015 (INDIO, 2022). Brazil's GDP was expected to grow in 2022 by 1.7%, instead of 0.8% as the IMF had previously forecasted, while the world GDP is expected to grow by 3.2%, lower than forecasted before, 2.8%, because of the deceleration in China's economy and the war in Ukraine (IMF, 2022b).

According to Bill Gates, Covid-19 could be the last pandemic if a GERM team is created. Germ stands for global epidemic response and mobilization, this team would be composed of epidemiologists, data scientists, logistic experts, and communications with the priority of pandemic prevention, while its mission is to stop outbreaks before it becomes a pandemic. This group would be coordinated by the World Health Organization (WHO), stationed in different locations in public health agencies around the world. Drills would have to be frequent to practice until a new outbreak happens, until then, they would work on secondary infection disease, above all to strengthen countries' health systems, this latter being the front line. Stopping an outbreak in the first 100 days before it rises exponentially can save many lives, if this would've been done during COVID-19, 98% of the lives would've been saved.

Countries like Australia were quick with diagnostic capacity, distancing, and quarantine policies, resulting in an overall death rate per capita of less than a 10th of other countries. Although the vaccines were the miracles of this pandemic, new vaccines that are easier to deliver need to be developed for new outbreaks. Devices like Lumira, need to be made to diagnose individuals. In summary, to stop new outbreaks, there's a need for investment in three broad areas: disease monitoring, research and development, and improved health systems, the latter being the most expensive. The cost of preventing a new pandemic would be billions of dollars, but it's worth it because it would save trillions, as the IMF estimated that COVID has cost nearly 14 trillion dollars. If all these steps are taken, Covid-19 can be the last pandemic, building a healthier and equitable world for the people, and closing the health gap between the rich and the poor (GATES, 2022).

Methodology

3.1 Empirical Strategy

3.1.1 A Short Introduction to Discrete Choice Model

Everyone is making decisions every day from wake-up time until bedtime. A person might decide what to drink during breakfast drinking either tea or coffee or eating bread with eggs or cereal. When going to work taking public transportation may be an option for many people, or by car, or bike. And depending on where an individual lives public transportation might include buses and the metro. When choosing between these options, everyday consciously or subconsciously, the person thinks about the weather, the road traffic, commuting time, and also the cost. Discrete Choice models help to analyze and predict the individual's behavior when deciding which option is the best.

Besides what to eat during breakfast or how to commute to work, the electricity run by the environment we live in is another behavioral choice. Renewable energy is more environmentally friendly, which is better for the environment and it helps control climate change. There's a cost for each energy, and many renewable energies are more expensive than non-renewable ones, although a lot of individuals are willing to pay more to help the environment. These trade-offs can be quantified by discrete choice models.

Not all choices are rational, some consumers buy objects based on individual preferences or brands, like cars, computers, smartphones, apartments, or houses to live in by renting or owning one, and even choosing a city or country to live in. These models also help to quantify these preferences. As counterintuitive as it might be the consumer choice, it's an individual choice that can be quantified by these models. The Discrete Choice Model accounts for the individual's behaviors when choosing one option over the other, and the chosen option can be quantified, analyzed, and predicted by the set of consumer choices.

The Discrete Choice Model uses Random Utility Model as the theoretical framework with applications in many empirical models such as Probit, Logit, Multinomial, and Conditional Logit. The Random Utility Model provides Economic interpretation for the Discrete Choice Models, and former Nobel Laureate Daniel McFadden derives the model to apply the Econometrics approach (MCFADDEN, 2000) with many applications (MCFADDEN, 1978a), (MCFADDEN et al., 1978b), (MCFADDEN, 1974b).

Discrete choice sometimes referred to as qualitative choice models are mostly used when there are alternatives, usually chosen or given because of a finite number of options.

Models with two alternatives for the outcome are binary models, and with more than two alternatives, they are called multinomial discrete choice models. Logit models use a logistic distribution function, while probit models use a standard normal distribution function. The logit model is an alternative to the probit model, the first has become more popular in recent decades since its distribution function is easier to work with. Both models estimate their parameters through maximum likelihood, the two models are an example of binary models, in which the outcome variable has possible outcomes of 1 or 0. When three or more alternatives in the choice set are considered, multinomial logit models are used (ALDRICH; NELSON, 1984). The objective of discrete choice modeling is to analyze how firm and individual factors influence the incidence of an individual working in the least healthy economic sector. The individuals have the choice to work in the sector, as well as the firms have the choice to employ the workers.

3.1.2 Discrete Choice Model

Measuring the value of non-marketed commodities like working in healthier conditions is a dilemma in health economics. The most common approach, wage-hedonics, recognizes that any kinds of amenities are characteristics of locations in which individuals can choose to live, work, and enjoy leisure time (HWANG et al., 1998). The technique uses information about an individual's choice of location and the tradeoffs between wages and (un)desirable firm attributes implicit in that choice (TIMMINS, 2007). Specifically, the individual is assumed to choose the place to work that maximizes his utility given the bundles of attributes that define the set of jobs in his choice set. Ceteris paribus, the individual who chooses to work in a firm with an undesirable health condition must do so because he is as well-off as he would be in a firm with a preferred health condition by receiving a better bundle of other job attributes.

Assuming that individuals can move freely between jobs, wage-hedonic theory suggests that incomes and prices for locally traded commodities will adjust so that all individuals achieve a common level of utility, V*, in equilibrium (ROBACK, 1982). Willingness-to-pay for a small change in a job attribute (e.g., C_j = health condition in location j) around this equilibrium can then be measured with the amount of wage the individual is willing to sacrifice in exchange for a marginal increase in C_j, holding fixed utility and choice of job. The technique developed in this thesis uses variations in labor markets, and settlement patterns to estimate the odds of a person working in an unhealthier firm and how it increases the incidence of contracting COVID-19.

A non-health condition is present in economic sectors where the individuals present a higher chance of contracting airborne contagious diseases, such as COVID-19, these economic sectors are the least healthy firms. In environments where agglomeration is present, the virus is spread easily, and individuals working in economic sectors with direct contact with other co-workers have a higher chance of being exposed and catching the virus (MA et al., 2021).

An individual chooses an economic sector given if it is least healthy or not, the chances of contracting the virus in different economic sectors vary. The variable C_j is not in the equation (3.1) because whether an environment has a good health condition or not, is determined by the number of individuals who tested positive for the virus in a specific economic sector, exogenous to the model, besides the individual chances of contracting the virus is captured by the healthier conditions variable mentioned next.

The model of optimal individual firm choice begins with the specification of utility. The utility, $U_{i,j,k}$, that an individual i of type k (defined by a vector of observable attributes) receives from working and optimally spending commuting time in firm j is assumed to be determined by his wage ($W_{i,j,k}$); the commuting distance that i would have needed to travel to work in firm j given his home location ($D_{i,j,k}$); healthier conditions ($H_{i,j,k}$); individual characteristics (X_{ik}); firm observed attributes ($Z_{i,j,k}$); firm unobserved attributes ($\varphi_{j,k}$); and an idiosyncratic stochastic component ($v_{i,j,k}$):

$$U_{ijk} = \beta_{0k} W_{ij}^{\beta_{Wk}} D_{ij}^{\beta_{Dk}} X_i^{\beta_{Xk}} Z_{ij}^{\beta_{Zk}} e^{H_{ijk}\beta_{hk}} e^{\varphi_{jk}} e^{v_{ijk}} \tag{3.1}$$

$\varphi_{j,k}$ is allowed to vary with firm and individual type, while $v_{i,j,k}$ differs with the firm and the particular individual. Flexibility is introduced into the utility function once the parameters are allowed to vary with individual type:

$$\beta_{\cdot k} = \beta_{\cdot 0} + \beta_{\cdot 1} z_{ik} \tag{3.2}$$

where $z_{i,k}$ is a vector of individual attributes that define i to be of type k. An individual's type is taken to be exogenous to the model. The indirect utility function is:

$$lnV_{i,j,k} = \beta_{0k} + \beta_{Wk} lnW_{i,j} + \beta_{Dk} lnD_{i,j} + \beta_{Xk} lnX_i + \beta_{Zk} lnZ_{ij} + H_{ijk}\beta_{hk} + \varphi_{jk} + v_{ijk} \tag{3.3}$$

v_{ijk} is assumed to be distributed i.i.d. Type-I extreme value across firms and individuals for all those of a particular type k. The modeling assumptions imply the following probability that a type-k individual chooses to work in firm j:

$$P(lnV_{i,j,k} \geq lnV_{i,l,k} \forall l \neq j)$$
$$= \frac{EXP\{\beta_{0k} + \beta_{Wk} lnW_{i,j} + \beta_{Dk} lnD_{i,j} + \beta_{Xk} lnX_i + \beta_{Zk} lnZ_{ij} + H_{ijk}\beta_{hk} + \varphi_{jk} + v_{ijk}\}}{\sum_{l=1}^{j} EXP\{\beta_{0k} + \beta_{Wk} lnW_{i,l} + \beta_{Dk} lnD_{i,l} + \beta_{Xk} lnX_i + \beta_{Zk} lnZ_{il} + H_{ilk}\beta_{hk} + \varphi_{lk} + v_{ilk}\}} \tag{3.4}$$

So that, given a large number of type-k individuals (H_k), their equilibrium population in firm j where the individual works are determined by

$$pop_{j,k} = H_k P(lnV_{i,j,k} \geq lnV_{i,l,k} \forall l \neq j) \tag{3.5}$$

There are firms with better healthier characteristics than others, where workers work in an environment with healthier conditions, which means there is a lower chance of contracting the virus. The economic sector the individual works in is more or less the propensity of contracting disease by transmission. Some economic sectors present a higher risk of airborne disease transmission, such as the health sector, where workers in this field mostly work in hospitals with patients that are already sick. Also in the education sector, where students and teachers meet in person and talk to each other in a classroom. Contracting COVID-19 might happen either way, commuting from home to work, or inside the firm while working, where the chances of contracting the virus in the last option depend on the economic sector in the individual works. The distance in equation (3.1) is an important factor because individuals with higher commuting distances take longer trips from home to work, being more exposed to the virus. Especially for the workers who use public transportation and share agglomerated buses, the longer the commuting distance, the higher the chance of infection with the use of public transportation during commuting time (ANDO et al., 2021).

The microdata is combined with data from Pernambuco State Health Department 2020 and RAIS 2019. The individual characteristics, X_i from (3.1) are composed of the following variables: Age, Men, Non-White, Complete Primary Education, Complete Secondary Education, Nominal Wage, Working Hours, Job Tenure, and Distance. The variables Men, Non-White, Complete Primary Education, and Complete Secondary Education are dummy variables. The firm characteristics Z_{ij} in equation (3.1) are composed of a dummy variable Employment Type CLT, Consolidation of Brazilian Labor Laws (DTTL, 2020), a categorical variable Establishment size ranging from 1 to 10, and another dummy Lockdown variable.

Again, the thesis's general objective is to analyze how individual and firm factors influence a person to work in the least healthy sectors using firms' and workers observed and non-observed characteristics using a Discrete Choice Model. The least healthy sector is measured by the number of infected people with COVID-19. The economic sectors of CNAE are Accommodation and Food, Administrative Activities and Complementary Services, Arts Culture Sports and Recreation, Construction, Education, Electricity and Gas, Financial Insurance and Related, Human Health and Social Services, Information and Communication, Other Service Activities, Processing Industries, Professional Scientific and Technical Activities, Public Administration, Defense and Social Security, Real Estate Activities, Trade; Repair of Motor Vehicles, Transportation Storage and Mail, and Water Sewage Waste Management.

The Lockdown variable is also a dummy variable for each economic sector. Lockdown measures led to a decline in economic activity across all sectors, but the reduction was more significant in non-essential sectors. Since the essential sectors were exempted from a national lockdown, workers in these sectors presented a higher risk of contagion (PORTO et al., 2022). Societies more geographically mobile have less strict policy interventions on human mobility during the pandemic. During the early stages of the pandemic, the policy interventions reduced human mobility effectively, including school closures, workplace closures, and stay-at-home orders. The effectiveness of these policies in reducing mobility declined, possibly due to pandemic fatigue and changes in individual behavior (CEPALUNI et al., 2022).

The essential economic activities were defined according to the Government of Pernambuco, and it was divided into economic activities (MOROSINI, 2021). The essential activities did not experience lockdown in 2020 or 2021, although some restrictive measures were applied, such as distance, wearing masks, and hand sanitizers. The Economic activities are based on the Brazilian National Classification of Economic Activities revision 2.0 (CNAE 2.0), which is based on the International Standard Industrial Classification (ISIC, rev. 4).

The economic activities that experienced lockdown are Accommodation and Food, Administrative Activities and Complementary Services, Arts Culture Sports and Recreation, Construction, Education, Financial Insurance and Related, Information and Communication, Professional Scientific and Technical Activities, Public Administration, Defense and Social Security, Real Estate Activities, and Other Service Activities.

Meanwhile, the economic activities that did not experience lockdown are essential activities such as Electricity and Gas, Human Health and Social Services, Processing Industries, Trade; Repair of Motor Vehicles, Transportation Storage and Mail, and Water Sewage Waste Management. All these essential and non-essential economic sectors mentioned are predictors estimated in the thesis model.

To estimate the Conditional Logit Model, a *choice* variable is created on a separate column indicating from what economic sector the individual belongs to, also another column for a variable called *mode* with all the available economic sectors. And for each separate economic sector, a column with each economic sector's name is created with dummy variables indicating if the individual falls into the specific economic sector. An *id* column also is created indicating the individual, and the *id* rows repeat themselves in the same number of the economic sectors. In the current model, there are 13,784 *id'*s, number of cases, and 41,352 observations. Each individual is repeated in the data 17 times, which is the number of economic sectors.

For the current thesis data, no column variable varies for each row when the *id* is repeated, making the model unable to be estimated. To identify the odds of an individual working in the least healthy sector, the Alternative-Specific Conditional Logit Model is estimated, known as McFadden's choice model. McFadden's choice model is a specific case of conditional logistic regression (MCFADDEN, 1974a). This Discrete Choice Model presents minor changes based on Cameron and Trivedi (2010) and Kenneth (2009) and presented in the Stata Manual (STATACORP, 2015).

