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ESSAYS IN HEALTH ECONOMICS

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I dedicate this thesis to my parents.

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Abstract

This dissertation focuses on employing various quasi-experimental methods to estimate causal effects within the health economics literature. In the first chapter, we examine the impact of age-based minimum wages on the health outcomes of young workers in the UK using data from the UK Household Longitudinal Study (”Understanding Society”) (2016 - 2021) and exploiting a Regression Discontinuity Design (RDD) framework. We find that the increase in minimum wage has a positive effect on the physical and mental health of workers when they turn 21, but it does not have significant effects at the other age cutoff points, however, this magnitude is slightly smaller if we adopt the ”cumulative multiple cutoffs” RDD approach.

Chapter two investigates the effects of minimum wage on the health outcomes of workers, leveraging on several reforms that progressively increased income levels for workers in Spain drawing data from the Spanish Survey of Living Conditions (ES-SILC). We rely on the Callaway and Sant'Anna Difference-in-differences (CSDID) model. The results indicate that increases of the minimum wage are associated with modest improvements in self-reported health.

This chapter examines the relationship between online vaccine-related information and vaccine hesitancy in the European Union. Using data from the 2019 Eurobarometer, it studies whether relying on the internet, including social networks and other websites, as a source of information about vaccination is associated with a higher likelihood of vaccine hesitancy among respondents. To address the potential endogeneity of information-seeking behaviour, the empirical analysis combines linear probability models with an instrumental variable strategy based on regional variation in fixed broadband coverage and lightning intensity. The results provides suggestive evidence of a positive association between internet-based vaccine information and vaccine hesitancy. The IV estimates are larger than the corresponding baseline estimates, consistent with an interpretation in terms of local average treatment effects for individuals whose online information exposure is shifted by the instruments. In general, findings are consistent with the role of the online information environment may play in shaping vaccination attitudes. They also point to the importance of ensuring that reliable and evidence-based vaccine information is visible and accessible online.

Introduction

Researchers have extensively examined various policies associated with the health of individuals, particularly in health economics literature. The enactment of public policies targeted at improving health is considered as a primary factor in addressing health and welfare concerns of individuals (Komro et al., 2020; Patel et al., 2023). Understanding how policies such as minimum wages translate into income effects that influence health outcomes, as well as the factors shaping vaccine hesitancy, is therefore necessary. Employing quasi-experimental methods presents a significant contribution in providing causal explanations to these phenomena.

The objective of this thesis is to advance the borders of research on these issues and improve our understanding of factors that influence health, particularly in developed economies where these policies are well structured. This dissertation is ordered in three different chapters. These chapters are attuned to health outcomes and health care, which are in line with the third goal of the 2030 Sustainable Development Goals (SDGs). Notably, this thesis plays a crucial role in the field of policy evaluation aimed at advancing health care.

The first chapter investigates the impact of age-based minimum wages on the mental and physical health outcomes of young workers.[1] This problem is of great concern since, as evidence shows, minimum wages, which could be seen as an additional increase in incomes, have direct repercussions on the variations in health. Around 90% of ILO member states currently have some type of minimum wage legislation or regulatory mechanism in place. Since the seminal paper of Card and Krueger (1994), the impact of minimum wages on employment, working hours, and productivity has been extensively investigated in several countries (Bosch and Manacorda 2010; MaCurdy 2015; Meer and West,2016). Even though there has been several evidences of how minimum wage affects the labour outcomes, welfare and inequality in the society. Little is known about how minimum wages affect health outcomes. Age-dependent minimum wage is a peculiar variant which aims to facilitate the entry of young workers into the labour market. This system has been adopted in the United Kingdom, Ireland, the Netherlands, Denmark, Australia, and New

[1] The co-authors on this chapter are Prof. Silvana Robone and Prof. Gilberto Turati.

Zealand. In this paper, we show how age-dependent minimum wages affect the mental and physical health of young workers. To do this, the study estimates series of regression discontinuity design models of health to evaluate the short and long-term causal impact of age-dependent minimum wage using the Understanding Society Longitudinal Study (2016-2021). Overall, the results of the analysis indicate that age-dependent minimum wage increased mental and physical health of only workers turning age 21 and much smaller effect when considering the cumulative multiple cutoff approach by Cattaneo et al. (2021). This provides some insight to policymakers to design more effective ways to implement minimum wage policies for young workers in the UK.

The second chapter examines the impact of minimum wage on workers' health outcomes, utilising various reforms that marginally raised income levels for employees in Spain.[2] This focus is closely related to the first chapter of this thesis, since minimum wage policy is also evaluated here. However, in this chapter, the research question is evaluated in the context of Spain employing a difference-in-difference with multiple timing. In 2017, the minimum wage has risen substantially, with 2019 witnessing the largest increase in recent Spanish history (approximately 22%) from about €735 to €900. These significant and persistent changes in the Spanish minimum wage policy constitute an excellent case study to understand the health-related effects of this policy reform. Studies (Gorjon et al., 2024; Laporta, 2022; López-Tamayo et al., 2017; Sabater (2022); Galán & Puente, 2015) that have used a similar policy in Spain have investigated its effect on labour outcomes. The effect of minimum wage on health is theoretically ambiguous. On the one hand, an increase in minimum wage increases investment in health, that is, better food and exercising; reduction of financial stress; on the other hand, it may lead to investment in unhealthy products and longer working hours or higher effort. From this, we investigate, in this paper, the empirical relationship between minimum wages and health outcomes, leveraging several reforms that have progressively raised income levels for workers in Spain since 2017. Here, we depart from the conventional difference-in-difference settings. And we adopt the Callaway and San't Anna difference-in-difference (CS DiD) estimator. Drawing on the occurrences of treatment groups over a period, the results indicated that increases in the minimum wage are related to modest improvements in self-reported health. We find that this effect persists over time. Overall, the results align with prior research indicating that the minimum wage can serve as an effective policy instrument not only for enhancing working conditions and decreasing income disparities, but also for advancing public health and diminishing health inequalities.

In the third chapter, we focus on the entire European Area and estimate the determinants of

[2]The second paper is co-authored by Prof. Dolores Rubio-Jiminez and Prof. Silvana Robone.

vaccination outcomes relying on media utilisation.[3] This topic is not completely independent of the other chapters in this thesis, since we consider the demand for health care and improving public health. Vaccines have been identified as one of the most effective tools for public health, since it saves about 2-3 million lives every year from avoidable death (Barus, 2017). After the spread of the SARS-CoV-19 virus, the adoption of vaccines has proved as crucial to limit the spread of pandemics and reduce mortality. However, many individuals have been reluctant to receive vaccinations against various diseases, including COVID-19, and a substantial number have refused them altogether (Brilli & Lucifora, 2020).Vaccine rollout has been a strenuous task, with various countries in the EU faced with restricted vaccines as a result of issues with testing, development, production, distribution, acceptance and confidence in vaccines, which has led to problems of patronage. This hesitancy attitude caused by the problem aforementioned is likely to be addressed with effective information and communication geared toward the safety and efficiency of vaccines. Therefore, understanding what drives vaccine attitudes is very relevant. In this chapter, we exploit the Eurobarometer 91.2 (2019) to investigate the effect of media utilisation on vaccine hesitancy. Using an instrumental variables approach to address the endogeneity issues, the results suggest that the use of internet makes people more vaccine hesistant. This suggest that policymakers and scientists should provide transparent messages, objectives and unambiguous information on vaccines.

[3]This chapter has Prof. Elena Cottini, Prof. Claudio Lucifora and Prof. Silvana Robone as co-authors.

1

Age-dependent Minimum Wages and Health Outcomes: Evidence from the UK

1.1 Introduction

Our paper investigates the impact of age-based minimum wages on health outcomes of young workers in the UK using data from the UK Household Longitudinal Study ("Understanding Society") (2016-2021) and exploiting a Regression Discontinuity Design (RDD) framework. By focusing on the health-related effects of minimum wage discontinuities, we consider the National Minimum Wage (NMW) regulation introduced in the UK in 1999 to examine how a possible exogenous increase in income may affect the health outcome of younger workers. An age-based MW system assigns a lower minimum wage (MW) to younger workers, increasing their attractiveness to employers, and thereby improving their chances of obtaining jobs that match their relatively limited skills and experience. The UK NMW introduced minimum wages varied by age. As of 2025, workers above the age of 21 year received £12.21, those in the ages of 18 and 20 received £10.00 and those below the ages of 18 received a wage of £7.55.

Since the seminal paper of Card and Krueger (1994) the impact of minimum wages on employment, working hours, and productivity has been extensively investigated in several countries (e.g. Machin et al., 2003; Stewart, 2004; Neumark and Wascher, 2004; Bosch and Manacorda, 2010; MaCurdy, 2015; Meer and West, 2016). Within this literature, in the last decade, some studies have focused on age-dependent minimum wage policies in the UK, Denmark and the Netherlands, with particular attention to their effects on the labour market outcomes of young workers. Taking into account data on British workers, Dickens et al. (2014) and Xu and Zhu (2023) report that an increase in minimum wages increases the labour supply of young workers; however, Kreiner et al. (2020) and Kabátek (2021), considering data from Denmark and the Netherlands, respectively, report that the increase in the minimum wage for young workers has a negative effect on their level of employment.

Notwithstanding the fact that studies on the effect of minimum wages have been mostly focused on labour market outcomes, nowadays it is recognized that policies can yield additional welfare effects, such as effects on the health of workers. Most of the papers that consider the link between minimum wages and health focus on developed countries, in particular the USA and the UK, and they report mixed results (e.g. Lenhart, 2017a; Horn et al., 2017, Reeves et al., 2017; Kronenberg et al., 2017; Leigh et al., 2019; Kuroki, 2021; Maxwell et al., 2022). And in China, Liu et al. (2024) found that the relationship between MW and health is negative. However, as far as we are aware, no study so far has investigated the possible health effects of age-dependent minimum wage policies for young workers. Our study aims to fill this gap in the literature.

The UK National Minimum Wage (NMW) regulation provides a very good setting to investigate our research question since in the UK minimum wages are updated every year and younger employees are exposed to a total of four cumulative increases in the minimum wage rate. Workers become eligible for minimum wages at the age of 16, with the applicable rate increasing at 18 and 21, until reaching the adult rate at the age of 25. Therefore, this setting allows us to identify the causal effects of minimum wage on health by exploiting a Regression Discontinuity Design (RDD) framework. However, this setting poses some challenges for performing empirical analyses. Since the youth minimum wage can be described as a stepwise increasing function of a worker's calendar age, we have to deal with multiple cutoffs when estimating our RDD models. We have addressed this issue by adopting both a standard "normalizing and pooling" approach and the novel "cumulative multiple cutoffs" approach by Cattaneo et al. (2020, 2021) (see Section 5 for an explanation of these methods). Whilst the standard RDD estimates the local treatment effect at a single cutoff, the multiple cutoffs approach estimates local treatment effects across different thresholds. Since the cutoffs are dependent on age, this cumulative multiple-cutoff approach can capture long-term trends of the treatment effect improving the external validity of results.

In our empirical analysis we consider as dependent variables two different measures of health, that is, mental and physical health. Our main results suggest that the increase in minimum wage has a positive effect on the physical health of workers when they turn 21, but it does not have significant effects at the other age cutoffs. The magnitude of this effect is slightly smaller if we adopt the novel "cumulative multiple cutoffs" approach instead of the standard "normalizing and pooling" approach. Our baseline results appear to be confirmed by several robustness checks. When looking at the heterogeneity of the effects by gender and focusing on the 21 years cutoff, in the short run the policy has a positive effect on the physical health of women and on the mental health of men. These effects seem to be persistent also in the long run. In the short run, the effects seem to be particularly relevant for part-time workers.

Our study adds to the existing body of literature in several ways. First, we consider jointly the two strands of literature described before, and we examine the effect of an age-dependent minimum wage policy on the health outcomes of young workers. To the best of our knowledge, this is the first study that addresses this research question. We investigate this research question by using data from the "Understanding Society" survey (2016 - 2022), therefore, exploiting longitudinal data. Second, we take into consideration a range of health measures regarding mental and physical health. Finally, we are one of the first studies that exploits the novel "cumulative multiple cutoffs" approach by Cattaneo et al. (2020, 2021) to evaluate empirically the effects of a welfare policy. This allows us to distinguish the "short term" effects from the "longer-term" effect of the minimum wage policy.

This paper draws on the conceptual framework that links wages to health through three main channels: affordability, psychosocial mechanisms, and behavioural as well as firm-worker characteristics, all of which have been substantiated in the literature (Leigh et al., 2019; Lenhart, 2017a). Higher wages may enhance health by increasing workers' capacity to spend on health-promoting goods and services such as healthcare, housing, and nutrition, although the overall impact on unhealthy consumption patterns remains theoretically unclear. A second pathway is psychosocial, higher wages can raise job satisfaction, perceived social status, and sense of control over one's life, all of which are linked to better mental and physical health. A further channel operates through the behavioural responses of both workers and firms. On the firm side, adjustments in working hours or employment levels may either amplify or counteract these health effects. On the worker side, higher wages can strengthen incentives to invest in health, shape future-oriented preferences, and change how time is allocated between work and health-enhancing activities. These mechanisms are likely to differ across settings and population groups. This study also identifies overtime hours and commuting distance as additional channels. Overtime affects the affordability pathway (by increasing earnings) while at the same time influencing psychosocial stress and reducing the time available for health investments, leading to ambiguous overall effects. Similarly, commuting distance affects net disposable income (via transport costs) and increases time pressure, stress, and exposure to pollution, all of which can alter health behaviours and outcomes.

The remaining of the paper is organized as follow. Section 2 presents a review of the literature on the various areas of minimum wage and health outcomes. Section 3 describes the minimum wage policy in place in the UK. The data employed for the empirical analysis and some descriptive statistics are outlined in Section 4. The empirical model and estimation strategy are presented in Section 5, while the results are illustrated in Section 6. Finally, Section 7 offers concluding remarks.

1.2 Related Literature

In this section, we briefly summarize the main findings of both the literature exploring the impact of minimum wage on the health of workers and the literature on the impact of age-dependent minimum wage policies on labour market outcomes for young workers, pointing out what is our contribution to these two strands of literature. In this paper, we consider jointly the two strands of literature described before, and we examine the effect of an age-dependent minimum wage policy on the health outcomes of young workers. To the best of our knowledge, this is the first study that addresses this research question.

The literature discussing the link between minimum wages and health provides mixed results (Liu et al., 2024). For instance, Lenhart (2017b) find a positive effect of an increase in minimum wage on the self-reported health and other health-related outcomes of low-earnings workers, however, Horn et al. (2017) find largely opposite results. The mixed results in the empirical literature are unsurprising since the impact of minimum wage on health is unclear from a theoretical standpoint (Chen, 2021). Several factors can play a role as mediators between minimum wage and health: living standards and income inequality, but also health-related behaviours and job satisfaction. The net effect on health depends on how these different factors combine.

First, an increase in minimum wage provides additional income to workers, which can be allocated to consumption bundles and produce very different effects on health. On the one hand, individuals might decide to invest more in health, as predicted by Grossman (1972), or to consume healthier foods. Evidence of this kind of effect is provided by, for instance, McGranahan and Schanzenbach (2013) and Clark et al. (2020). On the other hand, individuals might also decide to consume more unhealthy goods and less healthy foods (e.g., Kenkel et al., 2014, Apouey and Clark, 2015).

Second, minimum wage can reduce income inequality. Therefore, increases in minimum wage could additionally improve the health of workers by increasing the earnings of low-income groups, and reducing income inequality at the lower end of the income distribution (e.g., Bosch and Manacorda, 2010; Autor et al., 2016; Lin and Yun, 2014).

Third, increases in minimum wage could also influence health-related outcomes by affecting job satisfaction and the "work-leisure" time allocation. If firms - facing higher costs - require additional effort from workers and/or adjust non-wage compensation, then working conditions and job satisfaction can deteriorate, implying a negative effect on health (Clark and Oswald, 1996 and Faragher et al., 2005). Moreover, individuals might spend fewer hours in health-promoting activities (for instance, physical exercise or sports activities) due to the increase in the number of hours worked, implying additional negative effects on health.

Most of the papers which consider the link between minimum wages and health focus on developed countries, in particular on the USA and the UK (e.g., Leigh et al., 2019; Lenhart, 2017a). To identify the impact of minimum wage, most of the US-based studies exploit the differential timings of federal and state minimum wage increases (e.g., Horn et al., 2017; Kuroki, 2021). Some studies consider the impact of minimum wage on health due to changes in eating behaviours and dietary patterns. On one side, for instance, Meltzer and Chen (2011) study the impact of minimum wage rates on body weight, finding that a one-dollar increase in the hourly minimum wage is related to a 0.06 decrease in the average Body Mass Index. On the contrary, more recently, Andreyeva and Ukert (2018) found that the 2009 minimum wage increase is positively associated with the probability of being obese and negatively associated with daily fruit and vegetable intake, while it does not influence healthcare access.

Some studies focus on the heterogeneity across socio-demographic groups regarding the effects of minimum wage on health. As for racial differences, in the USA white women are more likely to report better health when experiencing a minimum wage increase while Hispanic men report worse health (Averett et al. (2018)). As for gender differences, Horn et al. (2017) use data from the USA behavioural Risk Factor Surveillance Survey (BRFSS) from 1993 to 2004 and report that minimum wage leads to worse health outcomes for men, particularly among the unemployed. Moreover, they find both worsening general health and improved mental health following minimum wage increases among women. Kuroki (2021) and Sigaud et al. (2022) focus on the post-Great Recession period and exploit BRFSS data from 2011 to 2019. Kuroki (2021) reports that increases in the minimum wage increase the number of bad mental health days among men. Sigaud et al. (2022) report that a higher minimum wage increases men's mental and physical health burdens but has an ambiguous effect on a more general measure of health; however, among women, the minimum wage improves general health and reduces their mental and physical health burdens.

Besides the USA, several studies focus on the UK and the effects that the introduction of the British National Minimum Wage (NMW) in 1999 had on the health outcomes of British citizens. Results are sensitive to the definitions used to identify the treatment groups, the model specification, and the dependent variable used. For instance, Reeves et al. (2017) shows that the income of low-wage workers increases due to the introduction of minimum wage, and this lowers the probability of experiencing mental illness, while Kronenberg et al. (2017) finds that the introduction of minimum wage does not have an impact on the mental health of low-wage earners. Lenhart (2017b) finds that the introduction of the national minimum wage improves self-reported health status and reduces the presence of health conditions of low-wage workers due to an increase in income. The potential channels for these effects are health behaviours, leisure expenditures, and reduced stress due to improved financial conditions. More recently, Maxwell et al. (2022) exploit 2016, 2017, and 2018 NMW increases as natural experiments, reporting that the estimated impact on mental and physical health is not statistically significant.

In addition to studies regarding the US and the UK, others investigate the effects of minimum wage on health by considering data from other countries. For instance, Chen (2021) exploits data from the China labour-force Dynamic Survey (CLDS) and reports that a higher minimum wage improves self-reported health and reduces the presence of health conditions (but has no effect on health behaviours such as drinking, regular exercise, smoking) of low-skilled workers. Similarly, Wong and Ye (2015) finds that after the introduction of a mandatory minimum wage in Hong Kong in 2011, the physical and psychological health of the population increased. Differently, the findings of the study of Liu et al. (2024), which use data on a representative sample of the Chinese population from the World Health Organization's Study on Global Aging and Adult Health (SAGE) in 2007-2010, show that minimum wage has a negative influence on several health outcomes particularly for full-time employees in the private sector. Basically, examining ten health domains, including mobility, sleep, and psychological well-being, to determine the net impact of salary regulations. The combination of higher productivity demands and longer hours can create a more stressful work environment, which negatively impacts mental and physical health.

When considering Western countries, Bai and Veall (2023) exploit the Canadian National Population Health Survey (NPHS) from 1994 - 2011 showing that increases in the minimum wage appear to reduce depression and distress, particularly for men. By focusing on Europe, Lebihan (2023) looks at subjective heath, and report that higher minimum wage increases self-reported health, income security, happiness and life satisfaction. Differently, Lenhart (2017b) looks at objective health and find that higher minimum wages are related to significant reductions in overall mortality rates and the number of deaths due to health conditions (stroke, diabetes, disease of the circulatory system) in 24 OECD countries for 31 years.

Concerning the second strand of literature, since the seminal paper of Card and Krueger (1994) on the fast-food industry in the USA, the impact of minimum wages on employment, working hours, and productivity has been extensively investigated in several countries (e.g. Machin et al., 2003; Stewart, 2004; Neumark and Wascher, 2004; Bosch and Manacorda, 2010; MaCurdy, 2015; Meer and West, 2016). Within this literature, in the last decade, some studies focus on age-dependent minimum wage policies and their impact on the labour market outcomes of young workers. By focusing on the UK, Dickens et al. (2014) exploits data from the UK Labour Force Survey between July 1999 and March 2009 by adopting the method of Regression Discontinuity Design (RDD). They show that the increase in the minimum wage that occurs at the age of 22 increases the employment of low-skilled individuals and that unemployment decreases among men but not among women. Xu and Zhu (2023) extend the RDD analysis of Dickens et al. (2014), by examining the heterogeneous effects of the increase in the age-dependent minimum wage on employment in the UK. They use data from the Quarterly Labour Force Survey (QLFS) from 2000-2018. They suggest that an increase in minimum wages increases the labour supply of young workers. This positive employment effect appears to be more pronounced in geographical areas with low unemployment rates.

Kabátek (2021) exploits administrative data from Statistics Netherlands (CBS) to analyse the effects of an age-dependent minimum wage on youth employment in the Netherlands, and he also adopts an RDD design. The system in the Netherlands distinguishes nine age brackets, starting at age 15 and reaching the adult rate at age 23. Differently from Dickens et al. (2014) and Xu and Zhu (2023), and Kabátek (2021) reports that the increase in the minimum wage has a negative and statistically significant effect on employment, indicating that the employment rate drops by approximately 0.3 percentage points at the birthday discontinuity. However, in each month past the discontinuity, the growth of the employment rate is 0.05 percentage points higher than it was prior to the discontinuity. Therefore, the immediate negative effect of minimum wage is gradually neutralized by the higher rate of labour market entry, becoming positive in 5 to 6 months past the discontinuity. Results similar to Kabátek (2021) are reported by Kreiner et al. (2020), who exploit monthly payroll records from the Danish Tax Agency between January 2012 and December 2015 and investigate the effects of a discontinuity (an increase) in the minimum wage caused by turning 18 years old. They argue that the increase in the minimum wage at 18 has a negative effect on employment of the youth, and this is mostly due to substitution effects.[1]

1.3 Minimum wage policy in the UK

The UK National Minimum Wage (NMW) was introduced in April 1999 with the objective of increasing the wages of approximately two million workers, with estimated average wage gains of nearly 30% (Low Pay Commission, 1998). Prior to the NMW, the Trade Board Act of 1909 required wage councils to set minimum wages for different industries and these were in place until 1993 while

[1]Employers might want to replace older workers with younger ones to pay them the "development" minimum wage rate instead of paying higher rates for the older ones.

between 1993-1999 there was no legal wage floor in the UK. This NMW policy pertains to nearly all sectors of the labour market (including casual, part-time and temporary workers), except for self-employed, directors and volunteers. Figure 1.1 and Table 1.A.1 in Appendix 1 illustrates the evolution of hourly minimum wage rates in the UK from its inception. MW are adjusted every year to account for inflation and the higher cost of living (Francis-Devine, 2023).[2]

Youth minimum wages have been a fundamental matter addressed by the Low Pay Commission (LPC) over the last 25 years. When the policy was introduced in 1999, as shown in Figure 1 and in Table A1 in Appendix 1, different rates were applied to individuals in the age group 18-21 and to individuals older than 22. Individuals younger than 18 were not covered by the minimum wage legislation. The youth minimum wages have been described as a stepwise increasing function of a worker's calendar age, with each wage rate expressed as a percentage of the median hourly pay. The basis for varying the minimum wage rates across age groups is that younger workers occupy a more vulnerable position in the labour market, with a larger need to acquire experience. It is therefore thought that if younger workers were eligible for the full minimum wage, they might be priced out of the labour market.

Over the last decades, other "cutoffs" than the age of 18 and 22 have been introduced for the application of differential minimum wage rates. As shown in Table 1.A.1, since 2004 the NMW policy was applied also to individuals in the 16-18 age bracket (with a lower rate than individuals who are 18+), and since 2010 to individuals less than 18 who works as apprentices.[3] Since 2016 the NMW regulation has applied different rates also to workers in the age bracket 21-24, introducing a further "cutoff" at 25.[4] Therefore, the NMW regulation currently differentiates between four age brackets, starting with a "development" minimum wage rate from age 16 and reaching the "adult" minimum wage rate at age 23.[5] The "adult" minimum wage rate is called the National Living Wage (NLW), it is the highest rate of the NWM and is currently set by the UK government to £10.42 per hour.

The paper focuses on the minimum wage policy from 2016 to 2021 for those affected at age 18, 21 and 25. To allow for more thresholds, this study relied on information from 2016, there was an increase in minimum wage to cover those at age 25 which was an additional minimum wage cutoff. Also the average percentages changes in the wage rates was a factor. The average percentage change in the wage rate for those affected at 18 and 21 years old is about 26% between this period and

[2]It has been estimated that about 1.6 million people were paid at or below the minimum wage in April 2022, which is about 5% of the labour force (Francis-Devine, 2023).

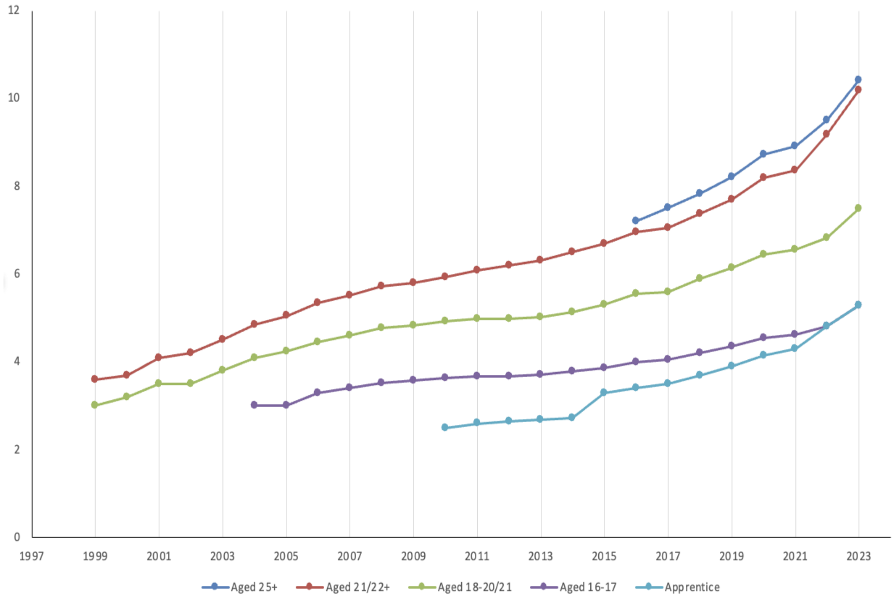
[3]In 2010, the "22 years old" cutoff was also lowered to 21 years.

[4]This age "cutoff" in the minimum wage rate was lowered to 23 years in 2021.

[5]In 2021 the "adult" minumum wage age was lowered to 23.

the average rate for those affected at 21 and 25 cutoff is about 5.96%. This indicates that there is substantial differences between the minimum wages in these cutoffs.

Figure 1.1: National Minimum Wage Hourly Rates, 1999 - 2023



Notes: Source: Low Pay Commission reports. This is a plot of the NMW Hourly rates, of the UK from 1999 to 2023. The rate for individuals aged 25 and above took effect in April 2016, while the rates for other age groups were implemented in October 2016. The apprentice rate applies to apprentices in their initial year of apprenticeship or those who are 19 years old or younger. Apprentices who do not meet this criteria are entitled to the minimum wage rate corresponding to their age group.

1.4 Data and Descriptive Statistics

This study exploits data from the UK Household Longitudinal Study (UKHLS, also called "Understanding Society"). The UKHLS, starting in 2009, is an extension of the British Household Panel Survey (BHPS). The BHPS was started in 1990-1991, with annual surveys of over 5,000 households and about 10,000 individual interviews, using a two-stage clustered systematic sampling method. It comprises 18 waves from 1991 to 2009. Participants originally included in the survey, including all adult members of their new households, were re-interviewed even if they moved. The UKHLS expanded on BHPS's scope and sample size, covering around 40,000 households over 13 waves. Our study utilizes data from 6 waves (2016 - 2021) of the UKHLS, benefiting from its detailed individual-level data on socioeconomic factors and health. These data comprise the birth records and the basic set of demographic descriptions of all respondents. Since the exact day of birth is unobserved due to privacy reasons, the year and month of birth is enough to approximate how close the individuals are to the "minimum wage". We restrict the sample to individuals from 15 to 30 years old in the labour force, in order to consider only individuals who are affected by the minimum wage regulations for the young population.[6]

Our outcome variables of interest are mental and physical health. More specifically, we rely on the SF-12 physical component summary scores (SF-12 PCS). The SF-12 is a psychometrically validated generic non-preference-based health measure, consisting of twelve dimensions including physical functioning, general health, body pain, mental health, social functioning, vitality and limitations due to physical and emotional health problems (Maxwell et al., 2022). We rely only on the eight dimensions of the SF-12 which are related to physical health (PCS). This variable is measured on a continuous scale ranging from 0 (low functioning) to 100 (high functioning).[7] We measure mental health with General Health Questionnaire (GHQ) which is a self-reported validated tool for identifying psychiatric traits, mostly employed by economists and mental health researchers (Kronenberg et al., 2017; Hauck and Rice, 2004; Apouey and Clark, 2015).[8] Responses are scaled between 0 (best score) and 3 for each element. These scores are then combined into a total which is between 0 and 36, where higher scores signify poorer mental health (Goldberg and Williams, 1991). However, we rescaled this variable from 0 to 36, in order to the variable to be increasing in good mental health.

In our regression model we account for factors that have been identified as important determinants of health and have been utilized as covariates in prior research exploring the impact of minimum wages on health outcomes (Reeves et al., 2017; Kronenberg et al., 2017; Chen, 2021, Maxwell et al., 2022, Liu et al., 2024). We control for individual socio-demographic characteristics, such as gender (dummy variable, male is the reference category), education level (categorized into primary, secondary (lower, higher) and tertiary education, with primary education as the reference category), marital status (categorized as married, never-married, separated, divorced, widow categories, being married as the reference group). Also, we included race (dummy variable for white and non-white, with white as the reference category) to capture ethnicity. Additionally, we include some controls at the household level such as household income and size. Household income is measured as the sum of all incomes in monetary terms from the household members, comprising

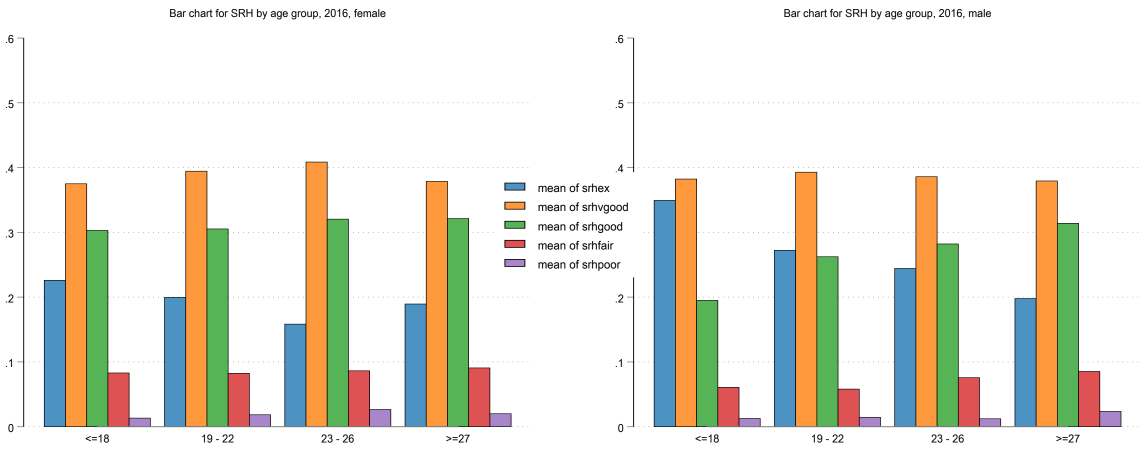
[6]Since 2004 the NMW regulation has expanded the application of minimum wages to individuals older than 16 (before it applied only to individuals older than 18). However, we do not study the effects of the minimum wages for individuals in the age bracket 16-18 and for apprentices, since very few individuals belong to this category; therefore, the estimated effects of the minimum wage policy for these individuals would be quite noisy.

[7]The SF12-PCS is based on physical functioning that is the ability to perform daily activities and physical tasks; role-physical which is the ability to perform daily activities without being limited by physical health; bodily pain that is the level of pain experienced by an individual and general health that is individual's perception of their overall health.

[8]The data boost of 12 elements of the GHQ, ranging from concentration, sleep loss due to worry, role perception, decision-making ability, stress, difficulties in problem-solving, enjoyment of daily activities, confidence, self-worth, general happiness, and experiences of depression or unhappiness.

their earnings from the main and secondary jobs, social security benefits, state and private benefits, private transfers and investment income. Household size is defined as the number of individuals in a particular household. We also include additional controls regarding the job characteristics of the individuals, such as the type of contract (full-time or part-time) and the type of employment industry. Finally, we include a set of year and regional dummy variables. The regional dummies are defined by the twelve major regions based on the NUTS 1 level of classification, ranging from London to Scotland.

Figure 1.2: Self-reported health status by age group at first wave



Descriptive statistics of the socio-demographic characteristics and health outcomes of the individuals in our sample are presented in Table 1.1. Mental and physical health scores (GHQ and SF-12 PCS) have an average of approximately 12 (out of 36) and 55 (out of 100), respectively, and a standard deviation of approximately 6 and 6.9 respectively. On average, more than half of the sample reported good or very good general health. Our sample appears to be representative of the UK population in terms of health since these statistics are in line with those of Jenkinson et al. (1999) (who report that in the UK SF-12 scores have a mean of 50 and a standard deviation of 10. Figure 1.2 shows the distribution of self-reported health status for males and females stratified by age groups. A fair age gradient is observed for both females and males. The proportion of respondents reporting excellent declines with age especially in males, whereas the shares reporting good, fair or poor health increase among older age groups. This pattern indicates a deterioration in self-perceived health as age advances. Across all age categories, the modal response is generally very good health, suggesting that most individuals assess their health positively. Gender differences are present but relatively modest. Females appear to report slightly lower proportions of excellent health and somewhat higher proportions of very good, good or fair health compared to males, particularly in older age groups. Nevertheless, the overall age related trend in self rated health is consistent across genders. Table 1.1 shows that the average age of the individuals in the sample is approximately 24 years old, and about 87% of them are never married. In the sample, there are slightly more women than men, notably, about 54% of the sample are females. About 49% of individuals in this sample had secondary school education and about 43% of them had tertiary education and the remaining (8%) constituted those who had primary education. Most individuals in the sample are white (with black, Asian, and other ethnicities representing only about 1%) and most of them reside in the cities. The average size of households is three people and the mean household income is about £1322 per month, with about 73% of the individuals working as full-time workers.

1.5 Empirical Strategy

In recent years, regression discontinuity design (RDD) has seen increasing use across a wide range of disciplines since its introduction by Thistlethwaite and Campbell (1960). In this study, we employ this method to examine the effect of qualifying for NMW when an individual crosses the age threshold set by the NMW policy, and we rely on age as a running variable.[9]

Our empirical strategy relies mostly on Dickens et al. (2014), who investigated the effects of a minimum wage discontinuity that occurs when British workers turn 22 years. A similar identification can be exploited in this context but considering more cutoffs. An indicator of whether someone has passed the respective minimum wage age birthday;

$$D_{it} = \begin{cases} 1 & \text{if } \; age_{it} >= c_j \\ 0 & \text{if } \; age_{it} < c_j \end{cases}$$

where age_{it} is the respondent's exact age measured in months in a particular year. c_j defines the birthday cutoffs (in months), where $j = 216$(18th birthday), 252(21st birthday), 300(25th birthday). We then estimate the standard RD specification of the form,

$$h_{it} = \gamma D_{it} + f(age_{it} - c) + \rho X_{it} + \nu_{it} \tag{1.1}$$

[9]Various studies have relied on age as a running variable in the literature. For instance, Giesecke and Jäger (2021) investigated the effect of retirement on mortality using age-based eligibility cutoffs. Chen (2017) also studied the impact of pensions on intergenerational living arrangements using discontinuity in age eligibility and Fidrmuc and Tena (2018) estimated the effect of age-specific minimum wage on employment using age at 22 as the cutoff when workers become eligible for the adult rate.

Table 1.1: Summary Statistics

	Mean	Std. Dev.	Min	Max	Obs.
Health outcomes					
mental health (GHQ)	11.76	5.96	0.00	36.00	21605
Physical health (SF12 PCS)	54.66	6.92	8.88	75.71	21474
Treatment status					
Treatment$_{@216}$	0.96	0.21	0.00	1.00	23227
Treatment$_{@252}$	0.80	0.40	0.00	1.00	23227
Treatment$_{@264}$	0.74	0.44	0.00	1.00	23227
Treatment$_{@300}$	0.47	0.50	0.00	1.00	23227
Running variable					
Age (years)	24.38	3.54	16.00	30.00	23227
Exact age (months)	292.42	42.51	192.00	360.00	23227
Controls					
Female	0.54	0.50	0.00	1.00	23224
Primary edu.	0.08	0.28	0.00	1.00	22654
Secondary edu.	0.49	0.50	0.00	1.00	22654
Tertiary edu.	0.43	0.49	0.00	1.00	22654
Married	0.12	0.33	0.00	1.00	23101
Never married	0.87	0.34	0.00	1.00	23101
Black	0.01	0.09	0.00	1.00	23166
White	0.99	0.09	0.00	1.00	23166
Income (/month)	1321.75	757.49	0.67	45000	17485
Income (/year)	15860.95	9089.92	8.04	540000	17485
Household size	3.44	1.74	1.00	15.00	23226
Type of contract					
Full-time	0.73	0.44	0.00	1.00	18116
Part-time	0.27	0.44	0.00	1.00	18116
Type of sector					
Agric/Energy/Mining	0.01	0.10	0.00	1.00	17395
Manufacturing/Construction	0.11	0.32	0.00	1.00	17395
Trade/Banking	0.32	0.47	0.00	1.00	17395
Transport/Service/Other	0.55	0.50	0.00	1.00	17395
N	23227				

N represents the number of observations focusing on those who are between the ages of 16 and 30 and in the labour force.

where h_{it} is the health-related measure of the individual i at the survey year t (mental and physical), $f(age_{it} - c)$ represents a flexible polynomial function of age. The set of controls is denoted by X_{it} and ν_{it} is the error term. The coefficient γ represents the causal effect on health of the increase in the NMW due to the adoption of the rate of "older" workers. This estimation relies on the assumption that the assignment to each side of the discontinuity at the cutoff is random. This ensures that individuals above the cutoff are assigned to the treatment group and those slightly below to the control group. The estimate of the discontinuity parameter γ is likely to be prone to variation depending on the functional form of the polynomial $f(age_{it} - c)$. In practice, we report a range of specifications for the age function $f(age_{it} - c)$, including linear and quadratic forms, where we constrain the parameters of the age polynomial to be the same on either side of the discontinuity. We explicitly estimate the equation below considering the terms explained above.

$$h_{it} = \alpha + (age_{it} > c)\gamma + f(age_{it} - c) + [(age_{it} > c)\delta \cdot f(age_{it} - c)] + \rho X_{it} + \epsilon_{it} \tag{1.2}$$

here, age is defined as the exact age minus the cutoff point c (where c is 216, the age in months at 18 years; 252 months (21 years) and 264 months (22 years)). These baseline controls include gender, education level, ethnicity, marital status, household income and household size. Additional controls are the type of job sector and the type of employment. The variable of interest γ captures the average causal effect of an increase in minimum wage on health outcomes and is estimated using ordinary least squares (OLS) for mental and physical health outcomes. When considering physical health as an outcome outcome we estimated an ordered probit model, since this variable is an ordered and categorical one.

To address the issue of dealing with a setting with multiple cutoffs we first adopt a standard "normalizing and-pooling approach" (Cattaneo et al., 2016). This approach essentially "averages over" the multi-cutoff features of the design (it basically implies normalizing the score, aggregating the observations, and setting to zero the common cutoff) Secondly, we adopt the novel "cumulative multiple cutoffs" approach proposed by Cattaneo et al. (2020) and Cattaneo et al. (2021). This approach is design-based as it exploits the presence of multiple RD cutoffs across different subpopulations to construct valid counterfactual extrapolations of the expected outcome of interest, given different scores levels, in the absence of treatment assignment.[10] The basic identifying idea of this approach is analogous to the "parallel trends" assumption in difference-in-difference designs (see, e.g., Abadie, 2005), but over a continuous dimension - that is, over the values of the continuous score variable.

Cattaneo et al. (2020) postulates an RD setting with cumulative cutoffs where individuals are administered with different sections of the treatment for different intervals of the running variable. The treatment is assigned to the fact that a running variable X_i in the standard RD design and a cutoff c yields $T_i = 1(X_i \geq c)$, where both the cutoff and the running variable are scalars. However, when the treatment is assigned on more than one cutoff or more than one running variable or both.

[10]"This approach imputes the average outcome in the absence of treatment of a treated subpopulation exposed to a given cutoff, using the average outcome of another subpopulation exposed to a higher cutoff. Assuming that the difference between these two average outcomes is constant as a function of the score, this imputation identifies causal treatment effects at score values higher than the lower cutoff" (Catteneo et. al 2021, p.1941).

In the case of multi-cutoff RD design, the treatment is created on the basis of a scalar variable with different groups of units facing different cutoff values. Here too individuals face different minimum wage rates based on their ages (running variable). Individuals are treated when they are eligible to accept the respective minimum wage subject to their ages. This multi-cutoff RD design assumes that the cutoff is a random variable C_i taking on J distinct values $C = c_1, c_2, \ldots, c_J$, as an alternative to a single known constant as in the standard RD design. The treatment assignment is associated to $T_i = 1(X_i \geq c)$, for $C_i \in C$, and also defining the treatment status for each cutoff as $T_i(c) = 1(X_i \geq c)$, therefore $T_i = T(C_j)$. When $C = c$ and $P[C_j = c] = 1$, we have the single-cutoff design, however, $P[C_i = c] \in (0, 1)$ for each $c \in C$ relates to the multi-cutoff RD design. This multi-cutoff design can be a non-cumulative, cumulative or multiple score approach. In our case, the cutoffs are cumulative since respondents receive a minimum wage but at different treatments (rates) and are assigned at distinct score levels (ages). Therefore making the cutoff faced by each unit a deterministic function of the individual's minimum wage value.

Subjects received treatment 1 if $X_i < c_1$, treatment 2 if $c_1 \leq X_i < c_2$ and others followed suit until the last subjects are treated at $X_i \geq c_j$. In general, every specific cutoff effect uses exclusively observations with scores equal to or exceeding the previous cutoff, but less than the subsequent cutoff. That is, for extreme cutoffs, c_1 and c_j, we retain $X_i < c_2$ and $X_i \leq c_{J-1}$ observations respectively and for each cutoff, c_j, we consider only $c_{j-1} \leq X_i < c_{j+1}$ observation for the analysis. We estimate our specification using the `rdmulti` package in Stata by Cattaneo et al. (2020). In sum, we first estimate cutoff-specific RD effects at each of the three age thresholds separately, exploiting local variation near each discontinuity. We then employ the multi-cutoff RD estimator proposed by Cattaneo et al. (2021) to recover a weighted average treatment effect across cutoffs. This approach relaxes the homogeneity restriction implicit in the normalise-and-pool strategy, while improving precision by aggregating information across cutoffs.

It is worth noting that although our data have a panel structure, we conduct our analysis focusing on pooled cross-sectional data, as done by Lee and Lemieux (2010). These authors claim that exploiting the panel structure of the data is unnecessary for identification in a regression discontinuity analysis. This is because the identification stems from comparing individuals just below and above the cutoff, a process that can be conducted using a single cross-section of data. According to Lee and Lemieux (2010) imposing more restrictions as a result of exploiting the panel structure of the data (by using, for instance, fixed effects) does not yield an improvement in identification. However, we include a set of time and regional fixed effects in the specification of our model to control for the number of cross-sectional data pooled collectively across time and for location effects, respectively.

In order to account for the evolution of the setting of minimum wage rate, from 2016 to 2021, three “age cutoffs” were adopted (18, 21 and 25 years old). Therefore, we have run separate RDD models based on the specifications presented in Equation 1.2. The RD cutoffs are determined by age, that is all respondents will be treated at some stage and will eventually meet the criteria for the application of “development” and “adult” minimum wage rates. Therefore, the eligibility criteria cannot be considered to be random. Our analysis relies on the assumption that there are no anticipation effects, that is the cohort at the left of the cutoff does not alter its behaviour because it expects to receive the treatment. Anticipation effects, for instance, occur when individuals adjust their labour supply behaviour in anticipation of announcements about welfare reform (such as a basic in-work benefit reform) (Blundell, 2011). These anticipation effects could be negatively or positively associated with the health status of the individuals. If workers expect a change in the NMW, they could be encouraged to seek preventive healthcare to positively influence their health, or, differently, they could adopt unhealthy coping mechanisms, such as smoking or eating junk food, which could affect health negatively. The presence of these anticipatory effects could lead to a biased RDD estimate of the health effect. However, we assume that there are no such effects in this case.

There are other considerations to be made. In all specifications, the age polynomial function is interacted with the treatment indicator on both sides of the cutoff to accommodate a change in slope at the cutoff since the method is inherently identical to a regression discontinuity approach. Also, it is prudent to pay attention to the bandwidth selection because the farther we move away from the cutoff on either side, the less the comparability of the cohorts. Therefore, our estimations rely on data-driven bandwidths and, as a sensitivity test, we analyze different intervals around the cutoffs based on this optimal bandwidth.

The baseline results of our analysis are validated by several robustness checks. To begin with, we evaluate the effects of the age-dependent minimum wage on health for diverse subgroups. Since women are among the focal groups for the minimum wage policy, as highlighted by Ruffini (2022), we examine subgroups stratified by gender. In addition, we also conduct separate analyses for samples stratified by the type of contract. Moreover, we adopted several specifications characterized by different bandwidths, employing the optimal bandwidth selections and bias corrections techniques suggested by Calonico et al. (2014) and Imbens and Kalyanaraman (2012). Following the suggestions of Imbens and Lemieux (2008) and Lee and Lemieux (2010), we use a triangular kernel, which is equivalent to estimating a standard linear regression over the interval of the selected bandwidth on both sides of the cutoff point.

Additionally, we perform some placebo test. That is, we consider the possibility that the estimated effects of age-dependent minimum wage could be due to data artifact or could be influenced by factors other than minimum wage policy. If age-dependent minimum wage were the contributing factor to our results, then we should not observe any effects on the health outcomes in years when there were no national wage policies. To test this hypothesis, we estimate the models described above exploiting data for years before the introduction of the minimum wage policy in 1999. As such, we consider the BHPS data for the period 1991 - 1998 and re-estimate the discontinuity model.