McFadden's choice model presents a set of unordered alternatives indexed by *1,2,…,J*. If y_{ij}, j = 1,…,J, is an indicator variable for the alternative chosen by the *i*th individual (case). This means the *id* variable is the case, for the current model, 13,784 individuals. Then, $y_{ij} = 1$ if individual i chose alternative j and $y_{ij} = 0$, otherwise. The main difference between the traditional Conditional Logit Model and this McFadden's choice model is that the independent variables come in two forms: alternative-specific and case-specific. The Alternative-specific variables vary among the alternatives, as well as the cases, and the case-specific variables vary only among cases.

Thus, for the thesis's model, the Alternative-specific variable is the *mode* column variable, the *mode* lists all economic sectors for each individual, *id*, then repeats for the next individual. The case-specific variables are the variables that do not vary for each individual, it only varies among cases, that is among different individuals or *id'*s. The case variables are Age, Men, Non-White, Complete primary education, Complete secondary education, Nominal

Wage, Working hours, Job Tenure, Distance, Employment Type CLF, and Establishment Size. Job Tenure is how long a worker has been working in the same job measured in months, and distance is the distance between the CEP an individual lives and his work. Some variables are common to the ones chosen by Negri et al. (2021). To estimate their logistic models, the authors kept the variables they thought were most important, containing individuals' information by combining the RAIS 2018 database and the Rio de Janeiro State Department of Health.

This means for each individual, *id*, these case variables repeat 16 times for the same individual, and the same id is shown 17 times through 17 rows. The base alternative option is one of the CNAE economic sectors that is a base to be compared to relatives, and the base alternative chosen is the economic sector of Human Health and Social Services. Finally, the vector U_{ijk} quantifies the utility the individual gains from the j alternatives. Individual *i* chooses the alternative that maximizes utility, and this maximization is done by the Maximum Likelihood Estimator.

Work stressors, such as job strain and long working hours, are associated with a higher risk of heart disease and stroke. Managing work stress is an important way to prevent cardiovascular disease and improve overall health (KIVIMÄKI; KAWACHI, 2015). Interventions such as stress management might be effective to improve employees' well-being in the workplace, increasing job satisfaction, and enhancing organizational performance (KLINK et al., 2001). Since long working hours are a work-related stress factor that influences overall health and well-being in the workplace, the variable Working Hours is used as a predictor in the model.

The individual has a work choice decision as to what economic sector to work in, working in the least healthy sector and commuting distance is a disutility in the function. The commuting distance impacts the individual's choice of what economic sector he works in, conditional on if the sector is the least healthy and to his characteristics, as well as the firms. People with higher commuting distances have a greater opportunity cost to choose where to work.

Larger metropolitan areas have higher levels of productivity due to the benefits of agglomeration. However larger cities present more congested commuting, which can reduce worker productivity (RAPPAPORT, 2016). The variable Distance is a predictor in the model, and it measures the distance from home to work. Since commuting distance is an important factor for the employee's well-being and productivity, workers face the trade-off between productivity and congestion. Flexible work arrangements can lead to reduced commuting time and less congestion during peak hours, leading to increased urban productivity by reducing the time and costs associated with commuting (MUN; YONEKAWA, 2006).

Workers are more inclined to accept a job located farther away from home if they can work from home (VOS et al., 2018). An increase in the rate of traffic congestion leads to low productivity. There is an inverse relationship between traffic congestion and workers' productivity, resulting in increased lateness, absenteeism, and reduced work hours (SOMUYIWA et al, 2015). The nearness to job opportunities can have an impact on various economic and social results, ranging from the financial well-being of the local area to the employment possibilities for residents, particularly those who are from low-income and minority backgrounds (KNEEBONE; HOLMES, 2015).

A high proportion of the elderly has reported poor self-rated health, resulting in income-related health inequalities. The residence was a determining factor responsible for the inequality, especially for older females who lived in rural areas, high higher commuting to the urban center. Health insurance schemes targeted at the elderly could reduce income disparities among this group (GU et al., 2019).

Therefore, greater commuting from home to work decreases the options a worker has regarding what economic sector to work in, compared to other individuals who live closer to the central business district. This mobility constraint is responsible for disparities in income, affecting especially the people who earn lower nominal wages, making it difficult to decrease inequality. The freedom of where to live influences the choice of which economic sector to work in, thus affecting the chances of contracting covid, so the immobility of poorer individuals with higher commuting distances decreases the chance of choosing to work in a healthy economic sector further away from home, which increases the chances of catching COVID-19.

And as commuting distance decreases, house prices tend to increase near the central business district, making people face the tradeoff between choosing between higher house prices closer to the CBD and less commuting distance or lower house prices further away from the CBD, but the higher commuting distance (BRATU et al., 2023). Either way, the less privileged population has a higher opportunity cost to choose where to work in. The individual is choosing the economic sector in the function of the wage's utility and disutility of health conditions that work can offer, the latter is measured by considering the least healthy sectors the ones with the most positive cases of COVID-19.

3.2 Dataset

3.2.1 Overview

Information on individual corona cases for the state of Pernambuco comes from SES-PE, Secretaria Estadual de Saúde do Estado de Pernambuco (Pernambuco State Health Department). The data contain variables such as age, sex, address, CPF (Cadastro de Pessoa Física – Individual Taxpayer Registry), and other variables. RAIS is the Annual List of Social Information (Relação Annual de Informações Sociais), this individual microdata has many labors information for the formal sectors, including which economic sector an individual works in, age, sex, how long an individual has been in the same job, in addition to other variables. Because the RAIS also contains CPF, the same individual from both data, SES-PE and RAIS, were matched through CPFs, resulting in one merged data.

The Ministry of Labor and Welfare (Ministério do Trabalho e Previdência) is responsible for RAIS every year since it was established by Decree number 76,900 of 12/23/75. And it aims to: supply the needs of controlling labor activity in the country, the provision of data for the elaboration of labor statistics, and the availability of information on the labor market to government entities. The data collected by RAIS constitute significant inputs to meet the needs: from the legislation on nationalization of work, control of FGTS Fundo de Garantia do Tempo de Serviço – Severance Indemnity Fund for Employees) records, the Collection and Concession Systems, and Social Security Benefits, technical studies of a statistical and actuarial nature; identification of the worker entitled to the PIS/PASEP (Programa de Integração Social – Program of Social Integration, which aims to finance the unemployment insurance system/ Programa de Formação do Patrimônio do Servidor Público – Civil Service Asset Formation Program, destined to public servants) salary bonus (RAIS, 2022).

The individual microdata from RAIS is not open and to obtain it there's a need to request the government for it, not everyone can request it. There's a list of bureaucracies and it takes time, for the government to send the microdata when they agree to send it. The microdata is usually available for request with more than one year of delay, thus, the year presented in this data analysis is 2019.

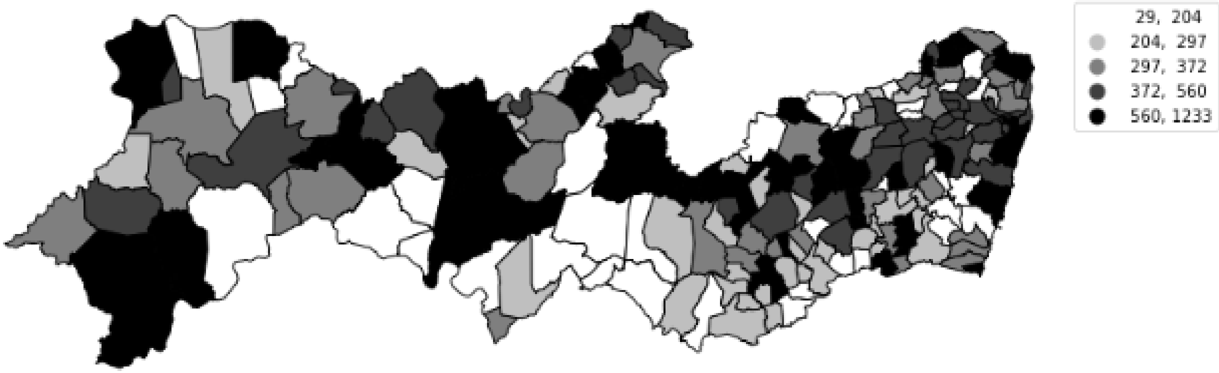
Brazil is composed of 26 states and a federal district. The RAIS for the state of Pernambuco was first extracted from the RAIS Northeast, microdata with all states from the Northeast region, over 10,000,000 observations. The RAIS individual microdata for Pernambuco contains 2,132,196 observations and 830,030 for Recife. Some of the columns are the municipality, CNAE 2.0 class one-digit identified by the alphabet (Classificação Nacional de Atividades Econômicas – National Classification of Economic Activities, economic sector) (CONCLA, 2021), based on the International Standard Industrial Classification (ISIC, rev. 4), CBO main subgroup identified by two-digits, (Classificação Brasileira de Ocupações – Brazilian Classification of Occupation, occupation), schooling years, sex, race, job tenure, name, age, date of birth, CEP (Código de Endereçamento Postal – Postal Addressing Code, zip code), CPF (Cadastro de Pessoa Física - Individual Taxpayer Registry, identification), and many others. The latter is used to merge with the microdata from Pernambuco State Health Department, which also has microdata containing the individual's CPF.

The microdata from Pernambuco State Health Department has information from the beginning of the first case in Pernambuco, beginning on March 12th, 2020, until May 8th, 2021. Most of the data does not contain many severe cases, thus the number of deaths is low, 83,063 out of 1,565,705, 5,3% in the original microdata. The data contains all municipalities in Pernambuco, although the focus of the thesis will be on Recife when running the model. The original microdata contains 1,565,705 rows and 104 columns with much different information such as telephone, name, e-mail, final test result, municipality, bairro (community or region within a city or municipality), CEP, age, race, sex, and many other variables, including CPF, that was used to merge with the individual microdata from RAIS. The CEPs from each individual were used to find the latitude and longitude. After merging RAIS 2019 data with SES-PE, the observations for are dropped to 252,397, and to approximately 86,000 for Recife.

The original microdata files were in .csv format, and most of the work was done using Python 3.9, including finding latitude and longitude from the individual CEPs and also from the individual establishments, finding the distance from home to CBD (Marco Zero, center of Recife), then the distance from work to CBD, and the distance from home to work, besides organizing the data, cleaning, most of the graphs and tables. The regression results were done using Stata 15.

3.2.2 Maps with Coordinates

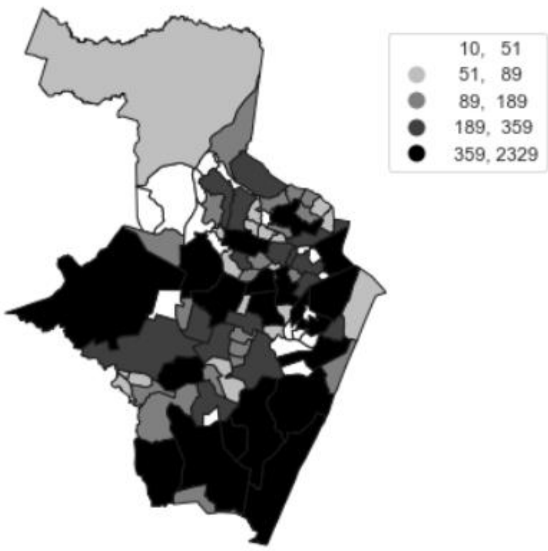
Figure 3.1 – Covid Rate in Pernambuco March 12th 2020 – May 8th 2021



Source: Elaborated by Author

The covid rate for the state of Pernambuco is displayed in Figure 3.1. To create the map the positive cases are summed and grouped by each municipality. Then, to measure the covid rate, all covid positive cases for each municipality are divided by the total population for each municipality estimated by IBGE, Brazilian Institute of Geography and Statistics, for the year 2020, and then multiplied by 100 thousand. All positive cases sum to 63,618 for the whole state of Pernambuco. So, Figure 3.1 represents the Covid rate for each municipality in the state of Pernambuco, which means the number of covid positive cases by 100 thousand individuals.

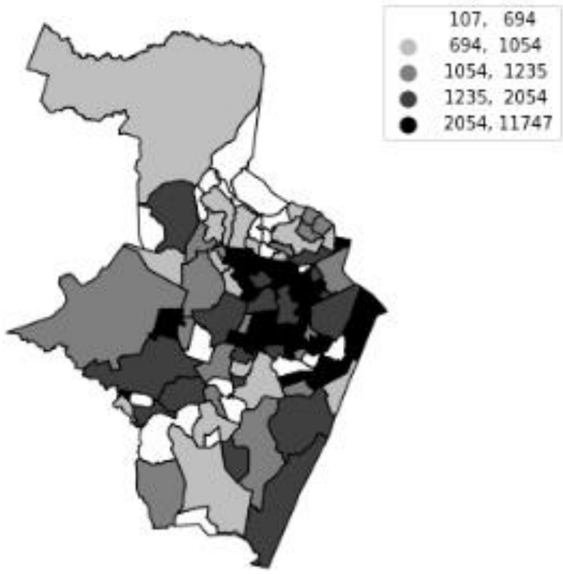
Figure 3.2 – Covid Cases in Recife March 12th 2020 – May 8th 2021



Source: Elaborated by Author

In Figure 3.2 the covid positive cases for the municipality of Recife are shown, and the darker areas be easily spotted. All positive cases are summed and grouped by each *bairro,* all *bairros* positive cases sums up to 21,321 positive cases for the whole municipality of Recife. On the extreme bottom of the map on the right side is Boa Viagem, the most populated *bairro* with 122,9 thousand people, still on the bottom left is located Cohab, 67,28 thousand, Ibura, 50,6 thousand, Imbiribeira, 48,5. On the west middle of the map is Várzea, the second most populated *bairro* with 70,4 thousand people. The *bairros'* populations are according to the last Census (IBGE, 2010).

Figure 3.3 – Covid Rate in Recife March 12th 2020 – May 8th 2021

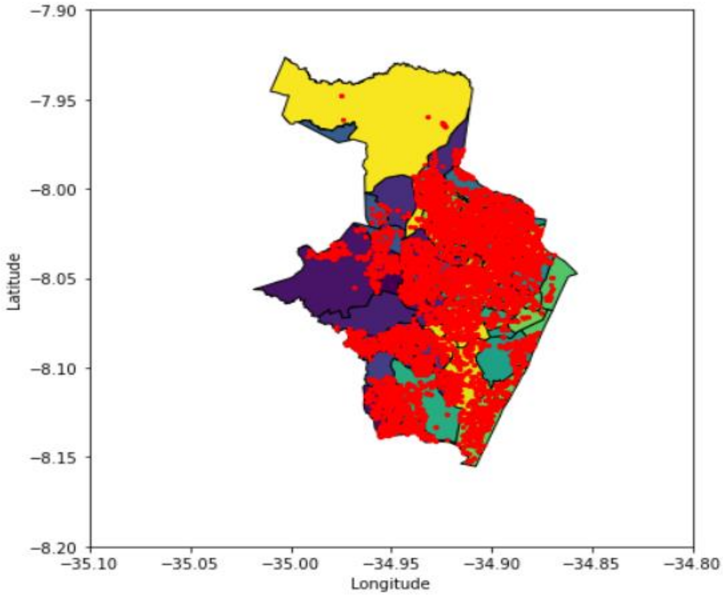


Source: Elaborated by Author

The covid rate for the *bairros* is measured by all covid positive cases for each *bairro* divided by the total population for each *bairro*. Unlike the estimation for each municipality that is done every year by IBGE, the estimation for each *bairro* is done in the Census that happens every ten years, IBGE is also responsible for the Census. The last Census happened in 2010, and the following Census happened in 2022, the two-year delay was because of budget constraints and the pandemic. Then, to measure the covid rate for each *bairro* a rule of three using direct proportion is used.

Recife's population was 1,537,704 in 2010 and 1,653,461 in 2020. One of the *bairros* Aflitos had a population of 5,773 in 2010 as disclosed in the Census by IBGE. The same *bairro* population is not known for 2020. Since, there's a direct proportion between time and population increase, at least for Recife, then Aflitos' population in 2020 can be estimated by multiplying Aflitos' population in 2010, 5,773, by Recife population in 2020, 1,653,461, and dividing by Recife's population in 2010, 1,537,704, which results in the estimated population for 2020 of 6,208 individuals for Aflitos in 2020. The same logic is applied to all the bairros. And to measure the covid rate, the same calculation was done as for the municipalities, taking all covid positive cases for each *bairro*, dividing it by the total population for each *bairro* in 2020, and multiplying it by 100 thousand, resulting in the number of covid positive cases by 100 thousand individuals presented in Figure 3.3. And Figure 3.4 represents the latitude and longitude georeferenced by individuals' CEP for Recife, where they live.

Figure 3.4 – Covid Cases by Individuals' CEP Coordinates Recife Shapefile



Source: Elaborated by Author

3.2.3 Data Analysis

Table 3.1 – Summary Statistics for Individual Characteristics Positive Cases

Variables	mean	std	25%	50%	75%	100%
Age	47.13	13.05	44.00	50.00	56.00	103.00
Men	0.44	0.50	0.00	0.000	1.00	1.00
Non-white	0.47	0.50	0.00	0.000	1.00	1.00
White	0.28	0.45	0.00	0.000	1.00	1.00
Uninformed race	0.25	0.43	0.00	0.000	0.00	1.00
Incomplete primary educ.	0.07	0.25	0.00	0.000	0.00	1.00
Complete primary educ.	0.43	0.50	0.00	0.000	1.00	1.00
Complete secondary educ.	0.47	0.50	0.00	0.000	1.00	1.00
Complete higher educ.	0.03	0.17	0.00	0.000	0.00	1.00
Nominal Wage	4,619.08	6,461.75	1,276.84	2,049.35	5,250.19	71,141.70
Minimum Wage	4.62	6.47	1.27	2.04	5.25	71.28
Working hours	37.75	8.82	36.00	40.00	44.00	44.00
No Working Days	11.60	40.88	0.00	0.00	0.00	365.00
Job tenure	127.05	126.12	21.73	82.90	192.90	567.90
Distance	5.15	3.01	2.79	4.93	72.30	20.71

Source: Elaborated by Author

Table 3.1 presents the summary statistics for individual characteristics for positive cases containing 13,806 observations, and displays the variables and their respective mean, standard deviation, 25%, 50%, 75%, and 100% percentile. The number of observations dropped after cleaning the data and filtering for only the positive cases. The minimum column is eliminated because roughly all minimum values are zero. The mean for Age is 47.13, while 44% of the data are Men, Non-white 47%, White 28%, and Uninformed race 25%. For the Discrete Model Choice, a dummy Non-white is used, 1 for being Non-white, and 0 otherwise.

As for schooling, Complete primary education represents 43% of the data, and Complete secondary education 47%. Because Complete higher education represents only 3% of the data, it is not inserted in the model because its low number does not allow the model to converge. The Nominal Wage mean is R$4,619.08 and the Minimum Wage mean is 4.62, the latter variable is kept for the model. The other two variables presented are Working hours and No Working Days, with respective means of 11.60 and 127.05. The Working hours are related to the hours the employees worked, and No Working Days, are the number of days the individual has not been working since his or her last job. The Distance mean is 5.15, it is the location from his home to his work, and both were georeferenced using CEP.

Table 3.2 – Summary Statistics for Economic Sectors Positive Cases

Variables	mean	std	25%	50%	75%	100%
Accommodation And Food	0.03	0.17	0.00	0.00	0.00	1.00
Administrative Activities and Comp. Services	0.10	0.29	0.00	0.00	0.00	1.00
Agri., Livestock, Forestry Product., Fishing and Aqua.	0.01	0.04	0.00	0.00	0.00	1.00
Construction	0.02	0.15	0.00	0.00	0.00	1.00
Education	0.09	0.29	0.00	0.00	0.00	1.00
Electricity And Gas	0.01	0.09	0.00	0.00	0.00	1.00
Extractive Industries	0.00	0.01	0.00	0.00	0.00	1.00
Human Health and Social Services	0.11	0.32	0.00	0.00	0.00	1.00
Information And Communication	0.02	0.15	0.00	0.00	0.00	1.00
Other Service Activities	0.02	0.15	0.00	0.00	0.00	1.00
Processing Industries	0.03	0.16	0.00	0.00	0.00	1.00
Professional, Scientific and Technical Activities	0.02	0.15	0.00	0.00	0.00	1.00
Public Administration, Defense and Social Security	0.33	0.47	0.00	0.00	1.00	1.00
Trade; Repair of Motor Vehicles and Motorcycles	0.14	0.34	0.00	0.00	0.00	1.00
Transportation, Storage and Mail	0.03	0.17	0.00	0.00	0.00	1.00
Water, Sewage, Waste Management and Decont. Act.	0.01	0.07	0.00	0.00	0.00	1.00
Arts, Culture, Sports and Recreation	0.01	0.09	0.00	0.00	0.00	1.00
Real Estate Activities	0.01	0.06	0.00	0.00	0.00	1.00
Financial, Insurance and Related Services Activities	0.03	0.16	0.00	0.00	0.00	1.00

Source: Elaborated by Author

Table 3.2 has the same 13,806 observations displaying the summary statistics for economic sectors. The three sectors with the highest means are Public Administration, Defense and Social Security, representing 33% of the data, followed by Trade; Repair of Motor Vehicles and Motorcycles, 14%, and Human Health and Social Services, 11%. This representation can also be verified in Figure 3.13. Due to the very low number of individuals working Extractive Industries sector, representing only 0.00724%, it was excluded from the estimations. The same for Agriculture, Livestock, Forestry Production, and Aquaculture representing only 0.152% of the data.

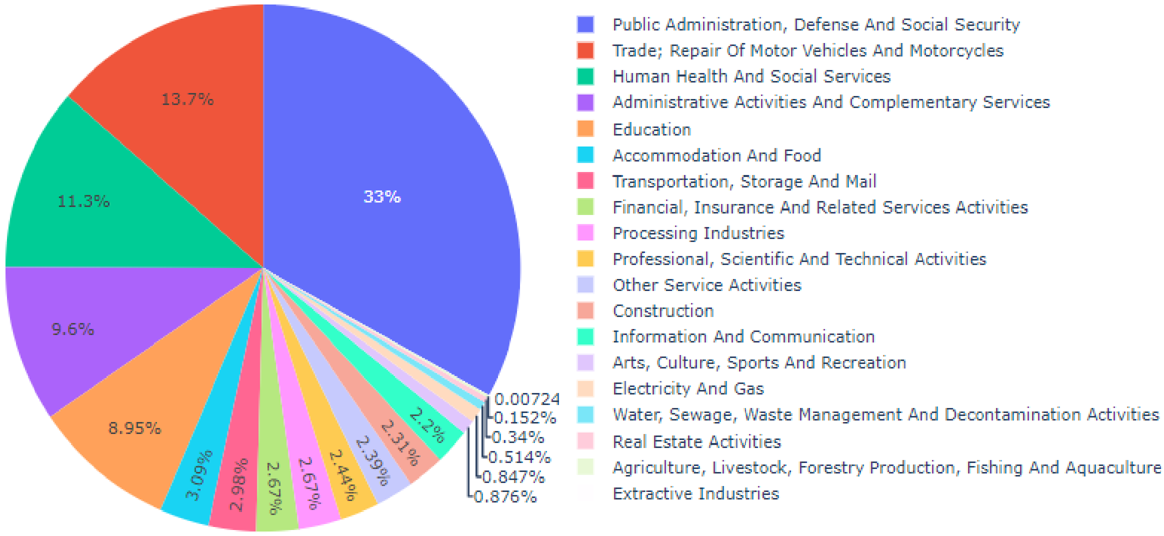
Table 3.3 – Summary Statistics for Firm Characteristics Positive Cases

Variables	mean	std	25%	50%	75%	100%
Establishment Size	7.35	2.81	5.00	8.00	10.00	10.00
1 to 4 Employees	0.01	0.10	0.00	0.00	0.00	1.00
5 to 9 Employees	0.06	0.23	0.00	0.00	0.00	1.00
10 to 19 Employees	0.06	0.24	0.00	0.00	0.00	1.00
20 to 49 Employees	0.08	0.27	0.00	0.00	0.00	1.00
50 to 99 Employees	0.10	0.30	0.00	0.00	0.00	1.00
100 to 249 Employees	0.06	0.25	0.00	0.00	0.00	1.00
250 to 499 Employees	0.08	0.27	0.00	0.00	0.00	1.00
500 to 999 Employees	0.06	0.24	0.00	0.00	0.00	1.00
1000 to 4999 Employees	0.07	0.25	0.00	0.00	0.00	1.00
5000 or above	0.42	0.49	0.00	0.00	1.00	1.00
Type Employment CLT	0.54	0.50	0.00	1.00	1.00	1.00
Type Employment Statutory Employee	0.01	0.10	0.00	0.00	0.00	1.00
Type Employment Other	0.45	0.50	0.00	0.00	1.00	1.00
Legal Nature Public Sector	0.36	0.48	0.00	0.00	1.00	1.00
Lockdown	0.68	0.47	0.00	1.00	1.00	1.00

Source: Elaborated by Author

Summary statistics for firm characteristics for positive cases are displayed in Table 3.3. The variable Establishment Size has a mean of 7.35, and it is a categorical variable ranging from 1 to 10. While 1 is 1 to 4 Employees, 10 means there are 5000 employees or above, while 2 to 9 represents the division between the categorical variables as presented in the same table. As for Type Employment, there are three categorical divisions, CLT, Statutory, or Other, with respective means of 0.54, 0.01, and 0.45. For the Discrete Choice model, a dummy variable is created indication if the employee is CLT or not. The Legal Public Sector is another dummy variable with a mean of 0.36, which means 36% of the employees work in the public sector, while the rest of 74% do not. Lockdown is important, because the economic sectors that did experience lockdown in 2020, mean of 0.68, were less exposed than the economic sectors that did not have it, exposing more of the individuals working in the sector to virus infections.

Figure 3.5 – CNAE Economic Sectors by Percentage of Positive Cases



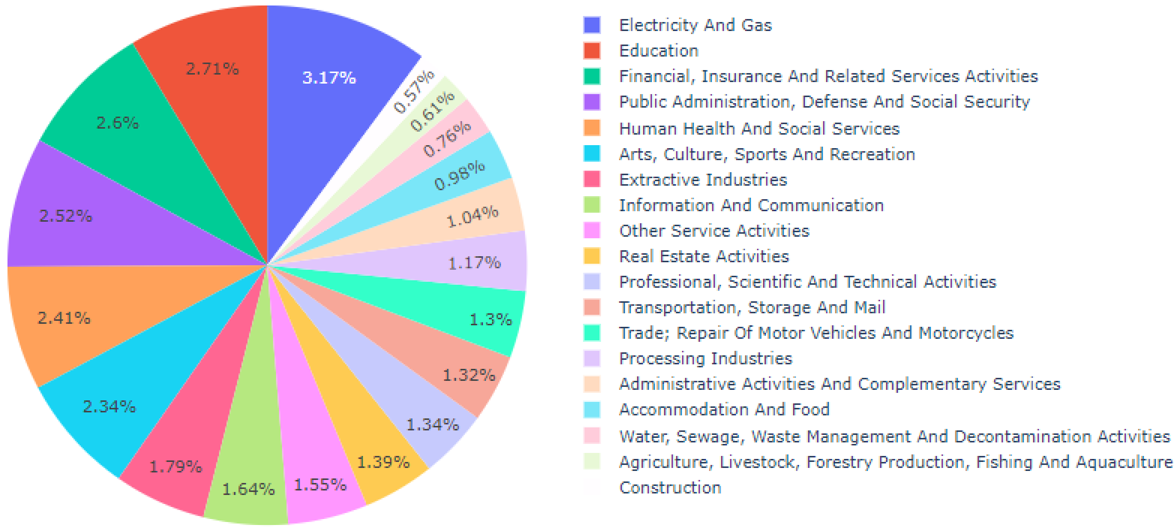
Source: Elaborated by Author

Since the economic sectors are important in the thesis, Figure 3.5 shows the economic sectors by the percentage of positive cases for the merged data, the latter is between RAIS 2019 and SES-PE 2020. About half the data is composed of two sectors respectively, Public Administration, Defense, and Social Security representing 4,557 (33%) and Trade; Repair and Motor Vehicles and Motorcycles representing 1,889 (13.7%) of the data. Followed by Human Health and Social Services, with 1,555 (11.3%) workers, the Administrative Activities and Complementary Services, 1,325 (9.6%), and the Education sector with 1,236 (8.95%).