1.6 Estimated Results

This section discusses the effect of the policy on mental (GHQ) and physical (SF-12PCS). In this section, we present the results, discuss our findings and also discuss the sensitivity of the results.

1.6.1 Graphical Evidence

Before presenting the parametric estimates of the effect of the policy on mental (GHQ) and physical (SF-12PCS) health outcomes, Figure 1.3 depicts the discontinuity graphs on health outcomes, considering the cutoffs of 18, 21 and 25 years old. The plotted points are unsmoothed averages of the outcome with a bin width of one. The solid line is the predicted values of a second-order polynomial with triangular weights and bandwidth shown in these figures. We observe a clear discontinuity at the passing cutoff of 0 defined by 21-year cutoffs however, this is not the case for the 18-year-old and 25-year-old cutoff, as we find some discontinuities but not significant. At the 21-year-old cutoff, an increase in minimum wage appears to improve health outcomes, since there is generally an increase in health among post-exposure cohorts, more specifically, there is an increase in physical health and a reduction in mental health. At the 18-year-old cutoff, we do not observe significant discontinuities in mental and physical health, since, the outcomes did not show clear discontinuities and this creates noisy estimates of those exposed to the minimum wage at this age. Equally, we do not find discontinuities when considering individuals affected by minimum wage at age 25 and as such we cannot rely on its estimates for inferences. Before going into quantifying this jump, it would be important to see if wages is driving this potential changes in health. Therefore, the study checks whether there are changes in wages around the 21 years old cutoff. We find a discontinuity at the cutoff at 21 for wages as depicted in Figure 1.C.2a. That is an increase in minimum wage appears to reflect on wages negatively even though wage are increasing over time. This result has also been documented by Dickens et al. (2014). Another discontinuity test focused on employment to claim this changes in health outcomes is not driven by employment either. From Figure 1.C.2b we do not find a clear discontinuity at cutoff at 21 even though employment increase after the policy but then decreases over time. Therefore it is appears this minimum wage policy around the cutoff at 21 years of age is capturing changes in health outcomes.

1.6.2 Test of Manipulation

Since our RDD analysis hinges on the assumption of exogeneity of the cutoffs and the absence of manipulations of the running variable by individuals, it is very important to justify the validity of these assumptions. Bajari et al. (2021) introduced a modified RDD estimator that remains reliable even when there is some manipulation of the forcing variable within a set of structural models. We rely on Cattaneo et al. (2019) version of the MCCRARY (2008) test of running variable manipulation. This test tries to determine whether there is evidence of a discontinuity in the units of the cutoff. Table 1.2 shows that the estimated discontinuity at the various cutoffs is not statistically significant, corroborating our hypothesis that the distribution of the running variable is continuous through the cutoff.

Table 1.2: Manipulation test

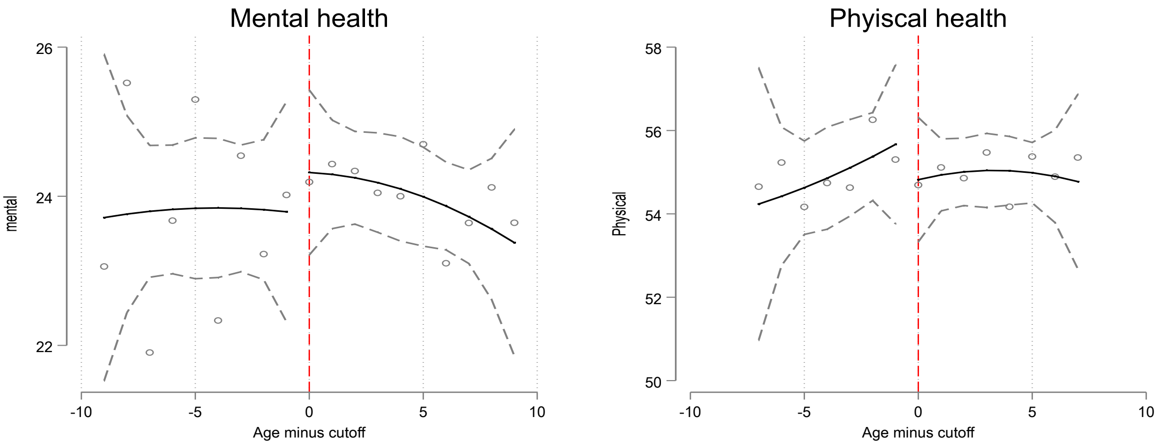
Age date minus cutoff	18	21	25
Robust Bias-Corrected p-value	0.0934	0.1128	0.7561
Robust Bias-Corrected SE	0.0016	0.0011	0.0009
Number of obs - left	1022	3519	7457
Number of obs - right	5196	7579	10866
Eff. number of obs - left	1019	2403	4131
Eff. number of obs - right	2300	3272	4437
Order est. (p)	2	2	2
Order BC. (q)	3	3	3
Bandwidth values - left	23	23	23
Bandwidth values - right	23	23	23

Notes: This table tests for manipulation of the running variable based on density discontinuity. All results are estimated with Cattaneo et al. (2019) package using an unrestricted model and a triangular kernel function and employing the jackknife standard errors estimator. The table suggests we cannot statistically detect manipulation in the running variable.

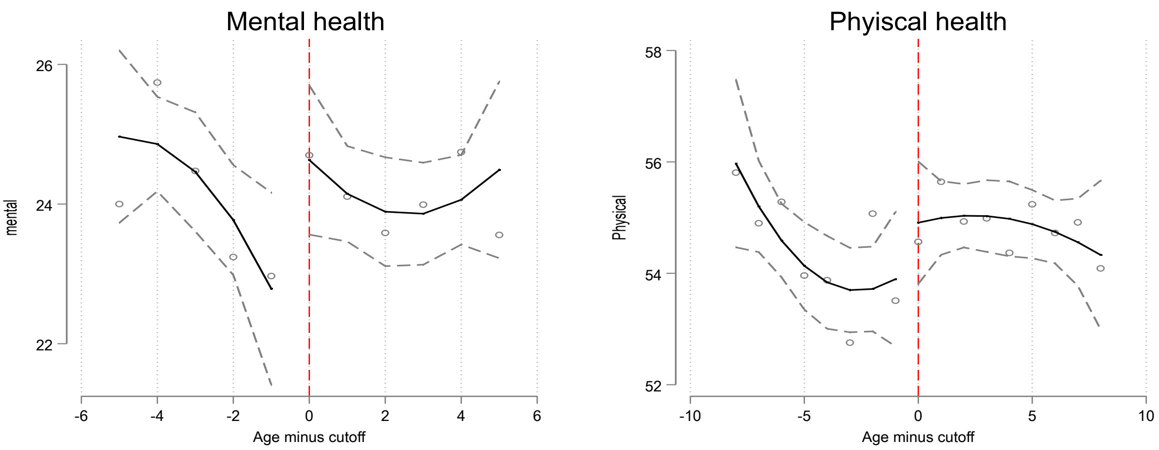
1.6.3 Balancing Test

Still stressing on the validity of our identification approach, we conduct a balancing test for the individual-level observed characteristics, which could potentially correlate with the dependent variables. For our analysis to be reliable, there should not be a substantial discontinuity in the charac-

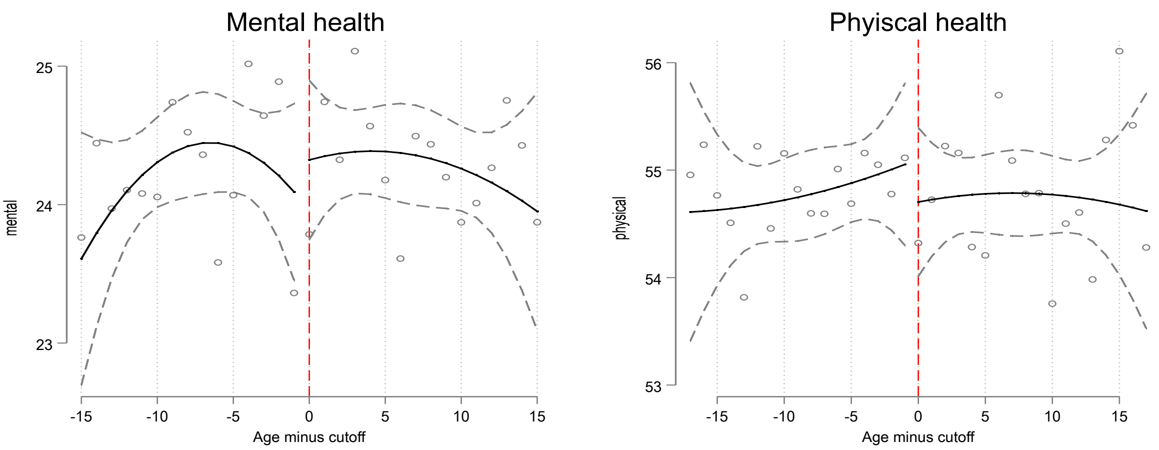
Figure 1.3: Discontinuity in health outcomes, 2016 - 2021



(a) cutoff at 18 years



(b) cutoff at 21 years



(c) cutoff at 25 years

Notes: Outcomes are mental (GHQ scores) and physical (SF-12 PCS) health. Plotted points are unsmoothed averages of the outcome with a bandwidth of one. The solid line in these figures predicted values of second-order polynomials with triangular weights. The optimal bandwidth is used in the figure.

teristics of the respondents. If this were the case, this could be evidence of self-selection across the cutoffs. The individual characteristics we consider include age, gender education, marital status, ethnicity, household income and household size. Therefore, a balance test is performed to compare individuals before and after a cutoff. To ensure comparability among respondents sampled within the same cutoff following an increase in the minimum wage, we conduct regression analysis using each observed characteristic on the treatment dummy and region and time-fixed effects. The results are outlined in Table 1.3. Respondents' characteristics around the cutoff do not differ for most of the observable characteristics (with the exception of never married and part-time which were 10% significant levels of some cutoffs). Therefore, overall, we do not find substantial evidence of discontinuous effects at the various cutoffs for these characteristics. We include all these observable characteristics as controls in all our specifications.

In the "Appendix B" section we present a set of figures depicting the relationship between the running variable and the control variables. The inspection of these figures also supports the validity of the regression discontinuity design.

Table 1.3: Covariates Balance around cutoff

	18				21				25			
Covariate	RD est.	Std. error	N	Bandw.	RD est.	Std. error	N	Bandw.	RD est.	Std. error	N	Bandw.
Female	-0.181	0.189	653	4.42	-0.054	0.067	2,400	10.27	0.015	0.041	5,695	15.59
Primary	-0.135	0.207	501	3.76	0.057	0.051	1,672	7.80	0.019	0.020	5,223	14.48
Secondary	0.154	0.149	639	4.07	-0.100	0.076	1,672	7.64	-0.022	0.044	4,879	13.10
Tertiary	-0.051	0.048	1,104	7.18	0.074	0.053	2,380	10.74	0.017	0.041	5,575	15.68
Married	0.025	0.019	1,123	7.35	0.014	0.020	2,126	9.52	0.030	0.026	4,947	13.43
N. married	-0.022	0.026	807	5.35	-0.019	0.022	2,126	9.00	-0.046*	0.027	4,570	12.64
Non-white	0.022	0.024	1,124	7.45	0.002	0.018	1,463	6.65	0.015	0.011	3,495	9.12
Income	-95.325	219.129	653	4.81	-125.989	104.314	2,666	11.63	9.803	95.138	5,334	14.42
Household size	0.229	0.350	968	6.05	0.125	0.222	2,400	10.27	-0.238	0.174	4,224	11.85
Part-time	0.123	0.148	608	6.009	0.141*	0.070	1,913	11.45	0.041	0.049	2,891	9.986
Agric	0.004	0.026	767	8.332	-0.006	0.014	2,002	12.06	-0.002	0.011	2,762	9.088
Manu	-0.080	0.112	501	5.404	-0.055	0.048	1,842	11.43	-0.022	0.033	3,619	12.14
Trade	0.063	0.184	501	5.484	-0.081	0.090	1,311	8.438	0.053	0.045	3,918	13.79
Trans	0.217	0.219	397	4.925	0.050	0.099	1,177	7.233	-0.014	0.047	4,200	14.66

Notes: The table reports estimates from a second-order polynomial. Robust standard errors in parentheses. All bandwidths are selected based on Calonico et al. (2014) package. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

1.6.4 Main Results

Table 1.4 presents the ordinary least squares estimates for mental health and physical health for Equation 1.2. The reported coefficients in this table are the average estimated effect in minimum wage across all cutoffs, that is cutoffs of age-dependent minimum wages, for models with controls and with sample stratified based on employed and unemployed individuals. The results presented in this table have been obtained by adopting the standard "normalizing and pooling approach" (Cattaneo et al., 2016). Focusing on the span of the data utilized for this analysis, we present results on the respective cutoffs considered in this study. Around each cutoff, we consider those close to the cutoff, and we do not allow for spillovers. For instance, at cutoff 18, the sample is restricted to those between the ages of 16 to 18 years to the left and 18 to less than 21 years to the right of the cutoff. For those who were affected by the cutoff at 21 years, the sample is restricted to those between the ages of 18 and 25 but then the sample for those who are treated at the cutoff at 25 is restricted to those who are between 21 years and 30 years. As argued before, we adopt specifications using controls based on some baseline characteristics (socio-demographic characteristics) and additional controls based on the labour market characteristics of respondents (type of contract and sector of employment). We estimate our regression model on the full sample of individuals between 18 and 30 in the labour force (column LF), and then we run our estimates by stratifying individuals in those who have had at least some spells on unemployment ("some times unemployed" individuals) (column UMP) and those who have been employed in all the waves ("always employed individuals") (column EMP and EMP). Since in the dataset there are many missing values for the labour market controls, we run a model for the "always employed" individuals with and without those controls (column EMP and EMP, respectively).

Noticeably, we find that minimum wage has a positive effect on physical health and mental health for those affected by the policy at 21 years old. Physical health and mental health increases by about 1.4 and 1.9 points when the minimum wage increase by one pound, respectively for all those in the labour market. These estimates are statistically significant at 5%. Focusing on the "sometimes unemployed" sample, we find that minimum wage has a positive effect on mental health, however it does not affect physical health. Differently, when looking at the "always employed" individuals, minimum wage increase affects physical health. Therefore, it appears that the overall effect on mental health can be attributed to the "sometimes unemployed" individuals and the effect on physical health seems to be driven by individuals who are always employed. However, we do not find statistically significant results for those turning 18 and 25 years old for all specifications. Despite yielding a relatively larger estimate than the linear specification, the quadratic polynomial of the treatment confirms a similarly significant impact on the outcomes.

Our results about the positive effect of minimum wage on health for the 21-year cutoff appear to be consistent with the results reported by Dickens et al. (2014). These authors report positive and significant discontinuity parameter on the rate of employment of low-skilled workers at age 22 years.[11] This increase in employment at age 22 years appears to some extent to be accounted

[11] They relied on the adult NMW rate at 22 years old from 1999 to 2008. From 2016, this adult rate was downgraded to 21 to 24 and another rate for those who are 25 years and above. And this informed our choices at 18, 21 and 25 years old.

Table 1.4: Estimated effects of minimum wage on health, "normalizing and-pooling approach

	Mental Health				*Physical Health*			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
cutoff 18								
Linear	0.543	2.637	-0.087	-0.487	-1.044	-3.023	-0.439	-0.586
	(0.844)	(1.943)	(1.133)	(1.266)	(1.139)	(2.628)	(1.148)	(1.240)
Quadratic	0.321	1.566	-0.064	-0.974	-1.109	-7.470	0.253	-0.726
	(1.315)	(3.599)	(1.790)	(2.053)	(1.940)	(4.858)	(1.833)	(1.902)
N	1,293	233	760	610	1,025	271	835	678
Bandwidth	9.449	6.487	7.234	7.234	7.198	7.698	8.394	8.394
cutoff 21								
Linear	1.914**	4.639**	0.995	0.914	1.372*	0.079	1.568*	2.141**
	(0.866)	(2.166)	(0.821)	(0.895)	(0.728)	(1.456)	(0.831)	(0.865)
Quadratic	3.089*	8.254**	1.723	1.527	0.704	-1.620	1.645	3.036**
	(1.581)	(3.712)	(1.390)	(1.543)	(1.184)	(2.210)	(1.364)	(1.434)
N	1,116	253	1,112	895	1,717	474	1,428	1,139
Bandwidth	5.883	7.847	6.591	6.591	8.690	12.71	8.148	8.148
cutoff 25								
Linear	0.082	-0.852	0.284	0.423	-0.375	1.934	-0.451	-0.244
	(0.346)	(1.712)	(0.405)	(0.436)	(0.398)	(2.028)	(0.426)	(0.460)
Quadratic	0.273	-1.285	0.477	0.719	-0.490	0.564	-0.469	-0.097
	(0.535)	(2.597)	(0.644)	(0.699)	(0.609)	(3.294)	(0.653)	(0.713)
N	5,113	377	3,794	3,258	5,747	404	4,654	3,999
Bandwidth	15.50	13.24	12.03	12.03	17.09	14.27	15.44	15.44
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Estimates from a first and second order polynomial using a triangular kernel. Robust standard errors in parentheses. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

for by reductions in unemployment for men and reductions in inactivity for women. Moreover, there does not appear to be major changes in the welfare system at the age of 22, since "the main changes in the benefit system happen to individuals at age 18 and then at 25 years" (Dickens et al. 2014, pag. 97). Our study is also in line with Chen (2021) who concludes that health state improves when minimum wages increases. Also Lenhart (2017a) reported that the introduction of the NMW in the United Kingdom improved the self-reported health status of individuals and reduced their financial stress. Lenhart (2017b) also showed that higher minimum wage levels are associated with significant improvements in population health (mortality, life expectancy, doctor consultations, etc.) and poverty. Lebihan (2023) reports that minimum wages improve individuals' self-reported health. Therefore, the positive effects we observe on health could be a spillover of the effect that minimum wage has on employment at this age.

Specifying similar models as before, we report the estimates using Cattaneo et al. (2020) "cumulative multiple cutoffs approach" in Table 1.5. The signs of the coefficients and their level of statistical significance are similar to those observed in Table 1.4, which reports results obtained with a standard approach. However, when focusing on all the specifications and considering the statistical significant effects, we can notice that the magnitude of the effects for the cutoff at 21 for both mental and physical health is slightly smaller in Table 1.5 (0.62 and 1.35, respectively) than in Table 1.4 (1.91 and 1.37, respectively). Therefore, the estimated effect of minimum wage on the mental and physical health of individuals when they turn 21 appears to be similar if we adopt the standard RDD approach or the novel approach of Cattaneo et al. (2020), which allows to improve external validity capturing long-term trend effects.

1.6.5 Heterogenous effects

In addition, we discuss whether the policy had heterogeneous effects on health outcomes in various subgroups, stratified by gender and type of job contract. The results have been obtained using both the standard RDD approach - which provides information on the short run effects - and the multi-cutoff approach - which provide information on the long run effects - and they are presented in Tables 1.A.11 and 1.A.12. As shown in Table 1.A.11 (heterogeneity by gender), in the short run the policy has a positive and statistically significant effect and on the physical health of women at the 21 years cutoff, while it has a positive and statistically significant effect on the mental health of men at the 21 years cut off. This effect for women seems to be driven by individuals who have always been employed (columns EMP and EMP), while the effects for men are driven by those who have had at least a spell of unemployment (columns UMP). These effects seem to be persistent also when considering the long run (panel B of Table 1.A.11). However, in the long run the policy has a positive and statistically significant effect also for the mental health of men for the 18 years cutoff. Moreover, for the 21 years cut off, in the long run the physical heath of men who have always been employed seems to be slightly affected in a positive way, while it seems to be slightly affected negatively for those who had some spells of unemployment. The observed gender heterogeneity in

Table 1.5: Estimated effects of minimum wage on health, "cumulative multiple cutoffs approach"

	Mental Health				*Physical Health*			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
18	0.474	2.226**	-0.211	-0.704	-0.384	-1.802	0.110	0.218
	[0.427]	[0.046]	[0.725]	[0.527]	[0.379]	[0.158]	[0.801]	[0.845]
N	2470	605	1842	1427	2090	571	1655	1269
Bandwidth	18.09	17.79	18.23	17.80	15.05	16.072	16.62	15.99
21	0.622	2.276*	0.074	0.249	1.354**	0.214	1.690**	2.124***
	[0.193]	[0.099]	[0.679]	[0.493]	[0.014]	[0.942]	[0.016]	[0.004]
N	2612	688	2133	1594	2804	592	1591	1284
Bandwidth	12.12	17.84	12.83	11.30	13.41	15.40	9.36	9.72
25	0.063	-0.398	0.078	0.132	-0.387	1.661	-0.451	-0.254
	[0.812]	[0.588]	[0.723]	[0.562]	[0.265]	[0.431]	[0.186]	[0.390]
N	9014	624	8180	6500	5087	521	5541	6737
Bandwidth	27.24	21.68	27.59	26.88	15.95	18.46	18.39	26.46
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. P-values are in parentheses. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individuals who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Columns EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

the results may reflect differing income effects of the NMW for men and women. Also, a possible explanation could be linked to the type of employment both men and women find themselves in, since men are likely to be found in more rigorous and labour-intensive jobs than women. Men are more likely to work in demanding physical environments, while women are more likely to work in care-oriented professions with emotional demands. This segregation, along with women's higher likelihood of performing routine tasks susceptible to automation, influences the perception of job rigour (Francis-Devine, 2020; Cifre et al., 2013; Brussevich et al., 2019).

In Tables 1.A.12, using both the standard and the multi-cutoff approach, the minimum wage policy seems to affect the health outcomes differently for individuals with a full-time and a part time job. In the short run (Table 1.A.12), the policy appears to increase the physical health of part time workers at the 21 years cutoff, since we observe positive and statistically significant effects.

However, in the long run physical health is affected in a positive way not only for workers with a part time job but also for those with a full time job (although the latter effects is less statistically significant).

In addition, segmentation the type of jobs into white and blue collar jobs, the study outlines the results of this heterogenous effects. With the exception of the cutoff 21, we do not find significant effects for the other cutoffs as indicated in Table 1.A.13. This significant effect was found for those working in white collar jobs. We find that minimum wage significantly increases physical health using the standard approach for white collar workers, same can not be implied for those working under blue collar jobs. Focusing on the multi-cutoff approach, we equally find that minimum wage increase the physical health of white collar workers more than it does for those who work under blue collar jobs. White-collar workers' health improves with rising income due to stress reduction and better access to healthy goods, while blue-collar workers' health sees less benefit from income increases because of ongoing exposure to physically demanding or hazardous work environments.

1.6.6 Potential pathways

The potential mechanisms investigated in this study centred around health behaviours (smoking, drinking) and other factors like satisfaction with work and satisfaction with life. We consider these factors as mediating factors when discussing the effect of minimum wages and health.

Table 1.A.6 show findings regarding the influence of minimum wage on health behaviours that could explain the association between age-dependent minimum wage and health. In tables in Table 1.A.7, we detail the results of regression analyses that incorporate health behaviours and satisfaction as control variables within the standard RDD framework for the various cutoffs. Correspondingly, results using the multi-cutoff method are summarized in Table 1.A.8.[12] We find that the results from using the standard and the multi cutoff approach are pretty similar.

We observe a negative and statistically significant effect for employed individuals at the 25-year smoking cutoff in Table 1.A.6. This result can be attributed to cigarettes being considered inferior goods, which leads to a decrease in smoking as income increases. This finding is supported by Adams et al. (2012). Some previous studies have argued that higher minimum wages may lead to increased alcohol consumption and alcohol-related traffic fatalities among younger individuals (Neumark, 2024; Sabia et al., 2019), while and other have yielded mixed conclusions (Allegretto and

[12] The factor fully mediates the relationship between minimum wage and health in instances where it correlates with minimum wage, yet minimum wage has no direct impact on health, whereas the factor does affect health when controlling for both variables. Conversely, it functions as a partial mediator when both the factor and minimum wage contribute to health outcomes, though the effect of the minimum wage is weaker (Hicks and Tingley, 2011; Imai et al., 2010).