Interestingly three economic sectors with the most positive cases experienced lockdown, Public Administration, Defense, and Social Security. Two other sectors that had to go through lockdown are among the ones with the most positive cases, Administrative Activities and Complementary Services, and Education. These last three economic sectors experienced lockdown and are not part of essential economic sectors, although they are among the ones with the most positive cases.

All cases for each economic sector mentioned are respectively 16,433 (34.7%), 6,518 (13.8%), 4,692 (9.91%), 4,416 (9.33%), and 4,294 (9.07%). These economic sectors mentioned represent more than 3/4 of the data 76.81%. The rest of each economic sector represents 3% or less of the data. The sector with the least workers is Extractive Industries with only 8 individuals (0.0169%), followed by Agriculture, Livestock, Forestry Production, Fishing and Aquaculture with 69 workers representing 0.146% of the data.

Figure 3.6 – CNAE Economic Sectors Prevalence by Percentage



Source: Elaborated by Author

Figure 3.6 displays the economy sector prevalence by percentage, all the positive cases from the merge file in each economic sector divided by all workers in the same economic sector from RAIS 2019 data, represented in percentage. The economic sectors with the higher prevalence are Electricity and Gas, with 117 positive cases out of 3,689 workers (3.17%), then Education including 1,236 positive results out of 45,648 workers (2.71%), Financial, Insurance and Related Services Activities having 369 positive cases out of 14,219 (2.60%), Public Administration, Defense and Social Security with 4,557 positive cases out of 180,660 (2.52%), and Human Health and Social Services with 1,555 positive cases among 64,566 workers in the same sector (2.41%). The rest of all economic sectors presented a prevalence of less than 2.4% each.

4 Results and Discussion

Once again, the thesis's goal is to identify the probability of an individual choosing to work in the least healthy economic sector given his individual observed and non-observed characteristics. As already mentioned in the last section, the model estimated is the Alternative Specific Conditional Logit Model. The model estimates the data only positive cases for Covid-19. The dependent variable *choice* refers to each of the 17 economic sectors the individual works in, the case-specific variable is *id*, for each individual, where 13,784 different *id's* show for each of the 17 economic sectors. The alternative variable is the *mode*, which contains each different economic sector and again the case variables are Age, Men, Non-White, Complete primary education, Complete secondary education, Nominal Wage, Working hours, and Job Tenure. The base alternative is Human Health and Social Services, one of the 17 economic sectors. In summary, there's a total of 234,328 rows for each 13,784 *id'*s, where each *id* shows 17 times for each economic sector.

Some of the case variables had to be excluded from the model for it to converge. Complete higher education and Uninformed race were omitted because of collinearity. Incomplete primary education, CEP to CBD, CEP Establishment to CBD, and No Working Days were also removed because the initial estimates failed. As for the economic sectors, Agriculture, Livestock, Forestry Production, Fishing, and Aquaculture were excluded because it is an outlier with less than 0,02% of the data, this sector resulted in very high coefficients, odd numbers, and standard error. Another sector that was excluded for the same reason with the same percentage of data is Extractive Industries. Complete Higher Education is not one of the variables displayed in the results because when this variable was inserted into the model it could not be estimated because only 3.27% of individuals have completed a college degree.

Table 4.4 (1) represents the measures of the Least Healthy Model Performance. In model (1) the least healthy sectors estimated are considered the economic sectors in most cases, meanwhile, in the second model (2), the least healthy sectors are the ones that did not experience lockdown. Therefore, for the second model (2), the least healthy sectors are the essential sectors. And both models (1) and (2) are grouped into two groups. the Least Healthy sectors and Others Sectors as shown in Table 4.2.

Given the data, the Log-likelihood describes how likely the model is. Although the Log-likelihood also measures how a model fits the data, the higher the Log-likelihood the better a given model fits the data, the value by itself does not add much to interpreting the model, the value of the log-likelihood is useful to compare models. When comparing models (1) and (2), the latter presents a higher Log-likelihood, which better fits the data. The odds ratio results for model (1) are presented in Table 4.6 and model (2) odd ratios results are presented in Table 4.7. The first and second model uses the base alternative Human Health and Social Services, the sector was also chosen as the base alternative to be estimated because the health sector contains the greatest exposure to airborne diseases for the workers in the field.

The Log-likelihood is estimated through the Maximum Likelihood Estimation, the latter takes known probability distributions to best fit the data, which means that an optimal distribution for the data is estimated using the Maximum Likelihood Estimation. First, $f(y|\theta)$ denotes a probability density function for a random variable represented by y, conditioned on a set of parameters θ. The function represents the process that generates the data with a given sample of data. The equation below is the joint density of n independent and identically distributed (i.i.d.) observations from this process, which is the product of individual densities as shown:

$$f(y_1, \dots, y_n|\theta) = \prod_{i=1}^{n} f(y_i|\theta) = L(\theta|y)$$

This joint density is the likelihood function defined with the unknown parameter vector, θ, while y indicates the data. The joint density is written as a function of the data conditioned on the parameters, while the likelihood function is written as a function of the parameters, conditioned on the data. To work better with the likelihood function, it is expressed as:

$$\ln L\,(\theta|y) = \sum_{i=1}^{n} lnf(y_i|\theta)$$

The function L$(\theta|data)$ = L$(\theta|y)$, the parameters are the interest given the data. L(θ) represents the likelihood function evaluated at θ, or just L, the same for the logarithm, ln L(θ), or just ln L. The Likelihood and Log-Likelihood Functions are estimated through the Maximum likelihood Estimate, MLE, a value of θ makes a sample most probable assuming a known distribution, so it can be derived for the specific distribution, for example, Normal or Poisson distribution (GREENE, 1980; 2018).

The Wald test shows which variables are contributing to the model, that is, which explanatory variables are significant. This test is also known as Wald Chi-Squared Test, and if the parameters for specific explanatory variables are zero, these variables can be removed from the model. Unlike the Likelihood Ratio Test, the Wald test can be run in a single model, but since there are two models, both are compared. The Wald test is estimated using MLE at the parameter values. To test a single parameter the Wald test takes the following expression:

$$W = \frac{(\hat{\theta} - \theta_0)^2}{var(\hat{\theta})}$$

The expression in the numerator is weighted by the curvatures of the log-likelihood function. The denominator is the variance of the estimated $\hat{\theta}$ through MLE of the unconstrained likelihood function compared to the value θ_0. The Wald test follows an asymptotic X^2-distribution (chi-square) with one degree of freedom, that is why it is also known as Wald Chi-Squared. When the square root is taken on both sides of the equation, the expression follows:

$$\sqrt{W} = \frac{(\hat{\theta} - \theta_0)}{se(\hat{\theta})}$$

Now it follows an asymptotic z distribution and $se(\hat{\theta})$ is the standard error of the MLE. The test can be derived into multiple parameters as well (WALD, 1943). The number 22 inside the parentheses indicates the degrees of freedom of the Chi-Square distribution used to test the Wald Chi-Square statistic, it is defined by the number of predictors in the model, which in this case is 22. Thus, Wald tests the hypothesis that at least one of the predictors' regressions coefficients is not equal to zero. The probability being greater than X^2 equals zero, which means this is the probability of obtaining the X^2 statistic 3,562.3 for the first model (1) and 3,573.0 for the second (2) if there is no effect of the predictor variables. A higher Wald Chi-Square value indicates a better predictive power for a set of variables. Since both Log-likelihood and Wald Chi-Square values are higher for model (2), as presented in Table 4.4, the latter provides a better fit to the data, presenting a higher level of explanatory power for the observed data.

The number of observations in the data for non-missing values for the outcome and predictor variables is 41,352, and the number of cases is 13,784. The coefficients result for the Alternative-Specific Conditional Logit Model are presented in the Appendix in Table A.4., A.5, and A.6, respective to the odds ratios results in Tables 4.1, 4.2, and 4.3. Results presented with the odds ratio are more interpretable compared to the coefficients displayed without the odds ratio. The following Table 4.1, displays the odds ratio by essential sectors, which are the economic sectors that did not experience lockdown, and there are 75,004 observations for the city of Recife. The essential sectors are Electricity and Gas, Processing Industries, Trade; Repair of Motor Vehicles and Motorcycles, Transportation, Storage and Mail, and lastly Water, Sewage, Waste Management and Decontamination Activities. Human Health and Social Services are used as a base alternative for the model, and it did not experience lockdown as well.

Starting from left to right on the columns table, first with Electricity and Gas economic sector, and analyzing the variables from top to bottom, only the results with p-value less than

0.1%. Starting with the Men variable, being a man increases the chances of working in the Electricity and Gas sector by 425.2 while being Non-White decreases the chances of working in the same sector by 45.6%. An increase in Minimum Wage increases the chances of an individual working in the sector by 14.9%. As Job Tenure increases by one month, the possibility of working in the sector increases by 0.6%, and being employed as a CLT increases the chances of working in the same sector by 208.9%.

Table 4.1 – A-S Conditional Logit Odds Ratio by Essential Sectors

Variables	Electricity and Gas	Processing Industries	Trade; Repair of Motor Vehicles and Motorcycles	Transportation, Storage and Mail	Water, Sewage, Waste Management and Decontamination Activities
Age	0.970* (0.012)	0.984** (0.005)	0.970*** (0.004)	0.999 (0.006)	0.961** (0.012)
Men	5.252*** (1.234)	4.269*** (0.570)	3.094*** (0.300)	9.996*** (1.387)	6.059*** (1.640)
Non-White	0.544*** (0.125)	0.855 (0.111)	0.684*** (0.064)	0.557*** (0.069)	0.611 (0.158)
Primary Educ.	0.915 (0.394)	0.718 (0.179)	1.257 (0.254)	0.857 (0.185)	0.367* (0.155)
Secondary Educ.	1.030 (0.421)	0.706 (0.187)	0.872 (0.186)	0.660 (0.156)	0.864 (0.348)
Minimum Wage	1.149*** (0.018)	1.080*** (0.016)	1.042** (0.014)	0.971 (0.017)	1.044 (0.026)
Working Hours	1.021* (0.010)	1.014* (0.007)	1.018*** (0.005)	1.008 (0.006)	1.090*** (0.026)
Job Tenure	1.006*** (0.001)	1.000 (0.001)	1.000 (0.001)	1.004*** (0.001)	1.002 (0.001)
Distance	0.924* (0.036)	0.999 (0.021)	1.023 (0.015)	1.000 (0.020)	1.139*** (0.046)
Employment Type CLT	3.089** (1.185)	1.361*** (0.254)	0.644*** (0.076)	1.369 (0.245)	0.816 (0.260)
Establishment Size	1.028 (0.065)	0.581*** (0.017)	0.510*** (0.011)	0.825*** (0.023)	1.451*** (0.140)

Exponentiated coefficients; Standard errors in parentheses * p<0.05, ** p<0.01, ***p <0.001

Source: Elaborated by Author

As for the Processing Industries economic sector, being a man raises the possibility of working in the sector by 326.9%. Moreover, an increase in Minimum Wage raises the chances of an individual working in the same sector by 8%, and being an employed CLT, the chances increase by 36.1%. And for the Establishment Size variable, as the number of employees increases, the chances of an individual working in the same sector decreased by 41.9%.

As for the Age variable, as age increases the chances of an individual working in the sector of The Trade; Repair of Motor Vehicles and Motorcycles decreases by 3%. Being a man also raises the chances of working in the sector by 209.4%, while being Non-White decreases the chances by 31.6%. And for Working Hours, a unit increase in working hours increases the chances of an individual working in the sector by 1.8%, moreover being employed as CLT decreases the chances by 35.6%, and for the Establishment Size variable, as the number of employees increases, the possibility of working in the same sector decreases by 49%.

The Transportation, Storage and Mail sector presents four significant variables. If an individual is a man, it increases the odds of working in the sector by 900% and being Non-White decreases the odds by 43.3%. As for the Job Tenure variable, for one unit increase, the chances of working in the sector raises by 0.4%. And for the Establishment Size, as the number of employees in a company increases, the chances of working in the sector decreased by 17.5%. Lastly, Water, Sewage, Waste Management and Decontamination Activities, present four significant variables with an odds ratio above one. Men, which is a man increases the chances of working in the sector by 505.9%, increased Working Hours by 9%, and Distance by 13.9%. And for Establishment Size, an increase in the number of employees increases the chances of working in the same sector by 45.1%.

Table 4.2 presents the odds ratio for the least healthy sectors. Two groups are being compared, the Least Healthy and Other Sectors. The least healthy sectors are now defined by the most positive cases, including the economic sectors that experienced lockdown, and the ones that did not experience lockdown. The number of observations is now 41,352 because the economic sectors are grouped into two groups, and the observations dropped compared to Table 4.1.

Starting with the Age variable, for one unit increase in age, it raises the chances of an individual working in the Least Healthy sector increases by 0.8%. As for being a man, it increases by 128.8%. While being Non-White, having completed Primary Education, or Secondary Education, the chances of working in the Least Healthy group decrease by respectively 24.8%, 52.2%, and 36.8%. A unit increases in Working Hours raises the odds of working in the same group sector by 1.3%. Meanwhile, being employed as CLT decreases the chances of an individual working in the same group sector by 93%. And for the Establishment Size variable, as the number of employees raises, it diminishes the chances of working in the group sector by 27.5%.

In the group of Other Sectors, as Age increases by one unit, the odds of working in this group diminishes by 1.2%. Being a man raises the chances of being employed by 260.6%, and being Non-White decreases the chances by 30.5% while having only primary education decreases the chances of working in this group sector by 53.6%.

Table 4.2 – A-S Conditional Logit Odds Ratio by Least Healthy Sectors as Most Cases

Variables	Least Healthy	Other Sectors
Age	1.008**	0.988***
	(0.003)	(0.003)
Men	2.288***	3.606***
	(0.152)	(0.262)
Non-White	0.752***	0.695***
	(0.046)	(0.048)
Primary Educ.	0.478***	0.464***
	(0.058)	(0.062)
Secondary Educ.	0.632***	0.827
	(0.078)	(0.113)
Minimum Wage	1.005	1.026***
	(0.007)	(0.007)
Working Hours	1.013***	1.017***
	(0.003)	(0.004)
Job Tenure	1.001*	1.002***
	(0.001)	(0.001)
Distance	1.017	1.018
	(0.010)	(0.012)
Employment CLT	0.070***	0.395***
	(0.005)	(0.037)
Establishment Size	0.725***	0.622***
	(0.011)	(0.010)

Exponentiated coefficients; Standard errors in parentheses * $p<0.05$, ** $p<0.01$, *** $p<0.001$
Source: Elaborated by Author

As for the variables Minimum Wage, Working Hours, and Job Tenure, the chances of an individual working in the group sector raises by respectively 2.6%, 1.7%, and 0.2%. Moreover, employed CLT workers have a decrease in working in this group sector by 60.5%. Lastly, for the Establishment Size variable, as the number of employees increases, the chances of working in this group sector diminish by 37.8%.

Table 4.3 displays the odds ratio by the least healthy sectors as essential sectors. In table 4.2 the least healthy sectors are defined as the economic sectors with the most positive cases. Now the least healthy sectors are defined as the essential sectors, which are the economic sectors that did not experience the lockdown. As Age increases in the Least Healthy group, the odds of working in the sector decrease by 1.3%, and being a man increases the odds of working in the same group sector by 260.9%. Being Non-White decreases the chances of working in the sector by 35.2%. Another variable with an odds ratio above one is Working hours, as it increases, the odds of working in the group sector increase by 2.1%. While being employed as CLT decreases the chances of being employed in the group sector by 78.7%. And lastly for the Establishment Size variable, as the number of employees increases, the chances of working in the Other Sectors group diminish by 39.6%.

Table 4.3 – A-S Conditional Logit Odds Ratio by Least Healthy Sectors as Essential Sectors

Variables	Least Healthy	Other Sectors
Age	0.987***	1.008**
	(0.003)	(0.003)
Men	3.609***	2.367***
	(0.269)	(0.156)
Non-White	0.648***	0.767***
	(0.046)	(0.040)
Primary Educ.	1.012	0.387***
	(0.143)	(0.046)
Secondary Educ.	0.691*	0.685**
	(0.102)	(0.083)
Minimum Wage	1.023**	1.007
	(0.008)	(0.007)
Working Hours	1.021***	1.011***
	(0.004)	(0.003)
Job Tenure	1.001	1.001**
	(0.001)	(0.001)
Distance	1.017	1.018
	(0.012)	(0.010)
Employment CLT	0.213***	0.084***
	(0.020)	(0.006)
Establishment Size	0.604***	0.729***
	(0.010)	(0.011)

Exponentiated coefficients; Standard errors in parentheses * p<0.05, **p<0.01, ***p<0.001
Source: Elaborated by Author

Looking at the Other Sectors, being a man increases the odds of working in the group sector by 136.7%. While being Non-White decreases the chances of working in the same group sector by 23.3%, and having completed Primary Education decreases it by 61.3%. Moreover, one unit increase in Working Hours raises the chances of working in the same group sector by 1.1%. CLT employees present diminished possibilities of working in the group sector by 91.6%, and finally for the Establishment Size variable, as the number of employees increases in the group sector, the chances of an individual working in the group sector decreases by 27.1%.

Table 4.4 - Least Healthy Model Performance

Model	(1)	(2)
Log-likelihood	-9,693.0	-9,232.6
Wald chi (22)	3,562.3	3,573.0
Prob > chi2	0	0
Number of observations	41,352	41,352
Number of cases	13,784	13,784

Source: Elaborated by Author

Table 4.4 presents the performance of the two different models that are displayed in Tables 4.2 and 4.3, models (1) and (2) respectively. Both models have the same number of observations, 41,352, and the same number of cases, 13,784. Moreover, both are grouped into two groups, Least Healthy and Other Sectors. The least healthy group sector in the model (1) is defined by the positive cases for Covid-19, and for model (2), the least healthy group sector is composed of the essential sectors. Model (2) presents a higher Log-likelihood and Wald-Chi Square, making it the model that best fits the data.

5 Conclusion

In conclusion, individual and firm factors influence a person to work in the least healthy sectors. An individual is more likely to contract the virus in the least healthy sectors, although the odds ratio of choosing which economic sector to work in varies. Individuals who are more likely to work in the least healthy economic sectors, such as The Public Administration, Defense and Social Security, Trade; Repair of Motor Vehicles and Motorcycles, Administrative Activities and Complementary Services, and Education using Human Health and Social Services as a base alternative, were most affected by the novel coronavirus.

When comparing among economic sectors considered essential sectors, the ones that did not experience lockdown, men present a higher chance of working in the essential sectors. These are Electricity and Gas, Processing Industries, Trade; Repair of Motor Vehicles and Motorcycles, Transportation, Storage and Mail, and Water, Sewage, Waste Management and Decontamination Activities. There is a lower incidence of older or non-white individuals working in the essential sectors. These individuals might encounter more difficulty to be employed in the essential sectors compared to the white race, and compared to other young people.

Sectors with higher minimum wages attract more workers among the essential sectors. There is also a higher incidence of workers in the sectors with higher working hours and job tenure. Distance shows to be significant for the Water, Sewage, Waste Management and Decontamination Activities sector, displaying a higher incidence of workers who lives farther compared to other sectors. Some sectors among the essential sectors tend to employ more CLT workers, such as the Electricity and Gas sector. And Establishment Size shows significance in most of the essential sectors with an odds ratio below one, as the number of employees increases, the incidence of workers working in the sectors decreases.

Grouping the economic sectors into two groups Least Healthy and Other Sectors, the first one being defined as the sectors with the most positive cases of the novel coronavirus, each economic sector is mentioned in the first paragraph of this section, and the second is the remaining of the sectors. Using the first definition, as individuals become older there is a lower incidence of workers employed in the Other Sectors, while there is a higher incidence of men working in this group. Individuals who are non-white or have completed only primary education tend to work in the Least Healthy group. The latter group attracts fewer workers with completed secondary education. The Other sectors present a higher incidence of minimum wage, working hours, and job tenure, attracting more workers. The last group attracts more individuals who are not CLT and tend to have a lower Establishment Size, and the number of employees, compared to the Least Healthy group.

Also grouping the economic sectors into two groups the Least Healthy and Other Sectors, but this time the Least Healthy was the essential sector that did not experience lockdown, instead of it being the economic sector with the most positive cases. There is a lower incidence of older individuals in the Least Healthy group, while men tend to work in the same group compared to the Other Sectors group. There is a higher incidence of individuals in the latter group, who are Non-White or have completed only Primary Education. The Least Healthy group presents a slightly higher incidence of Working Hours among its workers. This group also attracts more individuals who are not CLT and tend to have a lower incidence of the number of employees as well, compared to the Other Sectors group.

The exogenous factor assisted in identifying what sectors in the economy are the least healthy. Individuals who worked in the Least Healthy sectors were more susceptible to contracting the disease. Moreover, the exposure to an airborne disease through commuting distance showed significance in one of the sectors. When comparing models using different definitions for what a Least Healthy sector is when defining it by the sectors with the most positive cases, and then defining it as being composed of the essential sectors, the latter best fits the data.

Public policies can be directed to promote equal opportunities through racial quotas, gender equality, and income distribution. Besides more investment in the health system and education, and improvement of public transportation, and water supply and sanitation. Policies and targeted interventions are necessary to improve access to healthcare and reduce exposure to the virus among vulnerable populations, to promote health equity.

Social, economic, and labor policies can contribute to occupational health disparities. Such as minimum wage laws, workplace safety regulations, and healthcare reform. The policies need to prioritize the needs of vulnerable workers, including low-wage workers and workers in industries with high injury rates. Unfortunately, the workers in the informal sector are not protected by labor policies resulting in higher occupational health disparities (SIQUEIRA et al., 2014). Reduction in workplace presence led to a decrease in the number of COVID-19 deaths, the effect was stronger for counties with higher levels of workplace presence before the pandemic, and for counties with a higher proportion of workers in occupations that require close physical proximity. Reducing workplace presence can save lives during a pandemic, and policies targeted for workers to work remotely, or at least with different work schedules to avoid agglomeration should be applied during the period, or to future pandemics (MCLAREN; WANG, 2020).

Policies to design effective and efficient lockdown policies to combat infectious diseases in the future, incorporating both epidemiological and economic factors, optimizing the lockdown policy based on the severity of the disease and economic consequences of lockdowns (ACEMOGLOU et al., 2020). Telecommuting policies alleviate congestion and transport-related emissions (VOS et al., 2018). Also improved public transportation or telecommuting options, to mitigate the negative effects of commuting on worker productivity in larger metropolitan areas. Moreover, promoting flexible work arrangements could have a positive impact on both the economy and the environment resulting in the well-being of the employees in the workplace.

Policies aimed at reducing residential segregation, and policies that provide equitable access to healthcare might improve health outcomes for marginalized populations. Race is a crucial factor in understanding workplace inequality. Occupational segregation, earnings inequality, and hiring discrimination are influenced by race. Addressing race-based inequality in the workplace might promote fairness and social justice, with policy changes, organizational interventions, and individual-level strategies targeted at racial minority workers (JENNIFER; VALLAS, 2021).

The model results presented were predicted for Recife, Pernambuco, Brazil, and expectedly, it will be an example for other similar cities to elaborate new public policies or improve existing ones to enhance many lives. The informal economic sector was not considered in the present thesis. And other researches are necessary to analyze the economic sectors thoroughly.

REFERENCES

ACEMOGLU, DARON et al. A Multi-Risk SIR Model with Optimally Targeted Lockdown. *American Economic Review: Insights*, v.3, n.4, p. 487-502, 2021. DOI: 10.1257/aeri.20200590.

AHONEN, EMILY et al. Work as an Inclusive Part of Population Health Inequities Research and Prevention. *American Journal Public Health*, v. 108, n. 3, p, 306-311, 2018. DOI 10.2105/AJPH.2017.304214.

AHUMADA, HILDEGART et al. Sectoral Productivity Growth, COVID-19 Shocks, and Infrastructure. *Economics of Disasters and Climate Change*, n. 6, p. 1-28, 2022. DOI https://doi.org/10.1007/s41885-021-00098-z.

ALEXANDER, DIANE; CURRIE, JANET. Is it Who You Are or Where You Live? Residential Segregation and Racial Gaps in Childhood Asthma. *Journal of Health Economics*, v. 55, p. 186-200, 2017. DOI: https://doi.org/10.1016/j.jhealeco.2017.07.003.

ÁLVAREZ, ESTHER et al. Tuberculosis and Other Airborne Microbes in Occupational Health and Safety. *International Journal of Environmental Research and Public Health*, v. 17, n. 7088, 2020. DOI 10.3390/ijerph17197088.

ANDERSON, VERN et al. Occupational Fatalities, Injuries, Illnesses, and Related Economic Loss in the Wholesale and Retail Trade Sector. *American Journal of Industrial Medicine*, v. 53, p. 673-685, 2010.

ANDO, HAJIME et al. Effect of commuting on the risk of COVID-19 and COVID-19-induced anxiety in Japan, December 2020. Archives of Public Health, v.79, n. 222, 2021. DOI https://doi.org/10.1186/s13690-021-00751-9

ALANAGREH, LO'AI; ALZOUGHOOL, FOAD; ATOUM, MANAR. The Human Coronavirus Disease COVID-19: Its Origin, Characteristics, and Insights into Potential Drugs and Its Mechanisms. *Pathogens*, 9, 331, 2020. DOI https://doi.org/10.3390/pathogens9050331.

ALDRICH, JOHN H.; NELSON, FORREST D. Linear Probability, Logit, and Probit Models Series: Quantitative Applications in the Social Sciences. *Sage University Paper*, 1984.

ALVES, PEDRO. É um momento histórico para mim e para todos, diz técnica de enfermagem que recebeu 1ª dose da vacina em Pernambuco. *G1 PE*, 18 January 2021, < https://g1.globo.com/pe/pernambuco/noticia/2021/01/18/e-um-momento-historico-para-mim-e-para-todos-diz-tecnica-de-enfermagem-que-recebeu-a-primeira-dose-da-vacina-em-pernambuco.ghtml>. Accessed 14 April 2022.

BANERJEE, TANNISTA et al. Causal connections between socioeconomic disparities and COVID-19 in the USA. *Nature Scientific Reports*, v. 12, n. 15827, 2022. DOI: https://doi.org/10.1038/s41598-022-18725-4.

BARBIERI, TERESA; BASSO, GAETANO; SCICCHITANO, SERGIO. Italian Workers at Risk During the COVID-19 Epidemic. *Italian Economic Journal*, n.8, p.175-195, 2022. DOI https://doi.org/10.1007/s40797-021-00164-1.

BECKETT, WILLIAM. Occupational Respiratory Diseases. *New England Journal of Medicine*, n. 342, p. 406-413, 2000. DOI: 10.1056/NEJM200002103420607.

BELFORT, ANGELA. O esgoto é um problema para as cidades pernambucanas. *JC*, 31 May 2019, <https://jc.ne10.uol.com.br/canal/politica/pernambuco/noticia/2019/05/31/o-esgoto-e-um-problema-para-as-cidades-pernambucanas-380042.php>. Accessed: 19 May 2020.

BLANC et al. The Occupational Burden of Nonmalignant Respiratory Diseases. *American Journal of Respiratory and Critical Care Medicine*, v. 199, n. 11, 2019. DOI 10.1164/rccm.201904-0717ST.

BLS. Employer-Reported Workplace Injuries and Illnesses-2020. *Bureau of Labor Statistics*, 2020a.

BLS. National Census of Fatal Occupational Injuries in 2020. *Bureau of Labor Statistics*, 2020b.