Nadler, 2020; Andreyeva and Ukert, 2018). We find a negative and slightly statistically significant effect on drinking as a result of minimum wage increase at 18 years cutoff for individuals with some unemployment spell. The minimum wage increase also appears to have a positive effect on satisfaction with work at the 18 years cutoff. We do not find any statistically significant effect related to satisfaction with life. Results presented in under the cutoff 25 in Table 1.A.7 indicate that smoking has a substantial negative impact on mental health at the 25 cutoff. However, the findings for the 21 and 18 cutoffs (Table 1.A.7) lack validity, as minimum wage does not significantly predict smoking behaviour in those specific models. The results suggest that smoking reduces mental and physical health outcomes, meaning individuals just above the age threshold (those earning a higher minimum wage) are less likely to smoke, and this reduced smoking behaviour corresponds with better health. However, we do not have evidence to support the idea that drinking is a potential mechanism to explain the effect of minimum wage on health. Another link we found is satisfaction with work, which shows a positive effect on mental health at a cutoff point of 18 and no effect on physical health. Smoking and satisfaction with work have been identified as partial mediators in the relationship between minimum wage and health outcomes. These effects can not be relied on since they only after cutoff at 25.

Performing another investigation of checking some transmission mechanism, we focus on working conditions. To do this, we consider hours worked, overtime hours, distance to work, those working in a private firm and base pay rate. Table 1.A.4 in the Appendix present results on the effect of minimum wage on working conditions considering overtime hours and distance to work which appears to be possible mechanisms. However, results on the other factors have been presented in Table 1.A.9. For any of these to be a potential transmission mechanism, the effect of these working conditions on health in the presence of minimum wage is also presented for various cutoff is depicted in Tables 1.A.5 and 1.A.10 for the standard method and for the multi-cutoff aproach.

These result signals that minimum wage has effect on overtime hours and distance to work for those who are at the cutoff at 21. That is, an increase in minimum wage reduces overtime hours and distance to work. Research (Redmond and McGuinness, 2025; Gandhi and Ruffini, 2022) indicates that when the minimum wage rises, employers often decrease overtime and overall hours worked per employee to offset the increased cost of hourly wages. Increased minimum wages enhance the appeal of nearby employment for low-wage earners, lessening the necessity for them to travel far for higher paying prospects. On the other hand, elevated wages might also diminish low-wage job opportunities in far-off areas, prompting spatial shifts that bring jobs closer to where people live (McKinnish, 2017)

Considering the effect of working conditions on health, we find that overtime hours is potential in moderating effect between minimum wage and health. That is, under the cutoff 21, we find that overtime hours is significant and the effect of minimum wage is reduces substantially. Noticeably, working overtime reduces mental health. This suggests that while increased minimum wages can enhance worker health and well-being, the positive effects are negated when workers must undertake more overtime, leading to poorer mental health outcomes (Du and Leigh, 2018). Also, additional work hours due to overtime dilute the health gains associated with wage increases. Hours worked, employment in a private firm, and basic pay rate were other working conditions investigated as potential mechanisms; however, we do not find any significant effects.

1.6.7 Robustness results

To circumvent the issue that the data-driven selected bandwidth could be too large for the usual distribution approximations in the literature to be credible (Calonico et al., 2015), we select both small and large bandwidths so that inherent biases can be negligible. Therefore, we indicated results for both smaller and larger bandwidths than the optimal ones according to the selection procedures. An interval of 2 months before and after was used for all cutoffs. This selection was to allow for this estimation in the restricted samples. The results are presented in Figures in the appendix and these specification checks mostly corroborate the main results. With this, we re-estimate Equation (1.2) using alternative bandwidths relying on the labour force sample. Figure 1.C.1 presents the point estimates of this robustness check, along with 95 percent confidence intervals for our polynomial specification. These are consistent with our main results. As anticipated, the precision of estimates decreases for certain outcomes when using smaller bandwidths. Nevertheless, nearly all estimated effects are statistically insignificant at standard confidence levels and align closely with the corresponding estimates provided in Table 1.4 for those tuning 18 and 25 years old. However, the significant effects at the 21-year-old cutoff are persistent and align with the main results.

Moreover, considering other optimal bandwidth selector aside the Mean Square Error (MSE)-optimal bandwidth selector used in tmain results in Table 1.4. In Table 1.A.20, we present results of the main effects relying on other optimal bandwidth selectors, that is the Coverage Error Rate (CER) and the MSE/CER-optimal bandwidth selectors for the bias. The results is consistent with what was observed in the main results. Therefore, the results are robust to other optimal bandwidth selection criteria.

In addition, we have run some robustness checks using alternative measures of mental health , that is the GHQ-12 and SF12 MCS.[13]. The results we get when using these alternative measures (presented in Table 1.A.2) are quite similar to the core results in Tables 1.4 and 1.5 in terms of the direction and magnitude of the effect, although the level of statistical significance is lower.

Also, the findings presented up to this point depend on a particular functional form for the health state around the discontinuities. We have tested various functional forms, including quadratic and linear specifications. We now apply non-parametric RD techniques to assess the robustness of our findings. We utilize the approach from Hahn et al. (2001) and Porter (2003) to calculate local linear regressions within intervals flanking the discontinuity. In lieu of the polynomial in age used in equation (1.2) above, we now employ a local linear regression in age, detailed as follows:

$$h_{it} = f^h(age_{it} - c) + (age_{it} > c)\gamma + [(age_{it} > c)\delta \cdot f^h(age_{it} - c)] + \rho X_{it} + \epsilon_{it} \tag{1.3}$$

where f^h represents a local linear regression function with a bandwidth of h. In our empirical specification, we utilize a triangular kernel. We evaluated various kernel density functions, yet the findings did not significantly vary with the choice of kernel. This observation aligns with what is widely reported in the literature (Fan et al., 1996a,b). Imbens and Lemieux (2008) note that results which are sensitive to these sophisticated kernels also tend to vary with different bandwidth selections. Consequently, they recommend concentrating on the simple triangular kernel and testing the robustness of findings across various bandwidth choices. We select the optimal bandwidth using the method proposed by Imbens and Kalyanaraman (2012). The non-parametric estimation of our models which is presented in Table 1.6 also corroborates with results in Table 1.4 and Table 1.5. We also find a positive effect on physical health and on mental health. Comparing the magnitude of the effects for those affected at the cutoff at 21, the effect of minimum wage on the mental health of those turning 21 years old is about 1.98 points (1.91 in Table 1.4 and 0.62 in Table 1.5) and for physical health, we find an effect is 1.32 (1.37 in Table 1.4 and 1.35 in Table 1.5). The same conclusion can be found for those who are employed too. These estimates are statistically significant. Also, we do not find any significant effects for cutoffs at 18 and 25 years old as observed in the Table 1.4 and Table 1.5.

By performing some placebo tests, we assess whether the observed effects related to youth

[13]GHQ 12 - Caseness is based on 12 questions of the General Health Questionnaire (GHQ) to a single scale by recoding the values of individual variables of 1 and 2 to 0, and values of 3 and 4 to 1 before summing them. This generates a scale from 0 to 12, where higher values indicate worsening health. We adjusted this so that it now represents 0 - 12, with higher values indicating better health. The SF12 MCS is the short-form mental component summary score, which combines the vitality, social functioning, role-emotional and mental health SF12 items into a single mental functioning score, measured on a continuous scale with a range of 0 (low functioning) to 100 (high functioning).

Table 1.6: Estimated effects of minimum wage on health: non-parametric estimates

	Mental Health				*Physical Health*			
Variables	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
cutoff 18								
T	0.573	2.916*	-0.248	-0.664	-1.014	-2.681	-0.395	-0.688
Std. Error	(0.863)	(1.733)	(1.058)	(1.060)	(1.147)	(2.452)	(1.171)	(1.311)
N (l/r)	915/4706	317/949	598/3757	475/3076	908/4691	309/950	599/3741	478/3066
Bandwidth	8.914	6.586	8.056	9.488	6.909	7.832	7.503	6.543
cutoff 21								
T	1.975**	4.510**	1.018	0.913	1.319*	0.0863	1.579**	2.138**
Std. Error	(0.885)	(1.959)	(0.829)	(0.877)	(0.713)	(1.389)	(0.788)	(0.864)
N (l/r)	3192/6843	661/911	2531/5932	2065/5019	3184/6795	662/909	2522/5886	2058/4991
Bandwidth	5.668	8.150	6.611	6.672	8.859	14.862	8.472	7.957
cutoff 25								
T	0.0886	-0.816	0.266	0.376	-0.374	1.883	-0.442	-0.201
Std. Error	(0.330)	(1.537)	(0.371)	(0.410)	(0.405)	(1.822)	(0.433)	(0.479)
N (l/r)	6731/9784	896/730	5835/9054	4937/7775	6688/9721	895/710	5793/9011	4912/7741
Bandwidth	16.579	14.286	13.550	12.945	16.538	15.411	14.922	14.049
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Estimates from a first and second order polynomial using a triangular kernel. Robust standard errors in parentheses. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

minimum wages might be merely data artifacts or influenced by factors unrelated to the minimum wage policy. Our placebo test involves establishing artificial cutoff values and examining whether a treatment effect is present on our outcome variables within an RDD framework at these points. Our analysis concentrates on the period from 1991 to 1998 when no minimum wage policy was in effect. Table 1.A.3 in the appendix present the results of the placebo estimation on the wide range of specifications focusing on mental and general health using the standard and multi-cutoff RD. Mental health was measured with GHQ scores and general health was captured by self-reported health status. We focus on self-reported health and not on the SF12 health measure since the latter measure in characterized by too many missing values in the time span 1991-1998. Here too we focus on those in the labour force, both the individuals who had some spells of unemployment and those who have been continuously employed. The sample is very small at cutoff 18 and due to this, we are not able to estimate a model for the employed individual under general health when using the standard RDD model. The findings indicate that there is no relevant statistically significant health discontinuity at the 21 years cutoff, and thus they provide evidence in favour of our main results.

In addition, we consider other cutoffs as placebo effects, that is cutoffs like 19 years and 22 years where there was no policy changes. No effects at these additional cutoffs serves as a placebo effects. In Table 1.A.19, we show results of estimating the effect of minimum wage on health for cutoffs at 19, 22 and 23 years old. And as expected, the effects is not significant for individuals who are affected at these thresholds, suggesting that the result from the main analysis can be relied on.

Another angle to this is considering the effect on self-employed individuals. Since minimum wage usually affect people with low income and with lower working experience, we do not expect minimum wage to have an effect on self-employed individuals which has been depicted in the results in Table 1.A.18 for both the standard and the multi-cutoff approach. Indicating that minimum wage does not affect those who are self-employment for all cutoffs. Basically, self-employed workers are typically not covered by minimum wage laws. As such, they face no binding wage constraint, leading to no direct causal channel through which a change in the minimum wage affects their own earnings or labour supply (Sullivan, 2023; Ahn, 2024). That is self-employment remain unresponsive by wage floors.

We also focus on the sample of individuals who are below 60% of the income distribution. Since these individuals are more likely to be affected by minimum wages. We find similar conclusions as observed in the main results. Mental and physical health increase with an increase in minimum wage for those affected by the cutoff at 21 years whilst we do not find any significant effect for those affected by the cutoff at 18 years old and 25 years old from the standard approach in Table 1.A.14. Comparing with the main results, it is observed that minimum wage increases mental health about 1.8 for those in the labour force. Also, we find that physical health increases by about 1.6 when the minimum wage increases for those affected at the 21-year cutoff, which is much lower compared to what was found in Table 1.4. Looking at a much sustained effect observed in the Panel B in Table 1.A.14 using the multi-cutoff method. We find a much lower effect (1.5) on physical health compared to Table 1.5. The increase in mental health for individuals in the labourforce corresponds with findings that suggest alleviation of anxiety and depression associated with financial instability (Reeves et al., 2017). For those affected by aged 21, this might also improve self-efficacy related to sufficient wages. This effect from multi-cutoff suggests physical health improvements. For part-time workers, wage hikes may reduce the need for multiple jobs, lowering physical exhaustion (Ruhm, 2000). The requirement for sustained income gains is suggested by the smaller effect on physical health (1.6 in standard vs. 1.5 in multi-cutoff). As mentioned earlier, the need for multiple jobs may be reduced by wage hikes for part-time workers, which can lower physical exhaustion (Ruhm, 2000). It is worth noting that we also assess the heterogeneous effects within this sample of those below 60% of the income distribution, considering both gender and the type of contract. We find that it appears males perform better with their mental health relative to females for those affected by the cutoff at 21 (Table 1.A.15). However we do not find significant effects for physical health considering the standard approach. In the multi-cutoff method, we find only physical health in the long run. Improved mental health outcomes for males, compared to females at the age-21 cutoff, may be due to traditional gender roles in the labour market. Men, seen as primary earners, might get more psychological benefits from income boosts, reducing financial stress and boosting self-esteem. On the other hand, women, dealing with caregiving duties or lower-paid jobs, may still face stressors that limit mental health improvements from higher wages. This view is supported by Bambra and Eikemo (2009) analysis of welfare regimes, highlighting how gender roles shape health outcomes. Focusing on type of job contract in Table 1.A.16, it appears that the effect is more pronounced on the physical health of part-time contract workers relative to full-time workers under the standard approach. Similarly, minimum wage increase influences physical health of those working with a part-time contract as compared to full-time workers. Part-time workers show greater improvements in physical health. These roles, often found in retail or hospitality, usually involve physical strain. Wage increases can ease financial burdens, allowing for better health investments and reducing the need for multiple jobs. In contrast, full-time workers see smaller benefits, though workload increases may offset these. However, overall gains tend to outweigh such risks (Ruffini, 2022).

Arguing from the fact that those who are at the bottom of the income distribution are more likely to be affected minimum wage, we perform similar analyses rely on only those at the bottom 30% income distribution. These results have been presented in Table 1.A.17. From this, we find minimum wage affect on mental health positively for those affected by the 21 cutoff under the standard approach. However, we do not find any effect the other cutoffs and also physical health.

1.7 Conclusion

In our study we examine the impact of age-dependent minimum wages on the health outcomes of young workers in the UK using data from the Household Longitudinal Study ("Understanding Society") (2016 - 2021) and exploiting a Regression Discontinuity Design framework. By focusing on the health-related effects of minimum wage discontinuities, we consider the National Minimum Wage (NMW) regulation introduced in the UK in 1999 to examine how a possible exogenous increase in income may affect the health outcome of younger workers. The UK National Minimum Wage (NMW) regulation provides a very good setting to identify the causal effects of minimum wage on health by exploiting an RDD framework. However, since the youth minimum wages can be described as a stepwise increasing function of a worker's calendar age, we have to deal with multiple cutoffs when estimating our RDD models. We address this matter by adopting both a standard "normalizing and pooling" approach and the novel "cumulative multiple cutoffs" approach by Cattaneo et al. (2020, 2021). Where the standard approach explains the local treatment effect of age-dependent minimum wage on health, the multiple cutoff method explains longer term effects - that is local treatment effects across different cutoffs and different years. In our empirical analysis, we consider as dependent variables two different measures of health, that is mental and physical health. Our main results suggest that the increase in minimum wage has a positive effect on the physical health of workers when they turn 21, but it does not have relevant effects at the other age cutoffs. Similarly, we find that mental health increases when respondents turn 21 years old. The magnitude of this effect is marginally smaller if we adopt the novel "cumulative multiple cutoffs" approach by Cattaneo et al. (2020, 2021) instead of the standard "normalizing and pooling" approach. Our results appear to be confirmed by several robustness checks.

When looking at the heterogeneity of the effects by gender and focusing in the 21 years cutoff, in the short run the policy has a positive and statistically significant effect on the physical health of women, while it has a positive and statistically significant effect on the mental health of men. The effect for women seems to be driven by individuals who have always been employed, while the effects for men by those who have had at least a spell of unemployment. These effects seem to be persistent also in the long run. When looking at heterogeneous effects by type of job contract at the 21 years cutoff, the policy appears to increase the physical health of part-time workers in the short run, and of both part-time workers and full-time workers in the long run. The study also focuses on individuals who are 60% below the income distribution, since these individuals are those who are likely to be affected by minimum wage. The results are quite similar to what is observed from the main results. Also, considering on the sample of only individuals the bottom 30% and 60% of the income distribution, we find that our conclusions are consistent.

Our study has some limitations. For instance, in our study, we assume that individuals are not subject to anticipatory effects. Moreover, we investigate some of the potential mechanisms that could explain the connection between the age-dependent minimum wage and the health of young workers. Health behaviours, such as drinking or smoking, or job satisfaction, are factors which are likely to play a role as a transmission mechanism. We found that smoking and satisfaction of work are suitable channels in this case. Although this study explores some of these avenues, additional intriguing possibilities could involve examining indicators of leisure activities and financial stress (Lenhart, 2017a). In addition, overtime hours and distance was observed to be a potential mechanism in explain the effect of minimum wage on health outcomes. The investigation of these relationships is left for future research.

Notwithstanding its limitations, we believe our study provides some insights to policymakers to design more effective ways minimum wage policies for young workers in the UK. The general consensus from research about the NMW in the UK is that there is little evidence that it has harmed health. However, the appropriate age at which to implement the main adult rate is still a subject of debate (Dickens et al., 2014). This study provides results on the effect of the UK minimum wage on the health of young individuals that suggest that the most relevant switch in the minimum wage rate is at the age of 21. In more general terms, our findings indicate that minimum wage legislation has the potential to reduce existing health inequalities within society.

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Appendix

Appendix 1.A Tables

Table 1.A.1: National Minimum Wage Hourly Rates: UK, 1999-2023

			Aged 22+	Aged 18-21	Aged 16-17	Apprentice
1999			3.60	3.00		
2000			3.60	3.20		
2000			3.70	3.20		
2001			4.10	3.50		
2002			4.20	3.60		
2003			4.50	3.80		
2004			4.85	4.10	3.00	
2005			5.05	4.25	3.00	
2006			5.35	4.45	3.30	
2007			5.52	4.60	3.40	
2008			5.73	4.77	3.53	
2009			5.80	4.83	3.57	
			Aged 21+	Aged 18-20	Aged 16-17	Apprentice
2010			5.93	4.92	3.64	2.50
2011			6.08	4.98	3.68	2.60
2012			6.19	4.98	3.68	2.65
2013			6.31	5.03	3.72	2.68
2014			6.50	5.13	3.79	2.73
2015			6.70	5.30	3.87	3.30
		Aged 25+	21 – 24	Aged 18-20	Aged 16-17	Apprentice
2016	†	7.20	6.95	5.55	4.00	3.40
2017		7.50	7.05	5.60	4.05	3.50
2018		7.83	7.38	5.90	4.20	3.70
2019		8.21	7.70	6.15	4.35	3.90
2020		8.72	8.20	6.45	4.55	4.15
		Aged 23+	Aged 21-22	Aged 18-20	Aged 16-17	Apprentice
2021		8.91	8.36	6.56	4.62	4.30
2022		9.50	9.18	6.83	4.81	4.81
2023		10.42	10.18	7.49	5.28	5.28

Notes: †) Rate for people aged 25+ applied from April 2016. Other rates applied from October 2016. Source: Low Pay Commission reports

Table 1.A.2: Effect of minimum wage on other health measures

	Mental health (GHQ-12)				*Mental Health (SF12-MCS)*			
Variables	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Panel A: Standard approach							
cutoff 18								
Linear	0.375	1.588	0.268	-0.074	1.762	7.226*	0.865	0.860
	(0.424)	(1.077)	(0.627)	(0.701)	(1.743)	(3.867)	(2.265)	(2.507)
Quadratic	0.482	0.806	0.261	-0.587	3.272	8.458	1.963	-0.376
	(0.662)	(1.927)	(1.070)	(1.211)	(2.840)	(7.485)	(4.095)	(4.612)
N	1,293	233	649	528	1,149	271	643	527
Bandwidth	9.979	6.341	6.012	6.012	8.031	7.718	6.004	6.004
cutoff 21								
Linear	0.643	2.467**	0.122	0.075	1.498	8.271**	-0.367	-0.297
	(0.451)	(1.147)	(0.429)	(0.477)	(1.324)	(4.006)	(0.986)	(1.093)
Quadratic	0.968	4.563**	0.454	0.411	4.166*	18.332***	0.433	0.790
	(0.771)	(1.924)	(0.707)	(0.806)	(2.168)	(6.960)	(1.515)	(1.690)
N	1,327	253	1,272	1,021	1,717	250	2,648	2,170
Bandwidth	6.330	7.687	7.314	7.314	8.712	7.987	15.37	15.37
cutoff 25								
Linear	0.069	-0.240	0.160	0.204	0.590	-0.034	0.418	0.749
	(0.170)	(0.939)	(0.212)	(0.227)	(0.717)	(2.534)	(0.674)	(0.718)
Quadratic	0.114	-0.863	0.145	0.222	0.858	-1.536	1.040	1.668
	(0.259)	(1.609)	(0.333)	(0.359)	(1.109)	(3.781)	(1.038)	(1.115)
N	6,421	314	4,108	3,529	4,778	466	4,978	4,269
Bandwidth	19.01	11.86	13.06	13.06	14.06	16.36	16.74	16.74
	Panel B: Multi-cutoff approach							
18	0.301	1.208*	-0.087	-0.270	0.606	2.898*	-0.221	-1.252
	[0.288]	[0.051]	[0.840]	[0.671]	[0.321]	[0.095]	[0.924]	[0.873]
N	2353	605	1748	1427	2090	571	1748	1350
Bandwidth	17.891	17.901	17.395	17.221	15.896	16.034	17.169	16.386
21	0.021	1.178	-0.302	-0.278	0.554	4.468*	-0.155	-0.116
	[0.736]	[0.115]	[0.453]	[0.631]	[0.583]	[0.073]	[0.901]	[0.979]
N	2826	716	2668	1876	3890	827	3182	2024
Bandwidth	13.423	18.209	15.213	13.306	18.340	21.044	18.674	14.321
25	0.051	0.186	0.080	0.110	0.327	-0.352	0.250	0.594
	[0.708]	[0.945]	[0.542]	[0.422]	[0.651]	[0.790]	[0.745]	[0.411]
N	6421	797	5865	6271	6062	555	5541	4750
Bandwidth	19.951	26.010	19.173	24.090	18.150	19.163	18.855	18.989
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first and second order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector and the type of employment contract. Outcomes employed here are mental health (GHQ-12 Caseness) and mental health (SF12 MCS). Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

1.A.1 Placebo estimation

Table 1.A.3: Effect of minimum wage on health outcomes

	Mental Health				*General Health*			
Variables	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Panel A: Standard approach							
cutoff 18								
Linear	-3.321*	-5.825	-3.355	-3.227	-0.044		-0.044	-0.056
	(1.924)	(7.471)	(2.333)	(2.362)	(0.040)		(0.046)	(0.048)
N	180	40	131	130	295		254	250
Bandwidth	5.76	8.29	4.52	4.52	8.51		8.65	8.65
cutoff 21								
Linear	-1.646*	-2.958	-1.157	-0.899	-0.038	0.232	0.004	-0.005
	(0.905)	(4.717)	(0.931)	(0.913)	(0.037)	(0.235)	(0.045)	(0.044)
N	483	87	480	472	740	70	484	476
Bandwidth	7.24	10.77	8.31	8.31	11.75	8.53	8.83	8.83
cutoff 25								
T	-1.110*	-5.370**	-0.810	-0.903	-0.026	-0.154	-0.031	-0.034
	(0.672)	(2.304)	(0.671)	(0.675)	(0.024)	(0.131)	(0.025)	(0.025)
N	1,166	147	1,156	1,146	1,447	136	1,247	1,236
Bandwidth	12.82	20.54	13.26	13.26	15.57	18.07	14.95	14.95
	Panel B: Multi-cutoff approach							
18	-0.374	1.319	-0.609	-0.608	-0.038	-0.021	-0.052	-0.056
	[0.535]	[0.399]	[0.405]	[0.415]	[0.331]	[0.949]	[0.251]	[0.189]
N	592	95	468	457	453	158	411	402
Bandwidth	17.63	17.20	16.81	16.59	13.41	30.46	14.49	14.81
21	-0.312	-1.587	-0.069	0.058	-0.037	0.032	-0.032	-0.024
	[0.447]	[0.343]	[0.771]	[0.951]	[0.163]	[0.690]	[0.224]	[0.315]
N	932	127	876	918	937	163	936	983
Bandwidth	14.65	16.70	15.97	16.89	14.94	20.70	16.38	17.64
25	-0.842	-5.023**	-0.538	-0.577	-0.021	-0.163*	-0.027	-0.026
	[0.123]	[0.003]	[0.211]	[0.187]	[0.244]	[0.062]	[0.172]	[0.192]
N	1735	162	2050	2109	2406	124	1898	1962
Bandwidth	18.07	22.28	23.56	24.34	25.72	16.84	21.04	22.05
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors are in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates are from a first and second order polynomial using a triangular kernel. Robust standard errors in parentheses. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector and the type of employment contract. Outcomes employed here are mental health(GHQ-score) and general health (self-reported health). Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively. These estimates rely on the period 1991 to 1998.

1.A.2 Potential mechanism

Table 1.A.4: Effect of minimum wage on working conditions

	Overtime hours			*Distance to work*			*Overtime hours*			*Distance to work*		
	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP
	Panel A: Standard approach						*Panel B: Multi-cutoff approach*					
cutoff 18												
Linear	0.278	0.242	-0.142	-0.188	-0.308	0.369	-0.306	-0.268	-0.529	-1.300	-1.381	-0.583
	(0.869)	(0.844)	(0.899)	(1.399	-(1.416)	(1.612)	[0.727]	[0.717]	[0.400]	[0.411]	[0.414]	[0.607]
N	673	739	669	313	309	284	1401	1385	1159	560	555	551
Bandwidth	7.892	8.412	8.412	7.741	7.744	7.744	15.287	15.248	14.640	13.425	13.123	14.874
cutoff 21												
Linear	-1.458**	-1.453**	-1.364*	-2.684*	-2.816*	-2.729*	-1.269**	-1.279**	-1.149*	-2.493**	-2.665**	-2.799**
	(0.717)	(0.709)	(0.724)	(1.529)	(1.534)	(1.440)	[0.050]	[0.050]	[0.092]	[0.043]	[0.034]	[0.019]
N	1,573	1,564	1,422	658	655	598	1887	1872	1833	822	742	530
Bandwidth	10.43	10.79	10.79	9.755	9.646	9.646	12.360	12.340	13.211	11.159	10.755	8.915
cutoff 25												
Linear	0.010	0.000	-0.076	-0.086	-0.173	0.171	-0.018	-0.043	-0.111	0.229	0.185	0.451
	(0.467)	(0.460)	(0.476)	(1.112)	(1.109)	(1.154)	[0.916]	[0.885]	[0.835]	[0.808]	[0.828]	[0.635]
N	4,748	4,735	4,397	1,642	1,638	1,543	6076	6567	5140	2694	2685	2511
Bandwidth	17.22	17.79	17.79	12.67	12.73	12.73	22.824	24.225	20.695	20.962	20.970	20.103
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates are from a first polynomial using a triangular kernel. Robust standard errors in parentheses. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

Table 1.A.5: Effect of minimum wage and working conditions on health

	Mental health			*Physical health*			*Mental health*			*Physical health*			*Mental health*			*Physical health*		
	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP
	Panel A: Standard approach																	
	cutoff 18						*cutoff 21*						*cutoff 25*					
T	-0.038	-0.067	-0.166	-0.947	-0.792	-0.658	1.010	0.909	0.887	1.936**	1.882**	2.027**	0.274	0.388	0.457	-0.193	-0.202	-0.280
	(1.071)	(1.247)	(1.336)	(1.323)	(1.210)	(1.286)	(0.958)	(0.888)	(0.922)	(0.776)	(0.812)	(0.848)	(0.370)	(0.429)	(0.447)	(0.426)	(0.449)	(0.469)
Overtime hours	0.030	0.042	0.049	-0.035	-0.037	-0.002	-0.057	-0.064*	-0.063*	-0.054	-0.054	-0.064	-0.021*	-0.013	-0.016	0.001	0.001	-0.001
	(0.040)	(0.048)	(0.052)	(0.057)	(0.050)	(0.051)	(0.038)	(0.035)	(0.037)	(0.041)	(0.043)	(0.045)	(0.012)	(0.014)	(0.014)	(0.016)	(0.017)	(0.018)
N	816	644	584	653	718	648	792	938	852	1,215	1,207	1,086	4,099	3,319	3,089	4,601	4,077	3,792
Bandwidth	9.449	7.234	7.234	7.198	8.394	8.394	5.883	6.591	6.591	8.690	8.148	8.148	15.50	12.03	12.03	17.09	15.44	15.44
T	-1.753	-2.702	-2.766	-3.903**	-2.867**	-3.371**	0.355	0.669	0.519	2.806**	2.844**	2.462*	-0.331	0.085	0.256	0.911	0.936	0.685
	(1.681)	(1.981)	(1.992)	(1.580)	(1.436)	(1.515)	(1.326)	(1.223)	(1.274)	(1.158)	(1.201)	(1.278)	(0.550)	(0.641)	(0.660)	(0.674)	(0.716)	(0.750)
Distance to work	-0.064	-0.080	-0.110*	0.038	0.034	0.049	-0.036	-0.030	-0.008	0.034	0.038	0.014	0.029***	0.033***	0.042***	0.019	0.019	0.031**
	(0.048)	(0.055)	(0.062)	(0.044)	(0.039)	(0.046)	(0.038)	(0.036)	(0.040)	(0.022)	(0.024)	(0.026)	(0.010)	(0.012)	(0.015)	(0.012)	(0.013)	(0.013)
N	389	301	276	303	336	309	371	445	408	567	564	510	1,998	1,594	1,5	2,249	1,986	1,863
Bandwidth	9.449	7.234	7.234	7.198	8.394	8.394	5.883	6.591	6.591	8.690	8.148	8.148	15.50	12.03	12.03	17.09	15.44	15.44
	Panel B: Multi-cutoff approach																	
	Overtime hours						*Distance to work*											
18	-0.046	-0.148	-0.505	-0.165	-0.016	0.333	-1.282	-1.736	-2.427**	-1.176*	-0.731	-0.927						
	[0.960]	[0.900]	[0.733]	[0.541]	[0.635]	[0.880]	[0.223]	[0.124]	[0.042]	[0.075]	[0.153]	[0.116]						
N	1606	1589	1366	1356	1342	1216	690	686	580	514	510	462						
Bandwidth	18.286	18.211	17.935	15.587	15.491	15.196	16.541	16.376	15.050	12.877	12.711	12.712						
21	0.402	0.316	0.136	1.846***	1.835***	2.023***	0.075	0.116	0.025	2.627***	2.626***	2.372***						
	[0.379]	[0.450]	[0.604]	[0.004]	[0.004]	[0.004]	[0.872]	[0.770]	[0.877]	[0.004]	[0.004]	[0.008]						
N	1676	1807	1512	1673	1661	1372	1795	1710	1650	875	868	947						
Bandwidth	11.975	12.085	11.924	11.122	11.521	10.119	23.740	22.400	23.256	12.106	12.358	14.182						
25	0.115	0.106	0.128	-0.180	-0.177	-0.342	-0.530	-0.557	-0.459	0.738	0.690	0.455						
	[0.625]	[0.650]	[0.584]	[0.497]	[0.500]	[0.286]	[0.342]	[0.323]	[0.426]	[0.321]	[0.359]	[0.631]						
N	6408	6386	6139	6617	6848	5442	2491	2483	2539	2609	2600	2533						
Bandwidth	24.261	24.484	25.347	25.967	26.811	22.839	19.810	19.916	21.613	20.124	20.500	21.156						
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates are from a first polynomial using a triangular kernel. Robust standard errors in parentheses. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

1.A.3 Other Potential Mechanisms

Table 1.A.6: Effect of minimum wage on health behaviour

	Smoking				*Drinking*				*Satisfaction w/ work*				*Satisfaction w/ life*			
Variables	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
									Panel A: Standard approach							
cutoff 18																
Linear	-0.010	-0.011	-0.019	0.004	-0.163*	-0.378*	-0.056	0.001	0.084*	-0.026	0.134**	0.136*	0.025	0.153	-0.006	-0.035
	(0.052)	(0.079)	(0.059)	(0.062)	(0.090)	(0.222)	(0.096)	(0.102)	(0.044)	(0.019)	(0.061)	(0.071)	(0.061)	(0.122)	(0.076)	(0.083)
N	920	329	675	545	509	107	372	294	1,230	341	889	714	1,098	296	685	554
Bandwidth	6.290	8.513	6.402	6.402	6.459	5.505	6.927	6.927	8.406	8.853	8.004	8.004	7.654	7.936	6.597	6.597
cutoff 21																
Linear	-0.058	0.011	-0.068	-0.055	0.034	0.151	-0.004	-0.035	0.038	-0.006	0.043	0.062	0.073	0.182*	0.058	0.048
	(0.042)	(0.096)	(0.044)	(0.049)	(0.052)	(0.136)	(0.051)	(0.055)	(0.036)	(0.014)	(0.042)	(0.048)	(0.049)	(0.107)	(0.051)	(0.054)
N	2,016	456	1,660	1,332	1,154	270	1,170	926	2,106	318	1,741	1,399	1,876	467	1,558	1,240
Bandwidth	9.028	11.98	9.487	9.487	9.982	11.75	11.33	11.33	9.414	8.339	9.549	9.549	8.117	11.83	8.829	8.829
cutoff 25																
Linear	-0.038*	0.060	-0.048**	-0.051**	0.022	0.018	0.023	0.023	-0.034	-0.003	-0.036	-0.027	0.022	-0.006	0.036	0.044
	(0.023)	(0.075)	(0.024)	(0.026)	(0.028)	(0.112)	(0.028)	(0.029)	(0.022)	(0.019)	(0.023)	(0.025)	(0.028)	(0.099)	(0.034)	(0.036)
N	4,985	641	4,248	3,629	3,394	352	3,294	2,735	5,523	603	5,360	4,544	4,834	504	3,107	2,633
Bandwidth	14.07	20.30	13.63	13.63	17.57	20.69	18.83	18.83	15.71	18.75	16.87	16.87	13.25	15.01	9.841	9.841
									Panel B: Multi-cutoff approach							
18	-0.006	0.033	-0.024	-0.018	-0.059	-0.195*	-0.006	0.022	0.059	-0.017	0.097**	0.100**	-0.017	-0.004	-0.033	-0.031
	[0.761]	[0.549]	[0.478]	[0.603]	[0.197]	[0.053]	[0.940]	[0.476]	[0.044]	[0.406]	[0.019]	[0.032]	[0.811]	[0.728]	[0.367]	[0.455]
N	2191	645	1614	1210	1346	309	997	687	1942	593	1320	1054	2519	686	1758	1416
Bandwidth	15.67	17.052	15.430	14.538	16.59	14.951	16.469	14.710	13.40	15.339	12.963	12.742	17.771	18.999	16.209	16.139
21	-0.031	0.025	-0.058	-0.038	0.037	0.120	0.022	0.011	0.042	-0.006	0.051	0.065	0.030	0.132	0.019	0.019
	[0.321]	[0.615]	[0.102]	[0.292]	[0.268]	[0.186]	[0.517]	[0.827]	[0.161]	[0.970]	[0.167]	[0.118]	[0.399]	[0.175]	[0.534]	[0.527]
N	3608	721	2226	2105	2552	439	2449	1654	2852	994	2338	1735	4015	903	2915	2038
Bandwidth	16.60	17.011	12.382	14.742	20.38	18.815	23.040	20.301	12.597	23.775	12.377	11.932	17.524	21.076	15.767	13.739
25	-0.038**	0.049	-0.046**	-0.045**	0.020	0.020	0.022	0.017	-0.033	-0.002	-0.035	-0.027	0.003	0.015	0.001	-0.008
	[0.044]	[0.678]	[0.012]	[0.035]	[0.478]	[0.996]	[0.417]	[0.451]	[0.135]	[0.949]	[0.139]	[0.280]	[0.853]	[0.871]	[0.960]	[0.692]
N	7697	641	7275	5676	4560	396	4144	3881	5899	899	5360	4789	8673	640	8452	6881
Bandwidth	22.528	20.017	23.464	21.976	23.71	22.201	23.415	26.492	16.470	26.617	16.937	17.978	24.256	19.785	26.477	25.896
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first and second order polynomial using a triangular kernel. Robust standard errors in parentheses. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. The dependent variables considered here are smoking, drinking, satisfaction with work and satisfaction with life. All these dependent variables are captured as dummy variables (1 Yes and 0 otherwise). Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UM, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

Table 1.A.7: Effect of miminimum wage and health behaviours on health outcomes

cutoff 18	*Mental health*				*Physical health*			
	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
Linear	0.290	2.639	-0.558	-1.023	-1.003	-3.016	-0.387	-0.563
	(0.838)	(1.944)	(1.127)	(1.220)	(1.133)	(2.634)	(1.144)	(1.228)
satisfaction w/ work	3.512***	0.168	3.900***	4.389***	-0.410	0.548	-0.445	-0.216
	(0.819)	(5.567)	(1.009)	(1.066)	(0.921)	(4.023)	(0.869)	(0.928)
N	1,293	233	760	610	1,025	271	835	678
Bandwidth	9.449	6.487	7.234	7.234	7.198	7.698	8.394	8.394
Linear	0.503	1.579	0.111	-0.083	-1.036	-2.950	-0.448	-0.596
	(0.721)	(1.810)	(0.957)	(1.081)	(1.142)	(2.685)	(1.163)	(1.253)
satisfaction w/ life	7.025***	6.436***	7.426***	7.861***	-0.420	-0.530	-0.184	-0.163
	(0.443)	(0.953)	(0.632)	(0.727)	(0.687)	(1.217)	(0.747)	(0.831)
N	1,293	233	760	610	1,025	271	835	678
Bandwidth	9.449	6.487	7.234	7.234	7.198	7.698	8.394	8.394
Linear	0.463	2.182	0.504	1.592	-0.053	-4.720	0.783	0.769
	(0.991)	(2.484)	(1.291)	(1.487)	(1.611)	(3.351)	(1.662)	(1.839)
drinking	0.953	1.333	0.442	0.625	-1.332	-3.571**	-0.577	-0.026
	(0.652)	(1.548)	(0.914)	(1.138)	(0.892)	(1.635)	(0.879)	(1.094)
N	752	129	442	348	596	155	493	391
Bandwidth	9.449	6.487	7.234	7.234	7.198	7.698	8.394	8.394
Linear	0.474	2.672	-0.187	-0.562	-1.023	-3.012	-0.406	-0.553
	(0.843)	(1.974)	(1.137)	(1.261)	(1.141)	(2.638)	(1.150)	(1.238)
smoking	-2.651***	-3.445**	-2.863***	-3.303***	0.893	0.525	0.950	1.034
	(0.659)	(1.739)	(0.956)	(1.023)	(0.879)	(1.985)	(0.730)	(0.768)
N	1,291	233	759	610	1,024	271	834	678
Bandwidth	9.449	6.487	7.234	7.234	7.198	7.698	8.394	8.394
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Estimates are from a first and second order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector and the type of employment contract. Outcomes employed here are mental health(GHQ-score) and physical health (SF12 PCS). Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

cutoff 21	*Mental health*				*Physical health*			
	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
Linear	1.774**	4.626**	0.817	0.690	1.408*	0.104	1.610*	2.189**
	(0.861)	(2.180)	(0.814)	(0.884)	(0.732)	(1.464)	(0.836)	(0.865)
satisfaction w/ work	3.068***	2.999	3.129***	2.934***	-0.631	-2.571	-0.586	-0.536
	(0.542)	(3.501)	(0.509)	(0.552)	(0.530)	(2.200)	(0.554)	(0.515)
N	1,116	253	1,112	895	1,717	474	1,428	1,139
Bandwidth	5.883	7.847	6.591	6.591	8.690	12.71	8.148	8.148
Linear	1.229	3.353*	0.519	0.478	1.334*	0.071	1.533*	2.126**
	(0.772)	(1.909)	(0.739)	(0.801)	(0.733)	(1.497)	(0.834)	(0.867)
satisfaction w/ life	6.178***	7.450***	5.788***	5.555***	0.612	0.445	0.717	0.448
	(0.457)	(0.852)	(0.478)	(0.549)	(0.436)	(0.883)	(0.500)	(0.513)
N	1,116	253	1,112	895	1,717	474	1,428	1,139
Bandwidth	5.883	7.847	6.591	6.591	8.690	12.71	8.148	8.148
Linear	3.099**	7.093**	1.394	1.567	0.991	-2.185	1.693	1.934*
	(1.234)	(3.363)	(1.172)	(1.272)	(0.942)	(1.863)	(1.036)	(1.109)
drinking	1.562*	2.212	1.211	1.599	-2.083***	0.959	-3.114***	-3.019***
	(0.835)	(1.462)	(0.867)	(1.010)	(0.678)	(1.142)	(0.739)	(0.855)
N	643	146	639	505	1,003	291	834	657
Bandwidth	5.883	7.847	6.591	6.591	8.690	12.71	8.148	8.148
Linear	1.712**	4.596**	0.728	0.681	1.354*	0.155	1.571*	2.125**
	(0.862)	(2.190)	(0.810)	(0.882)	(0.732)	(1.447)	(0.836)	(0.874)
smoking	-2.637***	-2.660**	-2.779***	-2.544***	-0.444	-1.108	-0.161	-0.417
	(0.557)	(1.221)	(0.558)	(0.597)	(0.492)	(1.059)	(0.550)	(0.605)
N	1,115	253	1,111	894	1,716	474	1,427	1,138
Bandwidth	5.883	7.847	6.591	6.591	8.690	12.71	8.148	8.148
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Estimates are from a first and second order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector and the type of employment contract. Outcomes employed here are mental health(GHQ-score) and physical health (SF12 PCS). Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

cutoff 25	*Mental health*				*Physical health*			
	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
Linear	0.194	-0.844	0.383	0.455	-0.381	1.950	-0.458	-0.252
	(0.337)	(1.718)	(0.393)	(0.423)	(0.398)	(2.032)	(0.426)	(0.460)
satisfaction w/ work	3.483***	-1.106	3.506***	3.404***	-0.192	-1.907	-0.194	-0.371
	(0.252)	(3.564)	(0.285)	(0.301)	(0.296)	(3.600)	(0.312)	(0.333)
N	5,113	377	3,794	3,258	5,747	404	4,654	3,999
Bandwidth	15.50	13.24	12.03	12.03	17.09	14.27	15.44	15.44
Linear	-0.056	-0.487	0.044	0.206	-0.389	1.948	-0.466	-0.252
	(0.311)	(1.506)	(0.367)	(0.398)	(0.396)	(2.002)	(0.424)	(0.459)
satisfaction w/ life	5.789***	6.509***	5.640***	5.660***	1.515***	2.474**	1.369***	1.147***
	(0.219)	(0.867)	(0.259)	(0.288)	(0.279)	(1.018)	(0.307)	(0.344)
N	5,113	377	3,794	3,258	5,747	404	4,654	3,999
Bandwidth	15.50	13.24	12.03	12.03	17.09	14.27	15.44	15.44
Linear	0.038	-0.611	-0.080	0.195	-1.358***	1.193	-1.498***	-1.013*
	(0.467)	(2.588)	(0.526)	(0.568)	(0.475)	(2.466)	(0.501)	(0.536)
drinking	0.051	0.809	0.150	0.239	-1.762***	-2.145	-1.773***	-1.562***
	(0.335)	(1.518)	(0.378)	(0.420)	(0.372)	(1.648)	(0.398)	(0.451)
N	2,956	216	2,209	1,847	3,321	233	2,694	2,254
Bandwidth	15.50	13.24	12.03	12.03	17.09	14.27	15.44	15.44
Linear	0.041	-0.767	0.214	0.346	-0.393	1.849	-0.489	-0.282
	(0.346)	(1.711)	(0.405)	(0.437)	(0.399)	(2.041)	(0.427)	(0.461)
smoking	-1.327***	-0.493	-1.424***	-1.361***	-0.537*	0.471	-0.763**	-0.727**
	(0.272)	(0.937)	(0.327)	(0.354)	(0.298)	(1.113)	(0.328)	(0.362)
N	5,112	377	3,793	3,257	5,744	404	4,653	3,998
Bandwidth	15.50	13.24	12.03	12.03	17.09	14.27	15.44	15.44
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. Estimates are from a first and second order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector and the type of employment contract. Outcomes employed here are mental health(GHQ-score) and physical health (SF12 PCS). Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

Table 1.A.8: Effect of minimum wage and health behaviours on health outcomes: multi-cutoff approach

	Mental Health				*Physical Health*				*Mental Health*				*Physical Health*			
Variables	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Smoking								*Drinking*							
18	0.463	2.303**	-0.251	-0.711	-0.394	-1.779	0.087	0.205	0.681	2.309	0.171	0.188	-1.036	-3.800**	-0.254	-0.239
	[0.449]	[0.038]	[0.652]	[0.499]	[0.370]	[0.156]	[0.786]	[0.837]	[0.361]	[0.130]	[0.857]	[0.613]	[0.227]	[0.038]	[0.729]	[0.884]
N	2466	605	1838	1504	2086	571	1651	1268	1300	315	1056	775	1230	294	1020	816
Bandwidth	18.256	17.786	18.134	18.145	15.114	16.203	16.599	15.864	16.652	15.536	18.048	16.538	15.383	14.060	17.787	17.677
21	0.385	2.251*	-0.180	0.095	1.312**	-0.065	1.676**	2.088***	0.652	3.812**	-0.519	-0.193	0.424	-2.528*	1.326*	1.243*
	[0.351]	[0.078]	[0.971]	[0.643]	[0.016]	[0.761]	[0.016]	[0.004]	[0.306]	[0.030]	[0.687]	[0.883]	[0.426]	[0.095]	[0.054]	[0.082]
N	2610	748	2494	1592	2802	557	1590	1283	1514	343	1433	976	2237	340	1329	1283
Bandwidth	12.898	19.413	14.091	11.719	13.831	14.858	9.404	9.824	12.074	14.531	14.405	12.279	18.385	14.369	13.592	16.595
25	0.020	-0.445	0.026	0.074	-0.405	1.459	-0.494	-0.338	0.086	0.597	0.040	0.207	-1.788***	1.447	-1.562***	-1.006*
	[0.944]	[0.569]	[0.873]	[0.696]	[0.251]	[0.528]	[0.162]	[0.277]	[0.815]	[0.784]	[0.927]	[0.553]	[0.002]	[0.544]	[0.005]	[0.055]
N	9008	589	8175	6754	5086	491	5538	6248	4878	379	4085	3277	2183	317	2374	2541
Bandwidth	27.021	20.943	27.918	26.385	15.828	17.758	18.025	24.726	25.890	22.386	23.661	22.013	11.549	19.663	13.064	17.463
	Satisfaction w/ work								*Satisfaction w/ life*							
18	0.373	2.221**	-0.394	-0.852	-0.413	-1.788	0.101	0.185	0.538	1.950*	-0.019	-0.536	-0.368	-1.820	0.127	0.234
	[0.622]	[0.047]	[0.427]	[0.289]	[0.371]	[0.159]	[0.793]	[0.796]	[0.340]	[0.079]	[0.995]	[0.617]	[0.386]	[0.157]	[0.820]	[0.864]
N	2470	605	1748	1505	1953	571	1655	1269	2353	605	1842	1345	2090	571	1655	1350
Bandwidth	18.290	17.800	17.792	18.112	14.674	16.114	16.197	15.584	17.617	17.593	18.444	16.914	15.108	16.000	16.794	16.192
21	0.148	2.932**	-0.355	-0.239	1.380**	-0.108	1.720**	2.158***	0.169	1.170	-0.233	-0.153	1.308**	-0.189	1.643**	2.090***
	[0.605]	[0.048]	[0.702]	[0.963]	[0.012]	[0.735]	[0.015]	[0.003]	[0.525]	[0.261]	[0.890]	[0.941]	[0.016]	[0.701]	[0.018]	[0.004]
N	3061	521	2668	1876	2804	557	1591	1284	2612	749	2305	1735	2804	557	1591	1284
Bandwidth	14.183	13.242	15.264	13.029	13.295	14.938	9.346	9.689	12.849	19.175	13.997	12.940	13.668	14.702	9.440	9.864
25	0.148	-0.382	0.167	0.205	-0.392	1.532	-0.458	-0.267	0.020	-1.017	0.053	0.181	-0.405	1.668	-0.443	-0.240
	[0.601]	[0.595]	[0.510]	[0.428]	[0.259]	[0.503]	[0.182]	[0.371]	[1.000]	[0.310]	[0.789]	[0.436]	[0.244]	[0.628]	[0.188]	[0.409]
N	8365	624	7036	6015	5087	491	5541	6737	8064	467	8461	6271	5087	433	5541	6737
Bandwidth	25.550	21.889	23.133	23.259	15.925	17.787	18.342	26.199	24.762	16.322	28.094	24.553	15.840	15.890	18.572	26.427
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. P-values are in parentheses. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Outcomes employed here are mental health(GHQ-score) and physical health (SF12 PCS). Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