BROWN, ARLEEN et al. Structural Interventions to Reduce and Eliminate Health Disparities. *American Journal of Public Health*, v. 109, p. 72-78, 2019. DOI https://doi.org/10.2105/AJPH.2018.304844.

BRATU, CRISTINA et al. JUE Insight: City-wide Effects of New Housing Supply: Evidence from moving chains. *Journal of Urban Economics*, n. 133, 2023. DOI https://doi.org/10.1016/j.jue.2022.103528.

BUHEJI, MUHAMED et al. The Extend of COVID-19 Pandemic Socio-Economic Impact on Global Poverty. A Global Integrative Multidisciplinary Review. *American Journal of Economics*, v. 10, n. 4, p. 213-224, 2020. DOI https://doi.org/10.5923/j.economics.20201004.02.

BURGARD, SARAH; LIN, KATHERINE. Bad Jobs, Bad Health? How Work and Working Conditions Contribute to Health Disparities. *American Behavioral Scientist*, v. 57, n.8, 2013. DOI 10.1177/0002764213487347.

CAMERON, COLIN; TRIVEDI, PRAVIN. Microeconometrics Using Stata. Rev ed. College Station, TX: *Stata Press*, 2010.

CARDER, MELANIE et al. Occupational and work-related respiratory disease attributed to cleaning products. *Occupational and Environmental Medicine*, n. 76, p. 530-536, 2019. DOI 10.1136/oemed-2018-105646.

CASTRO, NICOLE; MOREIRA, GUSTAVO. Who worked from home in Brazil? Inequalities highlighted by the pandemic. In *SciELO Preprints*, 2021. DOI https://doi.org/10.1590/0103-6351/6687.

CEPALUNI, GABRIEL et al. Mobility and Policy Responses During the COVID-19 Pandemic in 2020. *International Journal of Public Health*, v. 67, 2022. DOI https://doi.org/10.3389/ijph.2022.1604663.

CHEN, YEA-HUNG et al. Excess mortality associated with the COVID-19 pandemic among Californians 18-65 years of age, by occupational sector and occupation: March through November 2020. *PLoS ONE*, n.16, v.6, 2021. DOI https://doi.org/10.1371/journal.pone.0252454.

CHOWKWANYUN, MERLIN. The War on Poverty's Health Legacy: What it was and why it matters. *Health Affairs*, v. 37, n.1, p.47-53, 2018. DOI: 10.1377/hlthaff.2017.1328.

CONCLA. Comissão Nacional de Classificação. CNAE Subclasses, *Instituto Brasileiro de Geografia e Estatística*, <https://cnae.ibge.gov.br/?view=estrutura>. Accessed August 5, 2021.

CONECTA RECIFE. Vacinômetro Indicadores de Imunização COVID-19. *Prefeitura do Recife*, 2022, <https://conectarecife.recife.pe.gov.br/vacinometro/>. Accessed 15 April 2022.

CONTICINI, EDOARDO et al. COVID-19 pneumonia in a large cohort of patients treated with biological and targeted synthetic antirheumatic drugs. Annals of the Rheumatic Diseases, 2020. DOI 10.1136/annrheumdis-2020-217681.

CORBURN, JASON et al. Slum Health: Arresting COVID-19 and Improving Well-Being in Urban Informal Settlements. Journal of Urban Health, 2020. DOI https://doi.org/10.1007/s11524-020-00438-6.

CRONIN, CHRISTOPHER; EVANS, WILLIAM. Total shutdowns, targeted restrictions, or individual responsibility: How to promote social distancing in the COVID-19 Era? *Journal of Health Economics*, n. 79, 2021. DOI https://doi.org/10.1016/j.jhealeco.2021.102497.

CULLINAN, PAUL et al. Occupational lung diseases: from old and novel exposures to effective preventive strategies. *Lancet Respiratory Medicine,* January 6, 2017. DOI http://dx.doi.org/10.1016/S2213-2600(16)30424-6.

CUTLER, DAVID; SUMMERS, LAWRENCE. The COVID-19 Pandemic and the $16 Trillion Virus. *JAMA*, v. 324, n. 15, p.1495–1496, October 15, 2020. DOI 10.1001/jama.2020.19759.

DIAS, C. M. et al. Achieving the Sustainable Development Goal 06 in Brazil: the universal access to sanitation as a possible mission. *Annals of the Brazilian Academy of Sciences*, v. 90, n. 2 p. 1337-1367, 2018. DOI http://dx.doi.org/10.1590/0001-3765201820170590.

DUA, ANDRÉ et al. US small-business recovery after the COVID-19 crisis. *McKinsey*, July, 2020.

DTTL. Labor Relations. *Deloitte Global*, December 2020, <https://www2.deloitte.com/br/en/pages/living-and-working/articles/labor-relations.html>. Accessed 12 November 2022.

EAGAN, TOMAS; GULSVIK, AMUND. BAKKE, PER. Occupational Airborne Exposure and the Incidence of Respiratory Symptoms and Asthma. *American Journal of Respiratory and Critical Care Medicine*, v. 166, p. 933-938, 2002. DOI 10.1164/rccm.200203-238OC.

FAKIR, ADNAN; BHARATI, TUSHAR. Pandemic catch-22: The role of mobility restrictions and institutional inequalities in halting the spread of COVID-19. *PLoS ONE*, v. 16, n. 6. DOI https://doi.org/10.1371/journal.pone.0253348.

FARUQUE, OMAR et al. Airborne occupational exposures and the risk of developing respiratory symptoms and airway obstruction in the Lifelines Cohort Study. *Thorax*, n.76, p. 790-797, 2021a. DOI http://dx.doi.org/10.1136/thoraxjnl-2020-216721.

FARUQUE, OMAR et al. Airborne Occupational Exposures and Lung Function in the Lifelines Cohort Study. *AnnalsATS*, v. 18, n.1, 2021b.

FINKELSTEIN, DANIEL et al. Economic Well-Being and Health: The Role of Income Support Programs in Promoting Health and Advancing Health Equity. *Health Affairs*, v. 41, n. 12, p. 1700-1706, 2022. DOI https://doi.org/10.1377/hlthaff.2022.00846.

FRAGA, FERNANDO. Brazil registers over 241 thousand cases of COVID-19. *Agência Brasil*, Brasília, 18 May 2020, <https://agenciabrasil.ebc.com.br/en/saude/noticia/2020-05/brazil-registers-over-241-thousand-cases-covid-19>. Accessed 18 May 2020.

FOOD AND DRUG ADMINISTRATION. FDA Takes Key Action in Fight Against COVID-19 By Issuing Emergency Use Authorization for First COVID-19 Vaccine. *FDA NEWS RELEASE*, 11 December 2020,<https://www.fda.gov/news-events/press-announcements/fda-takes-key-action-fight-against-covid-19-issuing-emergency-use-authorization-first-covid-19>. Accessed 14 April 2022.

FRAGA, FERNANDO. Brazil registers over 241 thousand cases of COVID-19. *Agência Brasil,* Brasília, 18 May 2020, <https://agenciabrasil.ebc.com.br/en/saude/noticia/2020-05/brazil-registers-over-241-thousand-cases-covid-19>. Accessed 18 May 2020.

G1 PE. Com 34% de crianças vacinadas contra Covid, municípios realizam 'Dia C' para reforçar campanha; veja locais e horários. *G1 Pernambuco*, 25 February 2022, <https://g1.globo.com/pe/pernambuco/noticia/2022/02/25/com-34percent-de-criancas-vacinadas-contra-covid-municipios-realizam-dia-c-para-reforcar-campanha-veja-locais-e-horarios.ghtml>. Accessed 15 April 2022.

GATES, BILL. We can make COVID-19 the last pandemic. *TED Vancouver BC,* April 2022, <https://www.ted.com/talks/bill_gates_we_can_make_covid_19_the_last_pandemic?language=en>. Accessed 24 April, 2022.

GILLIGAN, HEATHER. A Foundation for Health and Well-Being: Meaningful Employment. *Health Affairs*, v. 41, n. 10, 2022. DOI: https://doi.org/10.1377/hlthaff.2022.01069.

GREENE, WILLIAM. Econometric Analysis. *Pearson,* New York, 8th ed. 2018.

GREENE, WILLIAM. Maximum likelihood estimation of econometric frontier functions. *Journal of Econometrics*, v.13, n.1, p.27–56, 1980. DOI:10.1016/0304-4076(80)90041-x.

GREGO, GIULIA et al. Outcomes in Economic Evaluations of Public Health Interventions in Low- And Middle-Income Countries: Health, Capabilities and Subjective Wellbeing. *Health Economics*, n. 25, p. 83-94, 2016.

GU, HAI et al. Measurement and Decomposition of Income-related Inequality in Self-rated health among the elderly in China. *International Journal of Equity in Health*, v. 18, n.4, 2019. DOI https://doi.org/10.1186/s12939-019-0909-2.

HARGREAVES, SALLY et al. Occupational health outcomes among international migrant workers: a systematic review and meta-analysis. *Lancet Global Health*, v. 7, p. 872-82, 2019. DOI http://dx.doi.org/10.1016/S2214-109X(19)30204-9.

HERT, STEFAN. Burnout in Healthcare Workers: Prevalence, Impact and Preventative Strategies. *Local and Regional Anesthesia*, n.13, p.171-183, 2020. DOI 10.2147/LRA.S240564.

HOLM, ANDER et al. Employment effects of active labor market programs for sick-listed workers. *Journal of Health Economics*, n. 52, p. 33-44, 2017. DOI http://dx.doi.org/10.1016/j.jhealeco.2017.01.006.

HOY, RYAN; BRIMS, FRASER. The National Occupational Respiratory Disease Registry (NORDER): it is time to learn from failure. *The Medical Journal of Australia*. v. 216, n. 7, 2022. DOI 10.5694/mja2.51465.

HUANG, CHAOLIN et al. Clinical features of patients infect with 2019 novel coronavirus in Wuhan, China. *Lancet*, Jan. 2020. DOI https://doi.org/10.1016/S0140-6736(20)30183-5.

HUBER, MARTIN; LECHNER, MICHAEL; WUNSCH, CONNY. Workplace health promotion and labour market performance of employees. *Journal of Health Economics*, 2015. DOI http://dx.doi.org/10.1016/j.jhealeco.2015.07.002.

HWANG, HAE-SHIN; MORTENSEN, DALE; REED, ROBERT. Hedonic Wages and Labor Market Search. *Journal of Labor Economics*, v. 16, n. 4, p. 815-847, 1998. DOI https://doi.org/10.1086/209907.

IBGE. Cidades IBGE Pernambuco. *Instituto Brasileiro de Geografia e Estatística*, 2021a, <https://cidades.ibge.gov.br/brasil/pe/panorama>. Accessed 15 April 2022.

IBGE. Censo Demográfico. *Instituto Brasileiro de Geografia e Estatística*, 2010. <https://censo2010.ibge.gov.br/>. Accessed May 9, 2022.

IBGE. Cidades IBGE Recife. *Instituto Brasileiro de Geografia e Estatística*, 2021b, <https://cidades.ibge.gov.br/brasil/pe/recife/panorama>. Accessed 15 April 2022.

ILO. Snapshots on Occupational Safety and Health. The ILO at the World Congress on Safety and Health at Work 2017. *International Labour Organization*, 2017.

ILO. ILO Monitor: COVID-19 and the world of work. *International Labour Organization*, ed. 8, 27 October 2021.

IMF. World Economic Outlook: Countering the Cost-of-Living Crisis, *International Monetary Fund*, Washington, D.C., October, 2022b.

INDIO, CRISTINA. Brazil unemployment down to 8.9%, or 9.7 mi. *AgênciaBrasil,*<https://agenciabrasil.ebc.com.br/en/economia/noticia/2022-09/brazil-unemployment-down-89-or-97-mi>. Accessed October 15, 2022.

JUNIOR, ADMIR et al. COVID-19, public agglomerations and economic effects: Assessing the recovery time of passenger transport services in Brazil. *Transport Policy*, n. 110, p. 254-272, 2021. DOI 10.1016/j.tranpol.2021.06.004.

KIM, J.H., MARKS, F.; CLEMENS, J.D. Looking beyond COVID-19 vaccine phase 3 trials. *Nature Medicine* n. 27, p. 205–211, 2021. DOI https://doi.org/10.1038/s41591-021-01230-y

KIVIMÄKI, MIKA; KAWACHI, ICHIRO. Work Stress as a Risk Factor for Cardiovascular Disease. *Current Cardiology Reports*, 2015. DOI: 10.1007/s11886-015-0630-8.

KLEIN, RUDOLF. Health Inequalities: Bringing the Hidden Assumptions into the Open. *Health Economics*, n.9, n.7 p. 569-570, 2000. DOI 10.1002/1099-1050(200010)9:7<569::aid-hec556>3.0.co;2-j.

KLINK, JAC et al. The Benefits of Interventions for Work-Related Stress. *American Journal of Public Health*, v. 91, n. 2, 2001. DOI 10.2105/ajph.91.2.270.

KNEEBONE, ELIZABETH; HOLMES, NATALIES. The growing distance between people and jobs in metropolitan America. *Metropolitan Policy Program at Brookings*, 2015.

KUPFERSCHMIDT, KAI. The lockdowns worked – but what comes next? *Science*, v. 368, n. 488, p. 218-219, 17 April 2020. DOI 10.1126/science.368.6488.218.

LANDSBERGIS, PAUL et al. The Key Role of Work in Population Health Inequities. *American Journal Public Health*, v. 108, n. 3, 2018. DOI 10.2105/AJPH.2017.304288.

LANDSBERGIS, PAUL et al. Work Organization, Job Insecurity, and Occupational Health Disparities. *American Journal of Industrial Medicine*, v. 57, p. 495-515, 2014. DOI 10.1002/ajim.22126.

LANGLOIS, JILL. São Paulo's favelas are running out of food. These women are stepping in. *National Geographic Science Coronavirus Coverage*, 1 May 2020, <https://www.nationalgeographic.com/science/2020/05/coronavirus-brazil-sao-paulo-favelas-running-out-of-food-women-stepping-in/>. Accessed 18 May 2020.

LEWIS, DYANI. Why the WHO Took Two Years to Say COVID is Airborne. *Nature*, v. 604, 7 April, 2022.