Table 1.A.9: Effect of minimum wage on other working conditions

	Hours worked			*Private firm*			*Basic pay rate*			*Hours worked*			*Private firm*			*Basic pay rate*		
	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP
	Panel A: Standard approach									*Panel B: Multi-cutoff approach*								
cutoff 18																		
Linear	-2.233	-2.100	-1.772	0.008	0.010	0.021	3.566	3.652	0.541**	-0.983	-1.044	-0.571	0.013	0.015	0.027	3.694	3.777	0.337
	(1.648)	(1.655)	(1.242)	(0.063)	(0.064)	(0.066)	(2.753)	(2.897)	(0.241)	[0.298]	[0.281]	[0.287]	[0.898]	[0.942]	[0.819]	[0.197]	[0.185]	[0.628]
N	684	755	697	744	734	658	1,319	1,269	1,143	1615	1597	1204	1484	1373	1308	1319	1306	883
Bandwidth	7.993	8.063	8.063	8.965	8.840	8.840	22.91	21.06	21.06	17.523	17.617	14.758	16.017	15.803	16.237	22.204	22.054	15.551
cutoff 21																		
Linear	-1.064	-1.367	0.078	-0.034	-0.034	-0.032	-0.415	-0.373	0.184	-0.919	-0.947	-0.196	-0.036	-0.034	-0.031	2.094	2.157	-0.420
	(1.316)	(1.357)	(1.050)	(0.036)	(0.036)	(0.036)	(0.898)	(0.882)	(0.324)	[0.454]	[0.446]	[0.954]	[0.292]	[0.320]	[0.412]	[0.406]	[0.397]	[0.139]
N	1,317	1,311	1,199	2,219	2,199	1,964	737	733	665	3358	3335	2734	2045	2026	2104	2151	2205	1308
Bandwidth	8.824	8.157	8.157	14.37	14.63	14.63	9.888	9.887	9.887	20.270	20.036	18.371	13.039	13.600	15.043	26.618	27.282	18.973
cutoff 25																		
Linear	-0.057	-0.067	-0.154	0.006	0.008	-0.007	-4.182	-4.215	-4.383	-0.266	-0.213	-0.102	0.008	0.009	0.001	-4.406	-4.412	-4.719
	(0.527)	(0.522)	(0.398)	(0.028)	(0.028)	(0.027)	(4.120)	(4.149)	(4.406)	[0.650]	[0.767]	[0.843]	[0.672]	[0.645]	[0.931]	[0.272]	[0.271]	[0.265]
N	3,543	3,535	3,3	4,281	4,268	3,898	1,645	1,561	1,446	6275	5983	5333	6668	6643	5355	1645	1635	1516
Bandwidth	12.61	12.96	12.96	15.70	15.99	15.99	22.03	21.84	21.84	22.122	21.303	20.411	24.117	24.897	21.850	22.901	22.961	22.991
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls,

Table 1.A.10: Effect of minimum wage and other working conditions on health

	Mental health			*Physical health*			*Mental health*			*Physical health*			*Mental health*			*Physical health*		
	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP	LF	EMP	EMP
	Panel A: Standard approach																	
	cutoff 18						*cutoff 21*						*cutoff 25*					
T	-0.231	-0.269	-0.462	-0.942	-0.791	-0.646	0.990	0.902	0.919	1.928**	1.877**	1.929**	0.283	0.407	0.483	-0.250	-0.268	-0.311
	(1.046)	(1.202)	(1.262)	(1.294)	(1.191)	(1.243)	(0.967)	(0.896)	(0.928)	(0.782)	(0.819)	(0.847)	(0.368)	(0.426)	(0.441)	(0.426)	(0.450)	(0.467)
Hours worked	0.013	0.018	0.001	-0.028	-0.023	0.023	0.006	0.006	-0.003	0.004	0.006	0.011	0.022	0.025	0.041*	0.000	0.002	-0.010
	(0.023)	(0.027)	(0.045)	(0.036)	(0.032)	(0.047)	(0.028)	(0.026)	(0.031)	(0.023)	(0.024)	(0.036)	(0.016)	(0.018)	(0.023)	(0.015)	(0.016)	(0.022)
N	820	646	598	653	720	663	796	944	865	1,218	1,212	1,102	4,117	3,333	3,121	4,617	4,091	3,828
Bandwidth	9.449	7.234	7.234	7.198	8.394	8.394	5.883	6.591	6.591	8.690	8.148	8.148	15.50	12.03	12.03	17.09	15.44	15.44
T	-0.199	-0.111	-0.327	-0.783	-0.673	-0.583	0.789	0.660	0.439	2.001**	1.966**	1.943**	0.267	0.389	0.514	-0.380	-0.399	-0.368
	(1.077)	(1.255)	(1.343)	(1.359)	(1.239)	(1.313)	(0.969)	(0.894)	(0.904)	(0.820)	(0.857)	(0.843)	(0.366)	(0.424)	(0.446)	(0.424)	(0.448)	(0.468)
Private firm	-0.571	-0.632	-0.317	-0.529	-0.494	-0.063	-0.230	-0.375	-0.880	-0.208	-0.184	-0.415	0.228	0.203	0.156	-0.138	-0.164	-0.378
	(0.631)	(0.736)	(0.796)	(0.813)	(0.750)	(0.872)	(0.633)	(0.590)	(0.580)	(0.513)	(0.530)	(0.575)	(0.226)	(0.253)	(0.278)	(0.256)	(0.268)	(0.304)
N	806	636	572	643	707	635	794	941	842	1,214	1,205	1,069	4,143	3,348	3,073	4,645	4,118	3,773
Bandwidth	9.449	7.234	7.234	7.198	8.394	8.394	5.883	6.591	6.591	8.690	8.148	8.148	15.50	12.03	12.03	17.09	15.44	15.44
T	-0.874	-0.823	-1.012	-1.099	-1.090	-1.384	1.183	1.067	1.365	2.592**	2.531**	2.966**	0.573	0.778	1.292	-0.567	-0.744	-1.072
	(1.258)	(1.444)	(1.466)	(1.335)	(1.240)	(1.285)	(1.332)	(1.242)	(1.306)	(1.054)	(1.112)	(1.168)	(0.716)	(0.827)	(0.835)	(0.920)	(0.971)	(1.028)
Basic pay rate	0.013***	0.016***	-0.527**	-0.038***	-0.037***	0.191	0.127	0.144	0.140	-0.317*	-0.320*	-0.316	0.003**	0.003**	0.003**	-0.002	-0.002	-0.002
	(0.004)	(0.004)	(0.230)	(0.005)	(0.005)	(0.243)	(0.173)	(0.169)	(0.151)	(0.173)	(0.185)	(0.198)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	577	454	413	457	508	460	429	507	456	646	642	580	1,1	897	831	1,232	1,09	1,014
Bandwidth	9.449	7.234	7.234	7.198	8.394	8.394	5.883	6.591	6.591	8.690	8.148	8.148	15.50	12.03	12.03	17.09	15.44	15.44
	Panel B: Multi-cutoff approach																	
	Hours worked						*Private firm*						*Base rate pay*					
18	0.474	-0.434	-0.686	-0.384	-0.012	0.235	-0.382	-0.487	-0.847	0.042	0.166	0.436	-0.569	-0.670	-1.066	-0.569	-0.500	-0.468
	[0.427]	[0.719]	[0.551]	[0.379]	[0.625]	[0.826]	[0.709]	[0.661]	[0.515]	[0.657]	[0.747]	[0.905]	[0.536]	[0.517]	[0.354]	[0.335]	[0.386]	[0.455]
N	2470	1516	1397	2090	1351	1243	1510	1493	1342	1336	1322	1099	1179	1166	1058	1181	1168	962
Bandwidth	18.090	17.973	17.967	15.046	15.516	15.738	17.844	17.890	17.754	15.165	15.148	14.877	19.423	19.455	19.620	19.169	19.193	17.820
21	0.622	0.295	0.181	1.354**	1.773***	1.891***	0.139	0.072	-0.254	1.832***	1.856***	1.864***	0.374	0.425	0.205	1.742**	1.849***	2.432***
	[0.193]	[0.472]	[0.557]	[0.014]	[0.005]	[0.005]	[0.613]	[0.687]	[0.949]	[0.006]	[0.006]	[0.004]	[0.489]	[0.462]	[0.571]	[0.014]	[0.010]	[0.003]
N	2612	1675	1540	2804	1668	1395	1830	1814	1752	1521	1512	1487	1026	1017	868	1391	1296	1007
Bandwidth	12.122	11.771	11.825	13.411	11.794	10.719	12.561	12.606	13.059	10.845	10.543	11.669	13.589	13.117	12.396	18.472	17.849	14.621
25	0.063	0.118	0.160	-0.387	-0.235	-0.377	0.130	0.120	0.185	-0.396	-0.438	-0.415	0.547	0.516	0.565	-0.587	-0.712	-0.927
	[0.812]	[0.638]	[0.508]	[0.265]	[0.410]	[0.246]	[0.576]	[0.603]	[0.462]	[0.214]	[0.183]	[0.209]	[0.445]	[0.483]	[0.418]	[0.404]	[0.330]	[0.251]
N	9014	6153	6199	5087	7102	5970	6212	6441	5900	6444	5919	6094	1448	1440	1270	1370	1296	1267
Bandwidth	27.243	23.088	25.035	15.953	27.025	24.056	23.689	24.214	24.669	24.052	22.659	25.941	20.956	20.885	19.306	19.042	18.549	19.485
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

1.A.4 Heterogeneous effects

Table 1.A.11: Effect of minimum wage on health outcomes: gender

	Mental Health				*Physical Health*				*Mental Health*				*Physical Health*			
Variables	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Females								*Males*							
	Panel A: Standard approach															
cutoff 18																
Linear	-0.008	-4.092	-0.307	-0.884	-1.302	-4.542	-0.939	-0.496	1.343	4.690**	-0.369	-0.135	-0.982	-9.970*	0.676	-1.083
	(1.271)	(3.768)	(1.390)	(1.515)	(1.353)	(5.061)	(1.344)	(1.555)	(1.256)	(2.200)	(1.428)	(1.770)	(2.158)	(5.321)	(2.244)	(2.062)
N	553	77	477	389	606	96	542	440	599	199	400	321	354	98	276	223
Bandwidth	7.598	5.325	8.104	8.104	8.064	6.858	9.071	9.071	9.653	9.158	9.777	9.777	5.405	4.236	6.906	6.906
cutoff 21																
Linear	0.797	1.854	0.546	0.121	1.958*	3.593	2.000*	2.624**	2.063**	5.011*	0.235	0.599	0.125	-1.268	1.023	1.436
	(1.060)	(3.359)	(1.105)	(1.155)	(1.091)	(2.466)	(1.214)	(1.211)	(1.031)	(2.673)	(0.759)	(0.855)	(0.677)	(1.991)	(0.857)	(0.950)
N	817	151	701	563	1,023	175	776	618	708	161	864	694	1,480	256	780	633
Bandwidth	7.777	9.606	7.640	7.640	9.114	10.85	8.583	8.583	7.149	8.607	11.45	11.45	15.29	12.21	10.57	10.57
cutoff 25																
Linear	-0.062	-3.705	0.078	0.134	-0.115	1.393	-0.204	-0.075	0.655	0.370	0.657	0.765	-0.589	0.676	-0.689	-0.462
	(0.404)	(3.844)	(0.475)	(0.511)	(0.530)	(3.032)	(0.524)	(0.565)	(0.558)	(1.784)	(0.573)	(0.625)	(0.559)	(1.930)	(0.584)	(0.624)
N	3,778	92	2,658	2,287	3,575	202	3,329	2,869	1,818	313	1,491	1,274	2,417	330	1,886	1,612
Bandwidth	20.64	8.089	15.38	15.38	19.13	16.62	19.83	19.83	12.45	20	11.92	11.92	16.33	20.44	14.81	14.81
	Panel B: Multi-cutoff approach															
18	0.101	0.174	-0.304	-0.673	-1.010	-3.338*	-0.649	-0.044	0.888	3.343**	-0.243	-0.705	0.156	-1.112	0.780	-0.023
P-val.	[0.954]	[0.822]	[0.570]	[0.546]	[0.178]	[0.070]	[0.370]	[0.702]	[0.213]	[0.026]	[0.934]	[0.898]	[0.999]	[0.527]	[0.663]	[0.830]
N	1302	275	978	808	1109	238	871	721	1113	353	815	588	1115	323	768	620
Bandwidth	18.61	18.67	17.41	17.841	15.14	15.34	15.308	15.925	17.691	18.316	18.152	16.989	17.981	16.813	17.849	17.764
21	-0.076	0.054	-0.285	-0.604	2.088**	2.732	2.000**	2.379***	0.556	3.952**	-0.054	0.272	-0.201	-2.979*	0.859	1.386*
P-val.	[0.880]	[0.919]	[0.906]	[0.689]	[0.012]	[0.203]	[0.031]	[0.009]	[0.353]	[0.021]	[0.910]	[0.542]	[0.615]	[0.071]	[0.187]	[0.081]
N	1663	409	1408	1148	1409	352	999	970	1597	415	1166	819	2228	256	1077	697
Bandwidth	14.19	23.73	14.76	14.07	12.41	20.37	10.70	12.86	16.06	19.716	15.358	13.626	22.21	12.759	14.603	11.667
25	0.030	-0.954	0.092	0.183	-0.106	2.312	-0.238	-0.157	0.128	-0.152	0.127	0.118	-0.617	0.981	-0.757	-0.492
P-val.	[0.951]	[0.535]	[0.887]	[0.702]	[0.739]	[0.539]	[0.678]	[0.802]	[0.675]	[0.824]	[0.660]	[0.641]	[0.214]	[0.549]	[0.118]	[0.254]
N	4681	213	4494	3587	3764	232	4317	4119	3114	280	2520	2152	2250	330	2153	2251
Bandwidth	25.32	17.91	26.20	24.27	20.91	18.75	25.15	28.68	21.99	17.676	19.910	19.791	15.84	20.530	16.556	20.074
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

Table 1.A.12: Effect of minimum wage on health outcomes: type of contract

	Mental Health		*Physical health*		*Mental health*		*Physical Health*	
Variables	EMP	EMP_2	EMP	EMP_2	EMP	EMP_2	EMP	EMP_2
	Part-time employment				*Full-time employment*			
	Panel A: Standard approach							
cutoff 18								
Linear	-0.593	-0.805	-0.703	-0.659	-0.162	-0.456	-1.145	-1.415
	(1.208)	(1.250)	(1.303)	(1.362)	(1.862)	(1.946)	(2.626)	(2.828)
N	557	517	555	515	270	245	213	191
Bandwidth	9.356	9.356	9.221	9.221	9.661	9.661	7.726	7.726
cutoff 21								
Linear	2.396	2.271	3.521**	4.288***	-0.460	-0.502	1.334	1.356
	(1.751)	(1.914)	(1.370)	(1.463)	(0.670)	(0.684)	(0.873)	(0.905)
N	339	310	386	355	1,370	1,256	1,161	1,061
Bandwidth	6.219	6.219	7.582	7.582	13.56	13.56	11.38	11.38
cutoff 25								
Linear	-0.273	-0.171	0.238	0.071	0.629	0.673	-0.206	-0.200
	(0.778)	(0.810)	(1.407)	(1.475)	(0.480)	(0.496)	(0.480)	(0.497)
N	1,138	1,062	647	603	2,343	2,196	3,219	3,009
Bandwidth	20.27	20.27	11.94	11.94	10.92	10.92	14.40	14.40
	Panel B: Multi-cutoff approach							
18	-0.560	-0.972	0.403	0.272	0.302	0.137	-0.013	0.593
	[0.561]	[0.341]	[0.950]	[0.914]	[0.857]	[0.945]	[0.862]	[0.810]
N	1133	1039	1075	991	495	454	461	456
Bandwidth	22.00	22.020	20.737	20.018	15.081	15.051	14.913	15.308
21	0.633	0.505	1.794**	2.603***	-0.480	-0.515	1.347*	1.419*
	[0.443]	[0.506]	[0.034]	[0.004]	[0.562]	[0.612]	[0.085]	[0.078]
N	672	620	1005	867	1678	1460	1161	1061
Bandwidth	13.27	13.062	19.535	18.109	16.147	15.045	11.862	11.416
25	-0.000	0.083	-0.736	-0.569	0.206	0.206	-0.185	-0.278
	[0.993]	[0.950]	[0.589]	[0.714]	[0.430]	[0.439]	[0.461]	[0.386]
N	1652	1345	1272	1122	4529	4777	4507	3803
Bandwidth	29.16	25.30	22.30	21.02	20.40	23.011	20.794	18.062
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column EMP focuses on the full sample of individual who are employed (15-30 years old). Column EMP_2 considers the sample of individuals who have been employed in all the waves, with (additional) labour market controls, respectively.

Table 1.A.13: Heterogenous effects: White and Blue collar jobs

	Mental health				*Physical health*			
	EMP	EMP_2	EMP	EMP_2	EMP	EMP_2	EMP	EMP_2
	White collar		Blue collar		White collar		Blue collar	
	Part A: Standard approach							
cutoff 18								
T	-2.397	-3.824*	1.266	1.194	-0.009	1.021	-2.263	-1.977
	(2.139)	(2.256)	(1.418)	(1.495)	(3.594)	(3.168)	(1.490)	(1.555)
N	128	111	486	445	91	81	417	382
Bandwidth	7.045	7.045	7.275	7.275	5.480	5.480	6.489	6.489
cutoff 21								
T	0.327	0.466	1.317	-0.223	4.572**	4.960**	2.511	2.267
	(1.369)	(1.448)	(1.957)	(1.950)	(1.954)	(1.951)	(2.025)	(2.120)
N	664	598	588	524	399	360	663	593
Bandwidth	13.74	13.74	6.601	6.601	8.154	8.154	7.626	7.626
cutoff 25								
T	0.016	-0.042	0.115	0.335	-0.329	-0.324	-0.410	-0.434
	(0.515)	(0.537)	(0.609)	(0.630)	(0.568)	(0.595)	(0.704)	(0.736)
N	2,081	1,928	1,412	1,31	2,357	2,181	1,997	1,835
Bandwidth	14.74	14.74	14.91	14.91	16.49	16.49	20.37	20.37
	Part B: Multi-cutoff approach							
cutoff 18	-1.492	-3.005**	0.308	0.230	0.863	2.010	-0.654	-0.314
	[0.178]	[0.036]	[0.489]	[0.468]	[0.715]	[0.375]	[0.319]	[0.475]
N	220	169	1171	1017	238	190	1002	913
Bandwidth	13.994	12.942	18.845	17.752	14.264	13.603	15.641	15.820
cutoff 21	-0.290	-0.111	0.160	-0.219	2.107**	1.744**	1.319*	1.275*
	[0.886]	[0.994]	[0.655]	[0.945]	[0.017]	[0.045]	[0.082]	[0.093]
N	725	705	1292	994	721	786	1450	1390
Bandwidth	14.110	15.142	14.332	12.791	14.569	17.298	16.459	17.595
Cutoff 25	0.002	-0.020	0.052	0.149	-0.184	-0.295	-0.457	-0.533
	[0.846]	[0.924]	[0.937]	[0.882]	[0.571]	[0.467]	[0.425]	[0.389]
N	3425	3416	2297	2110	3531	2661	2288	2098
Bandwidth	24.043	26.828	23.523	23.487	25.128	20.540	23.933	23.449
Baseline cont.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	Yes	No	Yes	No	Yes	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column EM and EMP_2 focuses on a sample of individuals who have been employed in all the waves, without and with (additional) labour market, respectively. Sample has been segregated into white and blue collar jobs.