LUCCHINI, ROBERTO; LONDON, LESLIE. Global Occupational Health: Current Challenges and the Need for Urgent Action. *Annals of Global Health*, n. 80, p.251-256, 2014. DOI: http://dx.doi.org/10.1016/j.aogh.2014.09.006.

MA, SHUANG; LI, SHUANGJIN; ZHANG, JUNYI. Diverse and nonlinear influences of build environment factors on COVID-19 spread across townships in China at its initial stage. *Scientific Reports*, v. 11, n. 12415, 2021. DOI https://doi.org/10.1038/s41598-021-91849-1.

MATTEIS, SARA et al. Current and new challenges in occupational lung diseases. *European Respiratory Review*, v. 26, n.170080, 2017. DOI https://doi.org/10.1183/16000617.0080-2017.

MATTOS, ENLINSON et al. Sanitation and Health: Empirical evidence for Brazilian Municipalities. *Brazilian Review of Econometrics*, v. 39, n. 2, p. 269-302, Dec. 2019. DOI http://dx.doi.org/10.12660/bre.v39n22019.78963.

MAZUREK, JACEK; WEISSMAN, DAVID. Occupational Respiratory Allergic Diseases in Healthcare Workers. *Current Allergy and Asthma Reports*, v. 16, n. 17, 2016. DOI 10.1007/s11882-016-0657-y.

MCCOY, TERRENCE; TRAIANO, HELOÍSA. In Brazil, a desperate search for an open bed. *The Washington Post*, 14 May 2020, <https://www.washingtonpost.com/world/2020/05/14/coronavirus-brazil-manaus-hospital-bed-capacity-ambulance/?arc404=true.>. Accessed 18 May 2020.

MCFADDEN, DANIEL. Frontiers in Econometrics. Conditional Logit Analysis of Qualitative Choice Behavior. In: ZAREMBKA, PAUL. 1st ed. New York, NY: *Academic Press*, 1974a, p. 105-142.

MCFADDEN, DANIEL. The Measurement of Urban Travel Demand. Journal of Public Economics, n.3, v.4, p.303-328, 1974b. DOI https://doi.org/10.1016/0047-2727(74)90003-6.

MCFADDEN, DANIEL. Modeling the choice of residential location. *Transportation Research Record*, n. 673, p.72-77, 1978a.

MCFADDEN, DANIEL. The Nobel Prize Biographical. *The Sveriges Riksbank Price in Economic Sciences in Memory of Alfred Nobel*, 2000, <https://www.nobelprize.org/prizes/economic-sciences/2000/mcfadden/biographical/>. Accessed July 12th, 2022.

MCFADDEN, DANIEL; TRAIN, KENNETH; TYE, WILLIAM. An Application of Diagnostic Tests for the Independence from Irrelevant Alternatives Property of the Multinomial Logit Model. *Transportation Research Record*, n. 637, p. 39-46, 1978b.

MCLAREN, JOHN; WANG, SU. Effects of Reduced Workplace Presence on COVID-19 Deaths: An Instrumental-Variables Approach. *NBER Working Paper*, n. 28275, 2020. DOI 10.3386/w28275.

MELCHIOR, CRISTIANE; ZANINI, ROSELAINE. Mortality per work accident: A literature mapping. *Safety Science*, n.114, p.72-78, 2019. DOI https://doi.org/10.1016/j.ssci.2019.01.001.

MCLELLAN, ROBERT. Work, Health, and Worker Well-Being: Roles and Opportunities for Employers. *Health Affairs*, v. 36, n. 2, p. 206-2013, 2017. DOI https://doi.org/10.1377/hlthaff.2016.1150.

MENEZES, DIOGO. Grande Recife concentra 97% das favelas de Pernambuco. *JC*, 7 Nov. 2013, <https://jc.ne10.uol.com.br/canal/mundo/brasil/noticia/2013/11/07/grande-recife-concentra-97_porcento-das-favelas-de-pernambuco-104553.php>. Accessed 19 May 2020.

MIRABELLI, MARIA et al. Occupation and the Prevalence of Respiratory Health Symptoms and Conditions: The Atherosclerosis Risk in Communities Study. *Journal of Occupational and Environmental Medicine*, v.54, n.2, p. 157-164, 2012. DOI 10.1097/JOM.0b013e31823e3a52.

MOROSINI, LUIZA. Governo de Pernambuco decreta quarentena mais rígida a partir de quinta. *Diário de Pernambuco*, 15 March 2021, < https://www.diariodepernambuco.com.br/noticia/economia/2021/03/governo-de-pernambuco-decreta-quarentena-mais-rigida-a-partir-de-quint.html>. Accessed 15 October 2022.

MUN, SE-IL; YONEKAWA, MAKOTO. Flextime, Traffic Congestion and Urban Productivity. *Journal of Transport Economics and Policy*, v. 40, n. 3, p. 329-358, 2006. DOI https://www.jstor.org/stable/20053990.

NGUYEN, PHUC V.; HUYNH, TOAN L. D.; NGO, VU M.; NGUYEN, HUAN H. (2021): Race against time to save human lives during the COVID-19 with vaccines: Global evidence, GLO Discussion Paper, No. 958, Global Labor Organization (GLO), Essen.

NEGRI, FERNANDA et al. Socioeconomic factors and the probability of death by Covid-19 in Brazil. *Journal of Public Health*, v.43, n.3, p. 493-498, 2021. DOI https://doi.org/10.1093/pubmed/fdaa279.

NELSON, JENNIFER; VALLAS, STEVEN. Race and inequality at work: An occupational perspective. *Sociology Compass*, 2021. DOI https://doi.org/10.1111/soc4.12926.

NICOLA, MARIA et al. The socio-economic implications of the coronavirus pandemic (COVID-19): A review. *International Journal of Surgery*, v. 78, p. 185-193, 2020. DOI https://doi.org/10.1016/j.ijsu.2020.04.018.

NINGTHOUJAM, R. COVID 19 can spread through breathing, talking, study estimates, *Current Medicine Research and Practice*, 2020. DOI https://doi.org/10.1016/j.cmrp.2020.05.003.

NISHIDA, CHINATSU; YATERA, KAZUHIRO. The Impact of Ambient Environmental and Occupational Pollution on Respiratory Diseases. *International Journal of Environmental Research and Public Health*. v.19, n. 2788, 2022. DOI https://doi.org/10.3390/ijerph19052788.

PADHAN, RAKESH; PRABHEESH, K. The economics of COVID-19 pandemic: A survey. *Economic Analysis and Policy*, n. 70, p. 220-237, 2021. DOI https://doi.org/10.1016/j.eap.2021.02.012.

PAPADIMITRIOU, ELENI; BLASKÓ, ZSUZCA, BLASKÓ. Economic sectors at risk due to COVID-19 disruptions: will men and women in the EU be affected similarly? EUR 30327 EN, *Publications Office of the European Union*, Luxembourg, 2020, ISBN 978-92-76-21073-3, DOI 10.2760/50058, JRC121551.

PARK, CHEOLSUNG; KANG, CHANGHUI. Does education induce healthy lifestyle? *Journal of Health Economics*, n. 27, p. 1516-1531, 2008. DOI https://doi.org/10.1016/j.jhealeco.2008.07.005.

PATRICIA, ELAINE. São Paulo nurse is first Brazilian vaccinated against COVID-19. *AGÊNCIA BRASIL*, 18 January 2021, < https://agenciabrasil.ebc.com.br/en/saude/noticia/2021-01/sao-paulo-nurse-first-brazilian-vaccinated-against-covid-19>. Accessed 14 April 2022.

PECKHAM, TREVOR et al. Creating a Future for Occupational Health. *Annas of Work Exposures and Health*, v. 61, n.1, p.3-15, 2017. DOI: 10.1093/annweh/wxw011.

PEREIRA R.J. et al. The risk of COVID-19 transmission in favelas and slums in Brazil. *Public Health*, v. 183, p. 42-43, 2020. DOI https://doi.org/10.1016/j.puhe.2020.04.042.

PORTO, EDOARDO et al. Lockdown, essential sectors, and Covid-19: Lessons from Italy. *Journal of Health Economics*, n. 81, 2022. DOI: https://doi.org/10.1016/j.jhealeco.2021.102572.

RAIS. O que é RAIS? *Ministério do Trabalho e Previdência, Relação Anual de Informações* Sociais, 2022, <http://www.rais.gov.br/sitio/sobre.jsf>. Accessed May 1, 2022.

RAPPAPORT, JORDAN. Productivity, Congested Commuting, and Metro Size. *Federal Reserve Bank of Kansas City*, n. 16, 2016. DOI: https://doi.org/10.18651/RWP2016-03.

REIS, R. F. et al. Characterization of the COVID-19 pandemic and the impact of uncertainties, mitigation strategies, and underreporting of cases in South Korea, Italy, and Brazil. *Chaos, Soliton and Fractals*, 2020. DOI https://doi.org/10.1016/j.chaos.2020.109888.

REQUIA, WEEBER J. et al. Risk of the Brazilian health care system over 5572 municipalities to exceed health care capacity due to the 2019 novel coronavirus (COVID-19). *Science of the Total Environment*, n.730, 2020. DOI https://doi.org/10.1016/j.scitotenv.2020.139144.

RIM, DONGHYUN; NOVESELAC, ATILA. Occupational Exposure to Hazardous Airborne Pollutants: Effects of Air Mixing and Source Location. *Journal of Occupational and Environmental Hygiene*, v.7, p. 683-692. DOI 10.1080/15459624.2010.526894.

ROBACK, JENNIFER. Wages, Rents, and the Quality of Life. *Journal of Political Economy*, v. 90, n. 6, p. 1257-1278, 1982. DOI https://doi.org/10.1086/261120.

ROYAL COLLEGE OF NURSING. Meet the nurse who gave world's first COVID-19 vaccine. *RCN MAGAZINES*, 24 December 2020, < https://www.rcn.org.uk/magazines/bulletin/2020/dec/may-parsons-nurse-first-vaccine-covid-19>. Accessed 14 April 2022.

SELDEN, THOMAS; BERDAHL, TERCEIRA. Covid-19 and Racial/Ethnic Disparities in Health Risk, Employment, and Household Composition. *Health Affairs*, v. 39, n. 9, 2020. DOI: 10.1377/hlthaff.2020.00897.

SEPLAG. COVID-19 em Dados. Base Geral. *Secretaria do Planejamento e Gestão*, 2020. <https://dados.seplag.pe.gov.br/apps/corona_dados.html>. Accessed: June 7th, 2022.

SES-PE. Boletim Secretaria Estadual de Saúde – Novo Coronavírus. *Governo de Pernambuco*, 8 April 2022, <https://www.pecontracoronavirus.pe.gov.br/boletim-secretaria-estadual-de-saude-novo-coronavirus-197/>. Accessed 15 April 2022.

SHAN, BIAOAN et al. The Effect of Occupational Health Risk Perception on Job Satisfaction. *International Journal of Environmental Research and Public Health*, n. 19, 2022. DOI https://doi.org/10.3390/ijerph19042111.

SIQUEIRA, CARLOS et al. Effects of Social, Economic, and Labor Policies on Occupational Health Disparities. *American Journal of Industrial Medicine*, n. 57, p. 557-572, 2014. DOI: 10.1002/ajim.22186.

SOMUYIWA, ADEBAMBO et al. Analysis of the Cost of Traffic Congestion on Worker's Productivity in a Mega City of a Developing Economy. *International Review of Management and Business Research.* v. 4, n. 3, p. 644-656, 2015.

SORAINO, JOAN et al. Prevalence and attributable health burden of chronic respiratory diseases, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017. *Lancet Respiratory Medicine*, n. 8, p. 585-596, 2020. DOI 10.1016/S2213-2600(20)30105-3.

SOUZA, RENNIE et al. Work and health in a contemporary society: demands, control, and insecurity. *The Journal of Epidemiology and Community Health*, n. 57, p. 849-854, 2003. DOI: 10.1136/jech.57.11.849.

STATACORP. Stata 14 Base Reference Manual. *Stata Press*, College Station, TX, 2015. <https://www.stata.com/manuals14/rasclogit.pdf>. Accessed: April 8th, 2022.

STEEGE, ANDREA et al. Examining Occupational Health and Safety Disparities Using National Data: A Cause for Continuing Concern. *American Journal of Industrial Medicine*, v.57, n.5, p.527-538. DOI 10.1002/ajim.22297.

STRAZDINS, LYNDALL et al. Job Strain, Job Insecurity, and Health: Rethinking the Relationship. *Journal of Occupational Health Psychology*, v. 9, n. 4, p. 296-305, 2004. DOI 10.1037/1076-8998.9.4.296.

SZWARCWALD, CÉLIA et al. Health Inequalities in Rio de Janeiro, Brazil: Lower Healthy Life Expectancy in Socioeconomically Disadvantaged Areas. *American Journal of Public Health*, v. 101, n.3, p.517-523. DOI: 10.2105/AJPH.2010.195453.

TIMMINS, CHRISTOPHER. If You Cannot Take the Heat, Get Out of the Cerrado…Recovering the Equilibrium Amenity Cost of Nonmarginal Climate Change in Brazil. *Journal of Regional Science*, vol. 47, n.1, p.1-25, 2007. DOI https://doi.org/10.1111/j.1467-9787.2007.00497.x

TRAIN, KENNETH. Discrete Choice Methods with Simulation. *Cambridge University Press*, New York, 2nd ed, 2009.

VOS, DUCO et al. Working from Home and the Willingness to Accept a Longer Commute. *The Annals of Regional Science*, n.61, p. 375-398, 2018. DOI https://doi.org/10.1007/s00168-018-0873-6.

WALD, ABRAHAM. Tests of Statistical Hypotheses Concerning Several Parameters When the Number of Observations is Large. *Transactions of the American Mathematical Society*, v.54, n.3, p.426-482, 1943. DOI:10.2307/1990256.

WASDANI, KISHINCHAND P.; PRASAD, AJNESH. The impossibility of social distancing among the urban poor: the case of an Indian slum in the times of COVID-19. *Local Environment*, v. 25, n. 5, p. 414-418, 2020. DOI https://doi.org/10.1080/13549839.2020.1754375.