1.A.5 Heterogenous effect: Below 60% income distribution

Table 1.A.14: Effect of minimum wage on health outcomes (below 60% income distribution)

	Mental Health				*Physical Health*			
Variables	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Panel A: Standard approach							
cutoff 18								
Linear	0.711	2.782	0.282	-0.276	-1.402	-3.231	-0.731	-0.757
	(0.850)	(1.908)	(1.236)	(1.360)	(1.210)	(2.653)	(1.209)	(1.300)
N	1,249	232	620	508	849	270	798	652
Bandwidth	9.833	6.740	6.686	6.686	6.841	7.580	8.039	8.039
cutoff 21								
Linear	1.874**	4.666**	0.878	0.696	1.013	0.128	1.140	1.627*
	(0.904)	(2.176)	(0.871)	(0.971)	(0.761)	(1.437)	(0.862)	(0.905)
N	1,222	253	1,007	805	1,586	513	1,297	1,028
Bandwidth	6.090	7.750	6.927	6.927	8.881	13.14	8.437	8.437
cutoff 25								
Linear	0.174	-1.069	0.408	0.587	-0.390	2.013	-0.493	-0.251
	(0.397)	(1.770)	(0.458)	(0.497)	(0.528)	(2.130)	(0.493)	(0.543)
N	3,962	363	2,888	2,429	3,464	362	3,765	3,158
Bandwidth	15.92	13.48	12.60	12.60	13.50	13.88	16.11	16.11
	Panel B: Multi-cutoff approach							
18	0.540	2.334**	-0.203	-0.549	-0.504	-1.886	-0.055	0.160
	[0.335]	[0.043]	[0.850]	[0.677]	[0.339]	[0.152]	[0.692]	[0.758]
N	2270	598	1760	1364	1882	536	1583	1290
Bandwidth	17.85	17.63	18.14	17.78	14.87	15.91	16.33	16.00
21	0.445	2.078*	-0.114	-0.009	0.751	-0.313	1.240*	1.552**
	[0.334]	[0.097]	[0.933]	[0.763]	[0.162]	[0.720]	[0.065]	[0.020]
N	2417	785	2099	1566	3592	428	1623	1558
Bandwidth	12.98	20.88	13.76	12.30	18.05	11.67	10.10	12.76
25	0.120	-0.694	0.164	0.316	-0.408	1.947	-0.531	-0.245
	[0.687]	[0.459]	[0.565]	[0.359]	[0.340]	[0.494]	[0.238]	[0.446]
N	6443	602	5516	3716	3464	389	3530	3709
Bandwidth	26.0	21.13	24.50	19.24	13.10	14.87	15.67	19.54
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

Table 1.A.15: Effect of minimum wage on health outcomes: by gender (below 60% income distribution)

	Mental Health				*Physical Health*				*Mental Health*				*Physical Health*			
	Females								*Males*							
	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Panel A: Standard approach															
cutoff 18																
Linear	1.982	6.953**	-0.118	0.041	-0.820	-4.021	0.369	0.071	1.855	5.194**	-0.159	-0.472	-1.786	-10.185*	-0.128	-0.707
	(1.514)	(3.448)	(1.743)	(2.162)	(1.711)	(3.538)	(1.813)	(1.688)	(1.390)	(2.249)	(1.544)	(1.825)	(2.528)	(5.414)	(2.333)	(2.055)
N	450	111	294	235	513	138	365	298	514	179	368	298	333	97	254	208
Bandwidth	7.606	5.265	7.925	7.925	8.852	6.907	9.919	9.919	8.823	8.992	9.722	9.722	5.001	4.207	6.674	6.674
cutoff 21																
Linear	1.981*	4.802*	0.812	1.137	0.151	-0.973	0.557	1.073	2.251**	5.012*	0.519	0.911	-0.001	-1.259	0.639	1.145
	(1.035)	(2.532)	(1.067)	(1.258)	(0.928)	(2.102)	(1.058)	(1.238)	(1.125)	(2.674)	(0.898)	(1.043)	(0.771)	(1.995)	(0.982)	(1.128)
N	736	185	575	452	816	203	574	455	641	161	691	552	1,160	256	690	555
Bandwidth	8.166	9.487	8.179	8.179	9.202	10.91	8.668	8.668	7.218	8.603	10.28	10.28	13.71	12.15	10.12	10.12
cutoff 25																
Linear	0.357	1.504	0.637	0.704	-0.762	0.554	-0.824	-0.639	0.703	0.247	0.717	0.823	-0.755	0.938	-0.911	-0.779
	(0.515)	(2.706)	(0.598)	(0.639)	(0.759)	(2.183)	(0.647)	(0.698)	(0.624)	(1.850)	(0.628)	(0.670)	(0.681)	(1.896)	(0.747)	(0.805)
N	2,171	126	1,409	1,166	1,537	255	1,748	1,448	1,434	302	1,229	1,018	1,758	337	1,315	1,090
Bandwidth	20.35	8.093	15.20	15.20	14.01	16.83	19.37	19.37	13.74	19.88	13.59	13.59	16.99	21.80	14.82	14.82
	Panel B: Multi-cutoff approach															
18	0.240	0.194	-0.139	-0.520	-1.205	-3.507*	-0.828	-0.315	0.860	3.528**	-0.507	-1.081	-0.001	-1.263	0.581	0.355
	[0.886]	[0.811]	[0.725]	[0.670]	[0.140]	[0.061]	[0.297]	[0.549]	[0.227]	[0.026]	[0.973]	[0.719]	[0.981]	[0.499]	[0.707]	[0.940]
N	1270	272	951	784	999	236	782	698	1059	338	721	552	1061	318	719	581
Bandwidth	18.64	18.40	17.29	17.69	14.23	15.10	14.62	15.65	17.09	17.83	17.62	16.65	17.53	16.64	17.13	17.60
21	-0.244	0.066	-0.424	-0.869	1.628**	2.723	1.483*	1.388*	0.623	3.918**	-0.050	0.006	-0.315	-2.953*	0.629	1.048
	[0.930]	[0.918]	[0.753]	[0.440]	[0.040]	[0.210]	[0.080]	[0.099]	[0.330]	[0.022]	[0.887]	[0.807]	[0.531]	[0.072]	[0.350]	[0.206]
N	1669	407	1401	1140	1746	352	1110	1340	1357	412	1029	835	1906	256	955	777
Bandwidth	15.07	23.79	15.47	15.26	16.85	20.42	12.46	18.28	15.53	19.83	15.07	15.05	21.79	12.55	14.24	14.07
25	0.025	-1.553	0.140	0.307	-0.024	2.545	-0.044	0.151	0.307	-0.297	0.277	0.362	-0.714	1.003	-0.952	-0.665
	[0.980]	[0.424]	[0.734]	[0.514]	[0.763]	[0.531]	[0.801]	[0.984]	[0.543]	[0.762]	[0.490]	[0.418]	[0.275]	[0.651]	[0.157]	[0.264]
N	3488	206	3191	2261	2310	205	2534	2474	2268	271	2101	1528	1537	298	1503	1520
Bandwidth	23.01	17.18	23.98	19.73	15.86	17.34	18.92	21.14	21.54	17.71	23.07	20.33	14.75	19.37	16.20	20.29
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

Table 1.A.16: Effect of MW on health: type of contract (below 60% income distribution)

	Mental Health		*Physical health*		*Mental health*		*Physical Health*	
	Part-time employment				*Full-time employment*			
	EMP	EMP_2	EMP	EMP_2	EMP	EMP_2	EMP	EMP_2
	Panel A: Standard approach							
cutoff 18								
Linear	-0.667	-0.936	-0.812	-0.611	-0.556	-0.799	-0.823	-0.739
	(1.222)	(1.250)	(1.337)	(1.395)	(1.301)	(1.327)	(1.576)	(1.623)
N	545	509	543	507	486	456	377	358
Bandwidth	9.721	9.721	9.111	9.111	8.785	8.785	6.598	6.598
cutoff 21								
Linear	2.529	2.261	3.289**	4.072***	0.660	0.304	2.770**	3.521***
	(1.715)	(1.876)	(1.360)	(1.452)	(1.053)	(1.107)	(1.106)	(1.165)
Quadratic	3.034	3.197	3.777	5.081**	3.069*	2.826	3.774**	4.670***
	(3.166)	(3.490)	(2.381)	(2.450)	(1.725)	(1.827)	(1.685)	(1.787)
N	331	302	377	346	656	604	560	513
Bandwidth	6.262	6.262	7.767	7.767	13.88	13.88	11.29	11.29
cutoff 25								
Linear	0.460	0.521	-0.225	-0.169	0.875	0.939	-0.242	-0.150
	(0.448)	(0.461)	(0.597)	(0.622)	(0.591)	(0.607)	(0.618)	(0.645)
N	2,724	2,542	2,116	1,975	1,652	1,548	1,974	1,842
Bandwidth	17.40	17.40	13.55	13.55	10.48	10.48	12.72	12.72
	Panel B: Multi-cutoff approach							
18	-0.791	-1.057	0.155	0.302	0.889	0.302	-0.326	-0.013
	[0.460]	[0.290]	[0.814]	[0.904]	[0.574]	[0.857]	[0.743]	[[0.862]
N	1086	1001	1053	948	415	495	418	461
Bandwidth	21.77	21.69	20.37	19.45	14.43	15.08	14.81	14.91
21	1.142	0.661	1.727**	2.156**	-0.687	-0.480	0.687	1.347*
	[0.254]	[0.444]	[0.047]	[0.015]	[0.382]	[0.562]	[0.326]	[0.085]
N	601	551	979	900	1881	1678	1449	1161
Bandwidth	12.04	12.95	19.45	19.46	20.97	16.15	16.35	11.86
25	0.167	0.262	-0.444	-0.383	0.333	0.206	-0.113	-0.185
	[0.878]	[0.795]	[0.832]	[0.863]	[0.313]	[0.430]	[0.568]	[0.461]
N	1199	1006	1147	1007	3160	4529	3148	4507
Bandwidth	23.92	21.00	22.31	21.39	20.94	20.40	20.13	20.79
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	Yes	No	Yes	No	Yes	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column EM and EMP_2 focuses on a sample of individuals who have been employed in all the waves, without and with (additional) labour market, respectively.

1.A.6 Heterogenous effect: Below 30% income distribution

Table 1.A.17: Effect of MW on health outcomes (below 30% income distribution)

	Mental health				*Physical health*			
	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Part A: Standard approach							
cutoff 18								
Linear	-0.402	-0.051	-0.359	-0.799	1.017	0.316	1.704	2.268
	(1.468)	(1.240)	(1.452)	(2.268)	(1.952)	(1.655)	(2.113)	(3.294)
N	382	560	382	156	379	495	379	156
Bandwidth	6.643	9.331	6.852	6.852	6.589	8.856	6.008	6.008
cutoff 21								
Linear	3.752**	2.416**	2.646**	1.432	0.289	0.413	0.124	-0.180
	(1.529)	(1.208)	(1.269)	(1.985)	(1.305)	(1.227)	(1.377)	(1.900)
N	466	686	604	264	678	762	593	260
Bandwidth	6.474	9.375	8.898	8.898	9.661	10.81	8.984	8.984
cutoff 25								
Linear	0.243	0.228	0.240	1.380*	0.074	0.074	-0.009	0.302
	(0.770)	(0.799)	(0.670)	(0.831)	(0.890)	(0.890)	(1.027)	(1.433)
N	1,422	1,33	1,895	1,081	1,777	1,777	1,321	757
Bandwidth	15.80	14.78	20.14	20.14	19.23	19.23	14.96	14.96
	Part B: Multi-cutoff approach							
cutoff 18	0.733	0.254	-0.034	-0.616	-0.864	-0.094	-0.560	-0.513
	[0.252]	[0.877]	[0.830]	[0.763]	[0.211]	[0.836]	[0.292]	[0.313]
N	1751	288	1419	1081	1476	294	1287	979
Bandwidth	17.952	15.262	18.578	17.867	14.269	16.130	16.229	15.342
cutoff 21	0.455	2.926	0.144	0.485	0.573	0.277	1.142	1.795**
	[0.430]	[0.121]	[0.676]	[0.456]	[0.386]	[0.974]	[0.124]	[0.029]
N	1471	316	1096	770	2363	221	1176	1148
Bandwidth	14.425	25.282	12.967	11.627	23.105	18.448	13.467	17.603
cutoff 25	0.334	-1.259	1.014	1.976	-0.540	9.121**	-0.504	0.461
	[0.641]	[0.585]	[0.155]	[0.051]	[0.514]	[0.030]	[0.559]	[0.700]
N	1250	97	1307	728	929	104	1118	1248
Bandwidth	20.989	16.433	21.157	16.563	15.339	18.707	18.516	27.992
Baseline controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls, respectively.

1.A.7 Robustness Analysis

Table 1.A.18: Effect of MW on self employment

	Mental health		*Physical health*	
	EMP	EMP	EMP	EMP
	Panel A: Standard approach			
cutoff 21				
Linear	2.358	4.039	1.544	10.094
	(4.295)	(14.815)	(6.059)	(8.888)
N	53	30	60	36
Bandwidth	7.014	7.014	8.812	8.812
cutoff 25				
Linear	-1.168	-1.691	-0.268	0.432
	(2.826)	(2.918)	(2.177)	(2.438)
N	172	146	226	192
Bandwidth	13.03	13.03	16.31	16.31
	Panel B: Multi-cutoff approach			
cutoff 18	13.170	-163.550	22.240	-9.425
	[0.000]	[0.042]	[0.167]	[0.979]
N	40	18	35	26
Bandwidth	17.47	8.61	15.86	13.65
cutoff 21	0.792	1.139	6.458	7.179
	[0.152]	[0.491]	[0.033]	[0.002]
N	116	54	58	55
Bandwidth	15.61	10.93	9.96	10.13
cutoff 25	-0.452	-0.531	0.616	0.779
	[0.724]	[0.666]	[0.914]	[0.948]
N	275	276	248	209
Bandwidth	20.10	22.29	18.60	17.15
Baseline cont.	Yes	Yes	Yes	Yes
Add. controls	No	Yes	No	Yes
Region FE.	Yes	Yes	Yes	Yes
Survey FE	No	Yes	No	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. Estimates are from Cattaneo et al. (2020) package `rdmulti`. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column 1 focuses on the full sample of individual who are in the labour force (15-30 years old). Column EMP and EMP focuses on a sample of individuals who have been employed in all the waves, without and with (additional) labour market.

Table 1.A.19: Effect of minimum wage on health outcomes for other thresholds

	Mental Health				*Physical Health*				*Mental Health*				*Physical Health*			
Variables	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	Panel A: Standard approach								*Panel B: Multi-cutoff approach*							
cutoff 19																
Linear	-0.538	-0.704	-0.675	-0.269	-0.111	-1.394	0.452	0.588	-0.360	-0.061	-0.465	-0.142	-0.265	-1.327	0.077	0.175
	(0.572)	(1.477)	(0.631)	(0.685)	(0.743)	(1.211)	(0.855)	(0.934)	[0.450]	[0.910]	[0.395]	[0.694]	[0.818]	[0.345]	[0.801]	[0.708]
N	2,350	454	1,827	1,509	1,705	497	1,198	987	2814	599	2189	1509	2348	497	1948	1504
Bandwidth	13.64	11.62	13.44	13.44	9.013	12.30	8.967	8.967	16.092	15.702	16.020	13.453	13.267	12.483	14.538	13.778
cutoff 22																
Linear	0.505	2.416	-0.003	0.218	0.338	1.273	-0.167	0.162	0.472	0.567	0.195	0.589	0.503	0.397	0.372	0.644
	(0.515)	(1.511)	(0.601)	(0.639)	(0.530)	(1.341)	(0.590)	(0.628)	[0.195]	[0.466]	[0.845]	[0.184]	[0.210]	[0.761]	[0.390]	[0.123]
N	2,847	413	1,915	1,598	2,827	557	2,123	1,778	6214	887	3880	3977	6412	913	4747	4536
Bandwidth	11.13	9.661	9.060	9.060	11.90	13.74	10.47	10.47	24.029	22.684	18.098	22.696	25.741	23.198	22.594	25.266
cutoff 23																
Linear	-0.056	-0.271	-0.173	0.429	-0.216	2.965	-0.701	-0.873	-0.099	-0.825	-0.082	0.114	-0.442	1.901	-0.731	-0.865
	(0.443)	(1.554)	(0.523)	(0.559)	(0.546)	(2.000)	(0.524)	(0.556)	[0.688]	[0.364]	[0.737]	[0.830]	[0.238]	[0.054]	[0.037]	[0.021]
N	3,433	338	2,455	2,085	2,810	333	2,942	2,491	6731	1148	5592	5752	8261	1014	6975	6095
Bandwidth	11.65	8.532	9.564	9.564	9.613	8.274	11.11	11.11	23.813	32.929	22.551	27.321	29.552	27.476	28.390	29.838
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls,

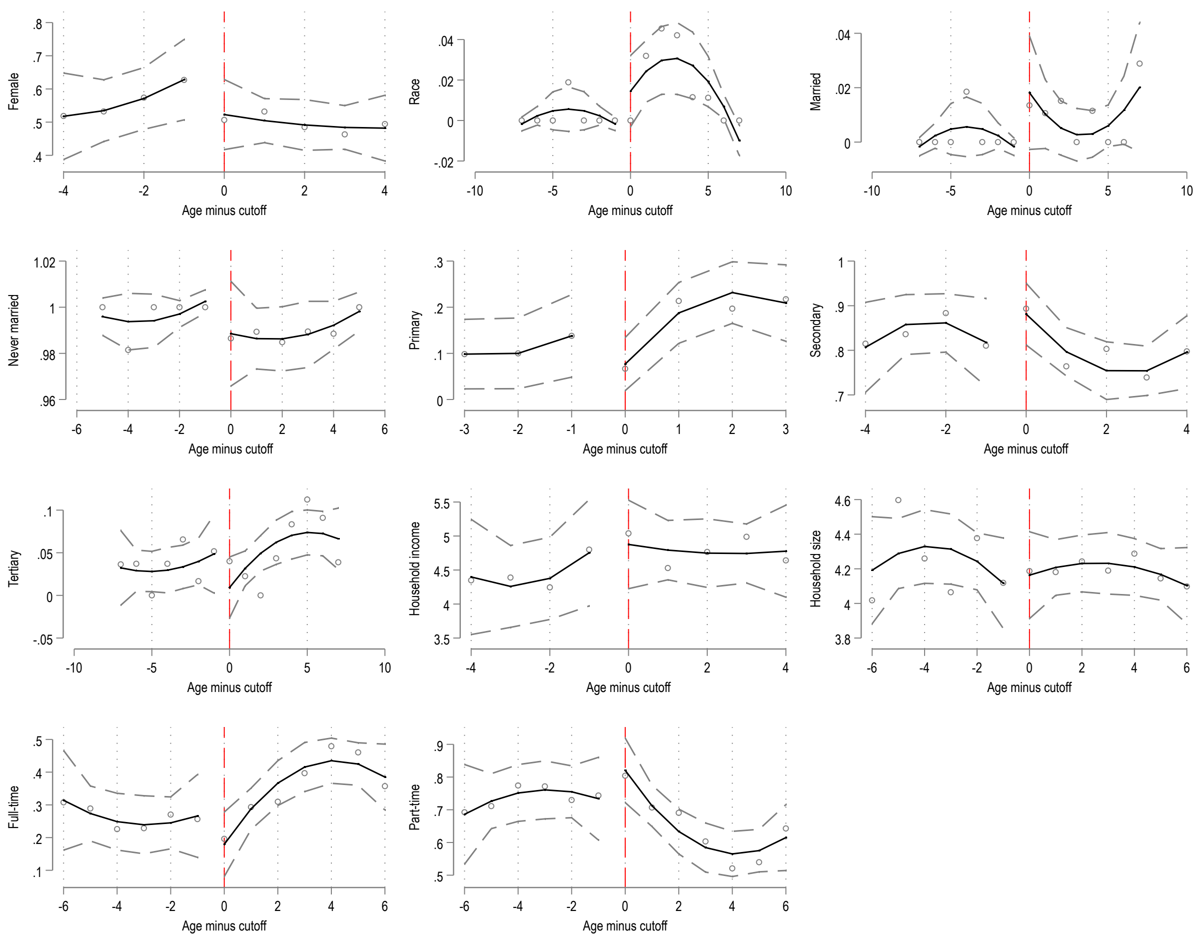
Table 1.A.20: Effect of minimum wage on health using other bandwidth selectors

	Mental health				*Physical health*				*Mental health*				*Physical health*			
	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP	LF	UMP	EMP	EMP
	CER-optimal bandwidth selector								*MSE-optimal/ CER-optimal bandwidth selector for the bias*							
Linear	0.643	2.914	-0.013	-0.900	-1.047	-5.066	-0.224	-0.763	0.498	2.923*	-0.354	-0.745	-0.637	-2.351	-0.021	0.066
	(1.052)	(2.500)	(1.486)	(1.664)	(1.542)	(3.368)	(1.444)	(1.500)	(0.669)	(1.555)	(0.932)	(1.029)	(0.881)	(1.918)	(0.894)	(0.976)
Quadratic	-0.241	6.282	-0.915	-2.413	0.086	-9.902	1.501	-0.644	0.507	1.696	0.205	-0.393	-1.517	-3.385	-0.729	-0.880
	(1.816)	(5.520)	(3.192)	(3.621)	(3.094)	(6.632)	(2.603)	(2.589)	(1.028)	(2.561)	(1.422)	(1.588)	(1.388)	(3.043)	(1.415)	(1.497)
N	881	161	427	348	592	193	543	443	1,958	379	1,035	832	1,562	450	1,246	1,009
Bandwidth	6.280	4.530	4.534	4.534	4.593	5.378	5.425	5.425	14.76	10.53	10.69	10.69	11.38	12.69	12.92	12.92
Linear	2.217*	5.729**	1.308	1.146	1.156	-0.845	1.799	2.741**	0.602	2.552*	-0.085	-0.113	1.345**	0.322	1.588**	1.926***
	(1.179)	(2.768)	(1.052)	(1.163)	(0.944)	(1.769)	(1.095)	(1.146)	(0.564)	(1.435)	(0.548)	(0.587)	(0.573)	(1.247)	(0.634)	(0.660)
Quadratic	2.110	10.334*	0.345	1.035	1.703	-3.539	2.966	4.943**	2.007**	5.322**	1.065	1.111	1.406	-0.284	1.792*	2.483**
	(3.037)	(5.392)	(2.102)	(2.290)	(1.724)	(2.905)	(2.005)	(2.153)	(0.902)	(2.315)	(0.859)	(0.921)	(0.878)	(1.742)	(0.987)	(1.034)
N	711	185	764	623	1,110	289	927	754	2,400	566	2,302	1,875	2,802	743	2,116	1,725
Bandwidth	3.763	5.431	4.387	4.387	5.445	8.818	5.139	5.139	11.83	14.43	13.30	13.30	13.46	19.90	12.91	12.91
Linear	0.085	-0.894	0.215	0.436	-0.537	0.765	-0.546	-0.231	0.048	0.033	0.024	0.081	-0.100	2.091	-0.404	-0.292
	(0.442)	(2.032)	(0.517)	(0.562)	(0.524)	(2.541)	(0.563)	(0.615)	(0.271)	(1.244)	(0.300)	(0.322)	(0.300)	(1.529)	(0.342)	(0.368)
Quadratic	0.246	-2.412	0.995	1.292	-0.637	2.968	-0.637	-0.233	-0.015	-1.466	0.244	0.352	-0.554	0.693	-0.564	-0.290
	(0.716)	(3.366)	(0.851)	(0.920)	(0.835)	(4.704)	(0.893)	(0.972)	(0.403)	(1.920)	(0.452)	(0.486)	(0.450)	(2.328)	(0.518)	(0.560)
N	3,464	249	2,321	1,995	3,446	252	2,877	2,474	8,048	661	6,169	5,279	9,535	686	6,994	5,987
Bandwidth	10	9.231	7.924	7.924	10.40	9.833	9.397	9.397	24.88	22.81	20.85	20.85	29.39	23.52	23.41	23.41
Baseline con.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. controls	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses in Panel A. P-values are in parentheses in Panel B. Estimates from a first order polynomial using a triangular kernel. All bandwidths are selected based on Calonico et al. (2014) package. Baseline controls contain gender, educational level, marital status, ethnicity, household income level, household size. Additional controls include the type of job sector, and the type of employment contract. Column LF focuses on the full sample of individual who are in the labour force (15-30 years old). The sample of individuals who had at least some spell of unemployment is considered in Column UMP, while Column EMP and EMP consider the sample of individuals who have been employed in all the waves, without and with (additional) labour market controls,