WORLD BANK. Population, total – Brazil. *The World Bank Data*, 2020, <https://data.worldbank.org/indicator/SP.POP.TOTL?locations=BR>. Accessed 14 April 2022.

WORLD HEALTH ORGANIZATION. Brazil: WHO Coronavirus Disease. *World Health Organization*, 14 April 2022, <https://covid19.who.int/region/amro/country/br>. Accessed 14 April 2022.

WORLD HEALTH ORGANIZATION. Coronavirus disease (COVID-19): Vaccines. *World Health Organization*, 16 March 2022, <https://www.who.int/covid-19/vaccines>. Accessed 15 April 2022.

WU, XIAO et al. Exposure to air pollution and COVID-19 mortality in the United States: A nationwide cross-sectional study. *medRxiv*, 2020. DOI https://doi.org/10.1101/2020.04.05.20054502.

ZEN. America’s Healthiest Workers. Business Know-How, *Zenbusiness,* July 31st 2020, <https://www.zenbusiness.com/blog/americas-healthiest-workers/>, Accessed August 30, 2022.

ZHOU, PENG et al. A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature*, v. 579, p. 270–273, 2020. DOI https://doi.org/10.1038/s41586-020-2012-7.

ZON, ADRIAAN; MUYSKEN, JOAN. Health and endogenous growth. *Journal of Health Economics*, v. 20, n. 2, p. 169-185, 2001. DOI: 10.1016/s0167-6296(00)00072-2.

Appendix

A.1 Additional details

The appendix additional tables with additional details. Table A.1 displays the summary statistics for individual characteristics for all cases, which is the complement for Table 3.1, the latter shows the summary statistics for individual characteristics for only the positive cases. The next table is Table A.2 which displays the summary statistics for economic sectors for all cases, a compliment for Table 3.2 which only shows the positive cases. Table A.3 shows the summary statistics for firm characteristics for all cases as well, which is the compliment for Table 3.3 what shows only the positive cases. These three tables with all cases contain each 47,328 observations because it has all cases, instead of 13,806 observations displayed before on tables 3.1, 3.2, and 3.3

As for Table A.4, it presents the alternative specific logit coefficients by the least healthy sectors as essential sectors, since Table 4.1 only shows the odds ratio. Table A.4 also contains 75,004 observations, and the essential sectors are the same economic sectors as on Table 4.1. The following table is A.5, displaying the alternative specific logit coefficients by the least healthy sectors, the latter defined as most positive cases. Table 4.2 only shows the odds ratio, and Table A.5 shows the coefficient results for the model. Both tables present 41,352 observations, and also have two grouped economic sectors, the Least Healthy and Other Sectors.

On Table A.5 as well as Table 4.2, the Least Healthy sectors are composed of the economic sectors with the most positive cases which are: Public Administration, Defense and Social Security, Trade Repair of Motor Vehicles, Administrative Activities and Complementary Services, and Education. The Human Health and Social Services sector is used as base alternative for comparison. And the Other Sectors are composed of the remaining economic sectors mentioned before as: Accommodation and Food, Arts Culture Sports and Recreation, Construction, Financial Insurance and Related, Information and Communication, Professional Scientific and Technical Activities, Real Estate Activities, and Other Service Activities.

Lastly, Table A.6 displays the alternative specific logit by least healthy sectors, the latter defined as essential sectors. Table 4.3 only shows the odds ratio, and Table A.6 displays the coefficient results. The economic sectors are grouped into two groups as well, the Least Healthy and Other Sectors, containing also 41,352 observations. The Least Healthy group is composed of economic sectors that are considered the essential activities, the economic sectors that did not experience lockdown: Electricity and Gas, Processing Industries, Trade; Repair of motor Vehicles, Transportation Storage and Mail, and Water Sewage Waste Management and Decontamination Activities. The Human Health and Social Services is used as a base alternative in the model for comparison, and it did not experience lockdown as well. And the Other Sectors group is composed by the remaining economic sectors that experienced lockdown: Public Administration, Defense and Social Security, Administrative Activities and Complementary Services, Education, Accommodation and Food, Arts Culture Sports and Recreation, Construction, Financial Insurance and Related, Information and Communication, Professional Scientific and Technical Activities, Real Estate Activities, and Other Service Activities.

The tables A.4, A.5 and A.6 shows the coefficients estimated by the model with a constant, differently than the odds ratio tables. The independent variables in these three tables are: Age, Men, Non-White, Complete Primary Education, Complete Secondary Education, Minimum Wage, Working Hours, Job Tenure, Distance, Employment CLT, and Establishment Size, also a Constant is presented.

To avoid confusion tables 3.1, 3.2 and 3.3 contain 13,806 observations each, it is the summary statistics for positive cases for Covid-19 only. While tables A.1, A.2 and A.3 have 47,328 observations for summary statistics for all cases, which means for all individuals who was tested, and not only the ones with positive results. Table 4.1 has 75,004 observations as well as Table A.4, they both present the alternative specific conditional logit by essential sectors, where the first one presents it by odds ratio and the second by the coefficients. Lastly, tables 4.2, 4.3, A.5 and A.6 all contain 41,352 observations.

Table A.1 – Summary Statistics for Individual Characteristics All Cases

Variables	mean	std	min	25%	50%	75%	100%
Age	46.65	13.49	0.00	42.00	50.00	56.00	105.00
Men	0.42	0.49	0.00	0.00	0.000	1.00	1.00
Non-white	0.46	0.50	0.00	0.00	0.000	1.00	1.00
White	0.28	0.45	0.00	0.00	0.000	1.00	1.00
Uninformed race	0.25	0.43	0.00	0.00	0.000	1.00	1.00
Incomplete primary educ.	0.06	0.24	0.00	0.00	0.000	0.00	1.00
Complete primary educ.	0.43	0.49	0.00	0.00	0.000	1.00	1.00
Complete secondary educ.	0.47	0.50	0.00	0.00	0.000	1.00	1.00
Complete higher educ.	0.03	0.18	0.00	0.00	0.000	0.00	1.00
Nominal Wage	4,294.57	6,024.37	0.00	1,240.41	2,001.67	4,791.87	99,666.30
Minimum Wage	4.29	6.03	0.00	1.23	2.00	4.79	99.86
Working hours	37.87	8.64	0.00	36.00	40.00	44.00	44.00
No Working Days	11.38	41.08	0.00	0.00	0.00	0.00	365.00
Job tenure	123.61	126.67	0.00	18.90	75.90	192.90	583.90
Distance	5.15	3.012	0.00	2.77	4.92	7.23	22.12

Source: Elaborated by Author

Table A.2 – Summary Statistics for Economic Sectors All Cases

Variables	mean	std	25%	50%	75%	100%
Accommodation And Food	0.03	0.17	0.00	0.00	0.00	1.00
Administrative Activities and Comp. Services	0.10	0.30	0.00	0.00	0.00	1.00
Agri., Livestock, Forestry Product., Fishing and Aqua.	0.01	0.04	0.00	0.00	0.00	1.00
Construction	0.02	0.14	0.00	0.00	0.00	1.00
Education	0.09	0.29	0.00	0.00	0.00	1.00
Electricity And Gas	0.01	0.08	0.00	0.00	0.00	1.00
Extractive Industries	0.01	0.01	0.00	0.00	0.00	1.00
Human Health and Social Services	0.09	0.29	0.00	0.00	0.00	1.00
Information And Communication	0.02	0.15	0.00	0.00	0.00	1.00
Other Service Activities	0.03	0.16	0.00	0.00	0.00	1.00
Processing Industries	0.03	0.16	0.00	0.00	0.00	1.00
Professional, Scientific and Technical Activities	0.03	0.16	0.00	0.00	0.00	1.00
Public Administration, Defense and Social Security	0.35	0.48	0.00	0.00	1.00	1.00
Trade; Repair of Motor Vehicles and Motorcycles	0.14	0.34	0.00	0.00	0.00	1.00
Transportation, Storage and Mail	0.03	0.16	0.00	0.00	0.00	1.00
Water, Sewage, Waste Management and Decont. Act.	0.01	0.07	0.00	0.00	0.00	1.00
Arts, Culture, Sports and Recreation	0.01	0.09	0.00	0.00	0.00	1.00
Real Estate Activities	0.01	0.06	0.00	0.00	0.00	1.00
Financial, Insurance and Related Services Activities	0.02	0.15	0.00	0.00	0.00	1.00

Source: Elaborated by Author

Table A.3 – Summary Statistics for Firm Characteristics All Cases

Variables	mean	std	25%	50%	75%	100%
Establishment Size	7.33	2.80	5.00	8.00	10.00	10.00
1 to 4 Employees	0.01	0.10	0.00	0.00	0.00	1.00
5 to 9 Employees	0.06	0.23	0.00	0.00	0.00	1.00
10 to 19 Employees	0.07	0.25	0.00	0.00	0.00	1.00
20 to 49 Employees	0.08	0.27	0.00	0.00	0.00	1.00
50 to 99 Employees	0.10	0.30	0.00	0.00	0.00	1.00
100 to 249 Employees	0.07	0.25	0.00	0.00	0.00	1.00
250 to 499 Employees	0.08	0.27	0.00	0.00	0.00	1.00
500 to 999 Employees	0.07	0.25	0.00	0.00	0.00	1.00
1000 to 4999 Employees	0.07	0.25	0.00	0.00	0.00	1.00
5000 or above	0.41	0.49	0.00	0.00	1.00	1.00
Type Employment CLT	0.52	0.50	0.00	1.00	1.00	1.00
Type Employment Statutory Employee	0.01	0.11	0.00	0.00	0.00	1.00
Type Employment Other	0.46	0.50	0.00	0.00	1.00	1.00
Legal Nature Public Sector	0.37	0.48	0.00	0.00	1.00	1.00
Lockdown	0.70	0.46	0.00	1.00	1.00	1.00

Source: Elaborated by Author

Table A.4 – A-S Conditional Logit by Essential Sectors

Variables	Electricity and Gas	Processing Industries	Trade; Repair of Motor Vehicles and Motorcycles	Transportation, Storage and Mail	Water, Sewage, Waste Management and Decontamination Activities
Age	-0.031* (0.013)	-0.016** (0.006)	-0.030*** (0.004)	-0.001 (0.006)	-0.039** (0.013)
Men	1.659*** (0.235)	1.451*** (0.134)	1.129*** (0.097)	2.302*** (0.139)	1.802*** (0.271)
Non-White	-0.609** (0.230)	-0.157 (0.130)	-0.380*** (0.093)	-0.586*** (0.123)	-0.493 (0.259)
Primary Educ.	-0.089 (0.430)	-0.331 (0.249)	0229 (0.202)	-0.154 (0.215)	-1.001* (0.423)
Secondary Educ.	0.029 (0.408)	-0.348 (0.264)	-0.137 (0.214)	-0.415 (0.236)	-0.146 (0.403)
Minimum Wage	0.139*** (0.016)	0.077*** (0.015)	0.041** (0.014)	-0.029 (0.018)	0.043 (0.025)
Working Hours	0.021* (0.010)	0.014* (0.007)	0.017*** (0.005)	0.008 (0.006)	0.086*** (0.024)
Job Tenure	0.006*** (0.001)	0.001 (0.001)	-0.001 (0.001)	0.004*** (0.001)	0.002 (0.001)
Distance	-0.079* (0.039)	-0.001 (0.021)	0.023 (0.015)	-0.001 (0.020)	0.130*** (0.040)
Employment Type CLT	1.128** (0.384)	0.308 (0.187)	-0.440*** (0.118)	0.314 (0.179)	-0.204 (0.319)
Establishment Size	0.027 (0.063)	-0.543** (0.030)	-0.674*** (0.022)	-0.192*** (0.028)	0.372*** (0.096)
Constant	-5.166*** (1.061)	1.603*** (0.508)	4.788*** (0.370)	-1.482*** (0.507)	-9.069*** (1.526)

Standard errors in parentheses * p<0.05, ** p<0.01, ***p <0.001
Source: Elaborated by Author

Table A.5 – A-S Conditional Logit by Least Healthy Sectors as Most Cases

Variables	Least Healthy	Other Sectors
Age	0.008**	-0.012***
	(0.003)	(0.003)
Men	0.828***	1.283***
	(0.066)	(0.073)
Non-White	-0.284***	-0.365***
	(0.062)	(0.069)
Primary Educ.	-0.737***	-0.767***
	(0.122)	(0.134)
Secondary Educ.	-0.459***	-0.190
	(0.123)	(0.136)
Minimum Wage	0.005	0.025***
	(0.007)	(0.007)
Working Hours	0.013***	0.017***
	(0.003)	(0.004)
Job Tenure	0.001*	0.002***
	(0.001)	(0.001)
Distance	0.017	0.018
	(0.010)	(0.011)
Employment CLT	-2.661***	-0.928***
	(0.078)	(0.092)
Establishment Size	-0.322***	-0.475***
	(0.015)	(0.016)
Constant	5.281***	4.380***
	(0.261)	(0.288)

Standard errors in parentheses * p<0.05, **p<0.01, ***p<0.001

Source: Elaborated by Author

Table A.6 – A-S Conditional Logit by Least Healthy Sectors as Essential Sectors

Variables	Least Healthy	Other Sectors
Age	-0.013***	0.008**
	(0.003)	(0.003)
Men	1.283***	0.861***
	(0.075)	(0.066)
Non-White	-0.433***	-0.265***
	(0.071)	(0.061)
Primary Educ.	0.012***	-0.950***
	(0.142)	(0.120)
Secondary Educ.	-0.370*	-0.378**
	(0.147)	(0.122)
Minimum Wage	0.022**	0.007
	(0.008)	(0.007)
Working Hours	0.020***	0.011***
	(0.004)	(0.003)
Job Tenure	0.001	0.001**
	(0.001)	(0.000)
Distance	0.017	0.018
	(0.012)	(0.010)
Employment CLT	-1.546***	-2.475***
	(0.093)	(0.077)
Establishment Size	-0.504***	-0.371***
	(0.016)	(0.014)
Constant	4.589***	5.227***
	(0.296)	(0.258)

Standard errors in parentheses * p<0.05, **p<0.01, ***p<0.001
Source: Elaborated by Author