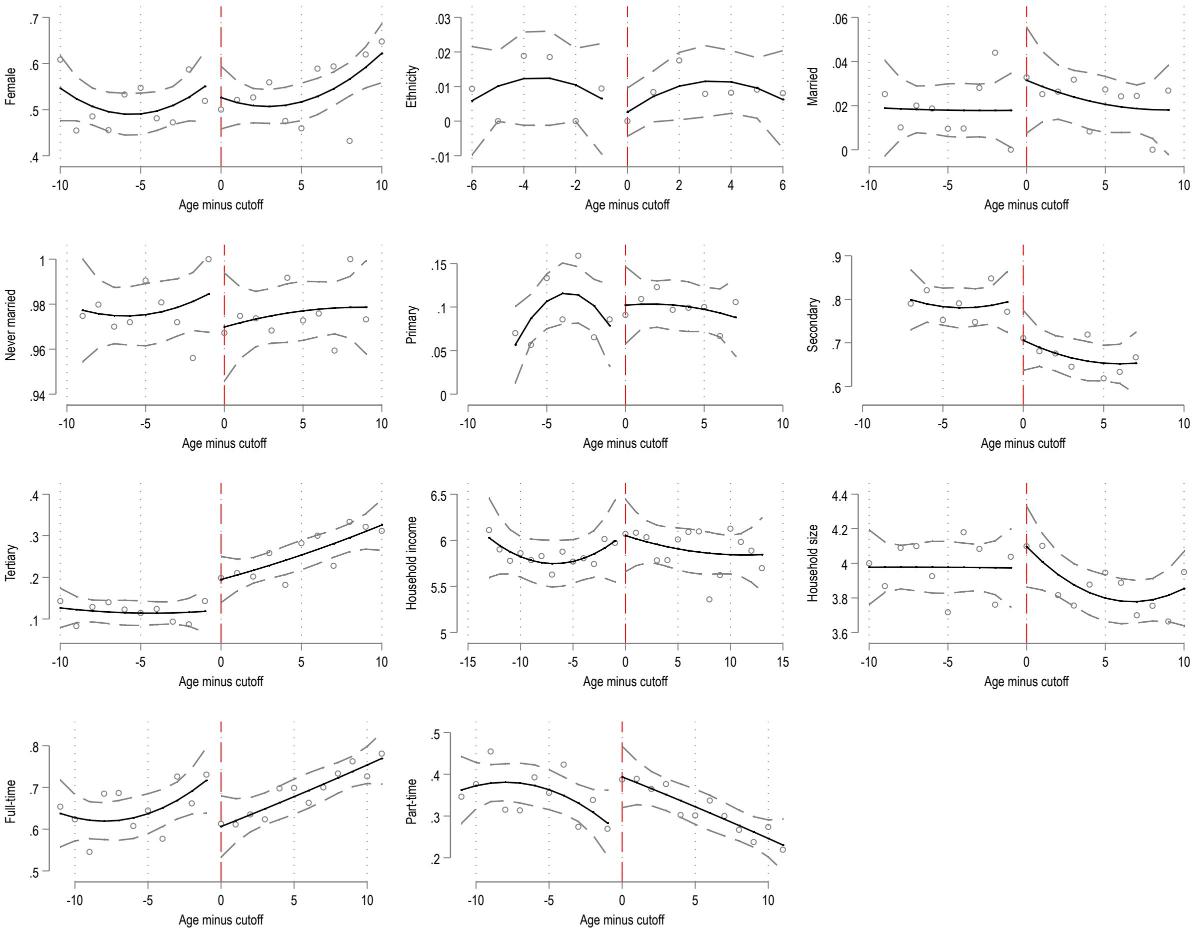
Appendix 1.B Discontinuity Identification

Figure 1.B.1: Discontinuity in Covariates, cutoff at 18



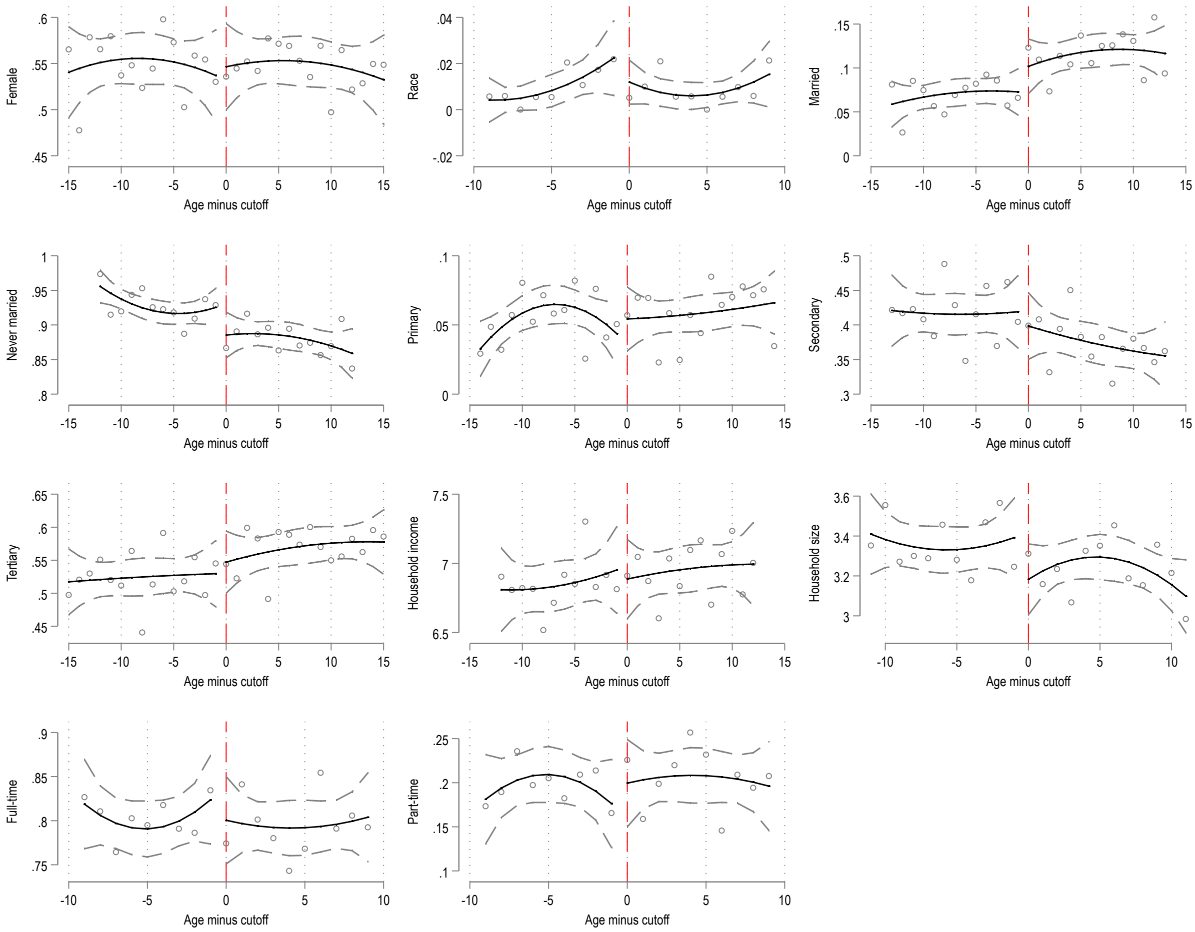
Notes: Each point is an unsmoothed average of the outcome with a bin width of one. The solid line is the predicted values of a second-order polynomial with uniform weights and a bandwidth noted in the figure. Sample: 2016 - 2021 and a cutoff at 18 years.

Figure 1.B.2: Discontinuity in Covariates, cutoff at 21



Notes: Each point is an unsmoothed average of the outcome with a bin width of one. The solid line is the predicted values of a second-order polynomial with uniform weights and a bandwidth noted in the figure. Sample: 2016 - 2021 and a cutoff at 21 years.

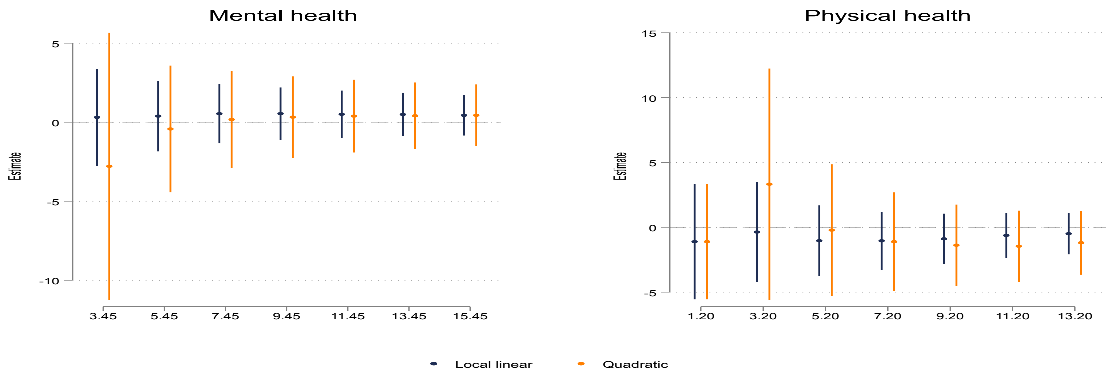
Figure 1.B.3: Discontinuity in Covariates, cutoff at 25



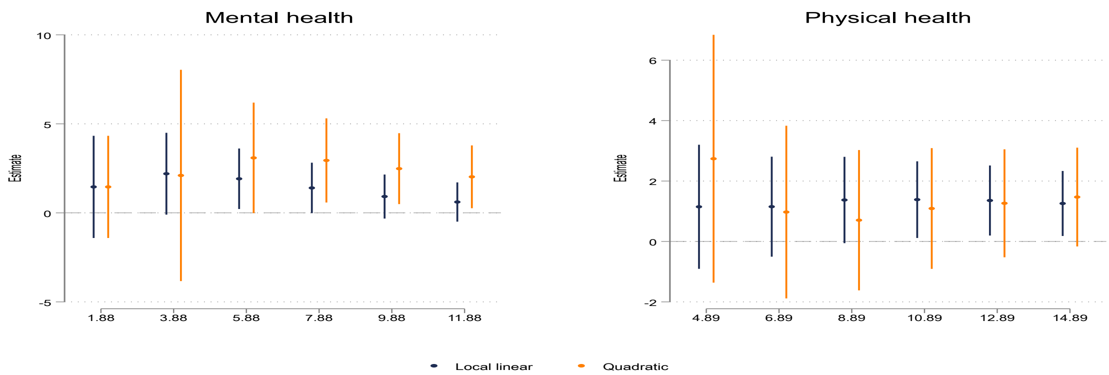
Notes: Each point is an unsmoothed average of the outcome with a bin width of one. The solid line is the predicted values of a second order polynomial with uniform weights and a bandwidth noted in the figure. Sample: 2016 - 2021 and a cutoff at 25 years.

Appendix 1.C Bandwidth Selection

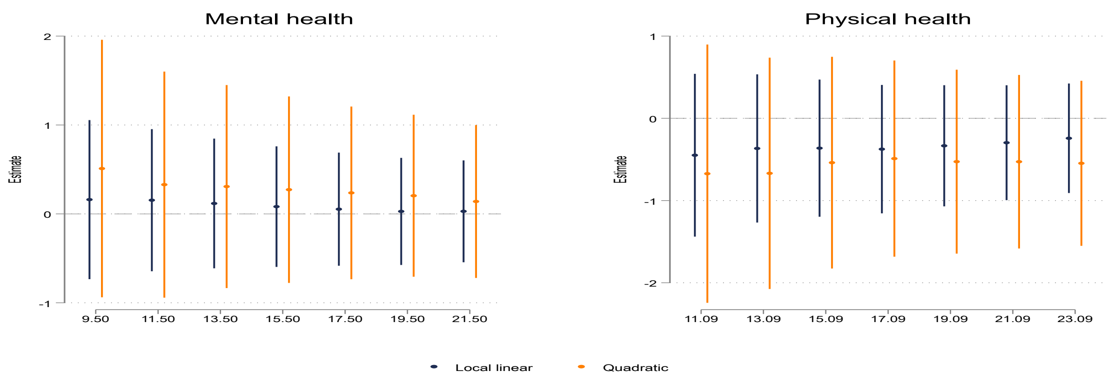
Figure 1.C.1: Bandwidth Selection in Outcomes



(a) cutoff at 18 years



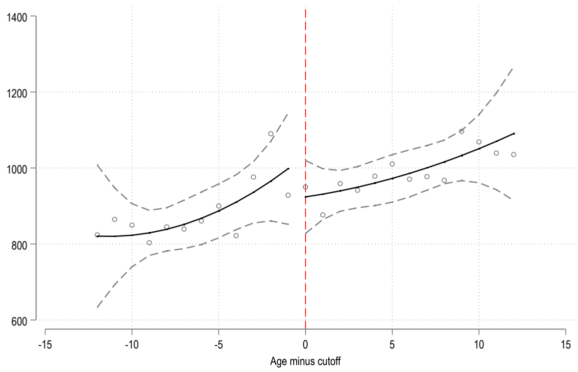
(b) cutoff at 21 years



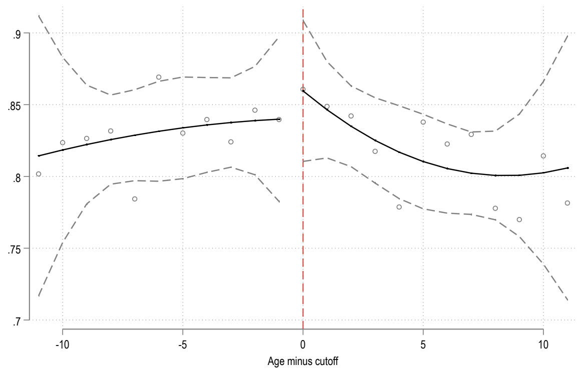
(c) cutoff at 25 years

Notes: Outcomes are mental (GHQ scores) and physical (SF-12 PCS). Estimates from a second order polynomial using selected bandwidths. Robust standard errors in parentheses. All models contain gender, educational level, marital status, ethnicity, household income level, household size, the type of job sector, and the type of employment.

Figure 1.C.2: Discontinuity in Wages and Employment at cutoff 21



(a) wages



(b) employed

Notes: Outcomes are wages (measured by salary from work) and employment. Plotted points are unsmoothed averages of the outcome with a bandwidth of one. The solid line in these figures predicted values of second-order polynomials with triangular weights. The optimal bandwidth is used in the figure.

2

Minimum Wages and Health Outcomes: Evidence from Spain

2.1 Introduction

Many developed and developing countries have introduced some form of minimum wage legislation to improve the well-being and living standards of vulnerable workers. Research on the effects of minimum wage (MW) on labour market outcomes has a long tradition in economics and remains central to debates on labour market interventions today (see, Card and Krueger, 2015; Neumark and Wascher, 2008). A large body of empirical research has documented a substantial association between MW and a range of labour market outcomes, from human capital formation to unemployment and employment dynamics (Gorjón et al., 2024, Cengiz et al., 2019). More recently, researchers and policymakers have placed growing attention on the potential effects of minimum wage regulations on public health, as reflected in the expanding empirical research on this field and the recommendations of leading health organizations (APHA, 2016).

Research on the effects of minimum wage (MW) on labour outcomes has a long tradition in economics and remains central to debates on labour market interventions today. A large body of empirical research has examined how MW affects a range of labour market outcomes, from human capital formation to unemployment and employment dynamics. More recently, a growing but to date limited literature has focused attention on the impact of MW on health-related outcomes. Overall, existing studies show mixed results regarding the influence of minimum wage on health outcomes. This study aims to contribute to this strand of literature by providing empirical evidence on the effect of an increase in minimum wage on the health of Spanish unskilled workers. We rely on a quasi-experimental setting for this investigation considering the substantial increase in minimum wage in Spain since 2017.

Empirical studies on the effect of the minimum wage on health have produced mixed results. Some studies find positive effects, especially on subjective indicators (Chen, 2021; Leigh and Du, 2018; Lebihan, 2023; Lenhart, 2017a; Lenhart, 2017b; Van Dyke et al., 2018; Wong and Ye, 2015), while others report negative or neutral results (Liu et al., 2024; Horn et al., 2017; Buszkiewicz et al., 2021; Averett et al., 2018; Maxwell et al., 2022; Narain and Zimmerman, 2019).

From a theoretical viewpoint, the effects of minimum wage regulations on health are also ambiguous. On one hand, an increase in the minimum wage leads to higher income, which, according to Grossman's model, can encourage individuals to invest more in their health (for example, through healthier eating, engaging in physical exercise, or adopting preventive habits). Higher income for low-wage workers can also improve access to healthcare, enhance overall living conditions, provide greater economic security, and reduce stress and anxiety levels. On the other hand, if companies respond to the minimum wage increase by reducing their workforce, some workers may face unemployment. Additionally, some firms might react to this legislation by requiring longer working hours, increasing workloads, or reducing non-wage benefits. Consequently, working conditions and job satisfaction could deteriorate, producing negative effects on health.

To contribute to this growing debate, in this paper we study the impact of recent MW policies implemented in Spain. Since 2017, the MW has been risen substantially, with 2019 marking one of the largest increase among OECD countries (OECD, 2023), and the largest in Spain in several decades (Consejo de Ministros, 2018). While the minimum wage intends to reduce poverty and improve workers' overall well-being, it remains an open question, however, whether it can also yield beneficial effects in terms of health outcomes. The aim of this study is to estimate the effects of minimum wage on the health outcomes of workers, focusing on a series of policy reforms that have gradually increased the earnings levels of workers in Spain since 2017. There has been an increase of approximately average of 6.6% increase in minimum wage with a notable increase in 2019 of about a 22% increase in minimum wage from €735 to €900. Data is drawn from the Spanish Survey of Living Conditions (ES-SILC), a survey which collects both cross-sectional and longitudinal information -with follow-ups conducted every four years- and which provides a wide range of relevant health and socio-demographic variables

This paper contributes to the existing literature in several important ways. First, the effects of MW policies on many aspects of individual welfare beyond the labour market has received limited attention in the literature. Our study address this gap by examining health outcomes and health related behaviours, offering a more comprehensive picture of the broader consequences of MW policies. Second, our study examines the effect of MW on health outcomes in Spain. To the best of our knowledge, this is the first study to analyse this relationship for Spain using a representative, population-wide survey covering the entire working population. The substantial and persistent changes in the MW legislation in Spain since 2017 make it an excellent case study for exploring the implications of the policy reform on health. Third, we use EU-SILC data, which provides extensive longitudinal coverage and allows us to track individuals over time. Much of the existing literature relies on cross-sectional data or covers relatively short time spans, limiting the ability to analyse dynamic as well as medium or long-term effects. Furthermore, a large share of the literature does not employ rigorous impact evaluation strategies, instead capturing associations rather than causal effects. In particular, we rely on Callaway and Sant'Anna difference in differences estimation techniques, which accounts for staggered treatment and treatment effect heterogeneity. Additionally, we complement the EU-SILC data with other datasets that allows use to explore a range of numerous potential mediating mechanisms -such as health behaviours, health care access and unmet medical care needs- providing important insights into the channels through which MW changes influence health outcomes.

The remaining sections of the study are organised as follows. Section 2 explores the related literature regarding the relationship between minimum wage and health outcomes. The description of the minimum wage legislation in Spain is presented in Section 3. Section 4 discusses the data employed for the empirical analysis, some descriptive statistics and presents the empirical model and estimation strategy. The results and discussions are shown in Section 5, and finally, the concluding remarks are presented in section 6.

2.2 Related Literature

This section summarizes the main findings of the literature exploring the impact of minimum wage on workers' health and life styles, diet, and access to health care. Overall, these results have yielded mixed or inconclusive results.

Minimum wage increases are likely to lead to greater investments in health and reduced stress levels, thereby fostering behavioural changes traits that promote healthier habits. In this regard, while several studies have found a positive effect of minimum wage on various health outcomes such as self-reported health, mortality, health diseases and quality of life (Chen, 2021; Leigh and Du, 2018; Lebihan, 2023; Lenhart, 2017a,b; Van Dyke et al., 2018; Wong and Ye, 2015), other studies have reported a negative impacts of MW on health dimensions such as BMI, alcohol consumption, drinking and smoking (Liu et al., 2024; Horn et al., 2017; Buszkiewicz et al., 2021). A smaller set of studies have concluded that the effects are either negligible or mixed (Averett et al., 2018; Maxwell et al., 2022; Narain and Zimmerman, 2019). Most of these studies have been cited by

Neumark (2024) in a systematic literature survey reviewing the impact of minimum wage on health-related behaviours and health. Using data from the Korean Welfare Panel Study, the study by Bai and Veall (2023) aligns with studies that have found a positive effect of minimum wage on health outcomes but focusing specifically on smoking and employing Callaway and Sant'Anna difference-in-difference estimation techniques. A more recent study conducted in Korea, which employed the Korean Longitudinal Study on Aging, indicated that an increase in minimum wage decreases cognitive function; however, there was no effect on self-reported health using a difference-in-difference strategy between 2016 and 2018 (Kim et al., 2025). While most studies have centered on the developed countries-particularly in the USA and the UK (Van Dyke et al., 2018; Averett et al., 2018; Maxwell et al., 2022; Buszkiewicz et al., 2021) a few there is a small but growing body of research that has examined developing countries (Majid et al., 2016; Ponce et al., 2018; Conklin et al., 2016, 2018). Studies focusing on the USA explore natural experiments by estimating state and federal minimum wage differential timing increases (Wehby et al., 2020; Clark et al., 2020; Kuroki, 2021). As far as Spain is concerned, the literature is not existent.

Some studies have elaborated on the effect of minimum wage on diet and obesity and overall on health. For instance, Clark et al. (2020) analyzed whether higher minimum wages leads to the increased consumption of fruits and vegetables, resulting in an improved diet and reduced obesity levels. They found an income elasticity of fruit and vegetable consumption of 0.12 as a result of minimum wages. However, Andreyeva and Ukert (2018) found that higher minimum wage in the US is related to a reduction in the consumption of fruit and vegetables and an increase in the probability of obesity. However, no effects were found regarding access to health care. On the other hand, the study by Chapman et al. (2021) showed that minimum wage increases in Minneapolis has no impact on dietary intake. However, higher minimum wages were found to reduce absenteeism due to workers' own illness, but not absenteeism related to children's illness in the US (Leigh and Du, 2018).

Finally, given the improved economic situation, in some contexts MW policies are expected to improve health care access and reduce unmet needs. However, Averett et al. (2018) found limited evidence that low-educated Hispanic women who are likely to be affected by minimum wage increases experienced any changes in access to care, health status or use of preventive care.

Drawing on data from the behavioural Risk Factor Surveillance Surveys, Horn et al. (2017) delved into the relationship between minimum wage increases in the United States and worker's health, leveraging detailed information on employment status. They suggest that, following a MW increase, health deteriorates among low-skilled men, particularly among the unemployed, while women experience poorer overall health but improved mental well-being using the BRFSS. Buszkiewicz et al. (2021) used data from the US National Health Survey data from 2008 to 2015 and reported a positive relationship between minimum wage and obesity or BMI for male working-age adults and a higher likelihood of hypertension in working-age women. However, for men, minimum wages were found to be associated to a lower probability of hypertension. Similarly, Sigaud et al. (2022) argued that there is a positive relationship between higher minimum wage and men's mental and physical health burdens in mean, but no statistically significant effect on their general health status. Wehby et al. (2020) posited that minimum wage hikes increase birth weight among mothers with low education levels. Conversely, minimum wage improves general health amongst women but decreases their mental and physical health burdens. Regarding racial or ethnic differences, evidence from the US shows that increases in the MW are associated with improved access to care for Black and Latino women, but reduced access among Black men and white women using data from the Behavioural Risk Factor Surveillance System (BRFSS) over the period 1993 to 2014 (Narain and Zimmerman, 2019). Also, they discussed that there is a positive, negative and mixed impact of minimum wages on the health outcomes of white men, white women and Latinos, respectively. Van Dyke et al. (2018) illustrated the relationship between the increase in state-level minimum wages above the federal minimum wage and the rate of heart disease deaths among working age from 1980 to 2015 from the CDC Wonder. They confirm that an increase in the minimum wage reduces heart disease deaths. Komro et al. (2016) asserted that an increase in the minimum wage is associated with a reduction in low birth weight births by 1-2% and a decrease in post-neonatal mortality by 4%. These studies collectively contribute to the understanding of minimum wage policies and their implications for various health attributes.

2.3 Minimum wage in Spain

The literature on the effect of the minimum wage in Spain has largely focused on its impact on labour market outcomes. For decades, studies have concentrated on the effect of minimum wages on inequalities, earnings, incomes and employment (MaCurdy, 2015; Meer and West, 2016; Neumark and Wascher, 2004; Bosch and Manacorda, 2010). Minimum wage policies are key tools for addressing inequalities in most economies around the world. These wage regulations usually make it easier for younger generations to enter the workforce since they are more susceptible to economic downturns. Manning (2021) argues that the extensive body of research on the effects of minimum wage on labour outcomes are still quite controversial due to the conflicting nature of the empirical findings. Also Cardoso (2019) estimated the impact of high youth minimum wages relying on linked employer-employee data and a major law change that is the young minimum wage enacted in 1987. This author found that there were short-run wage gains from high minimum wages and this does not endanger employment whilst hours worked changes by part-timers increases job attachment. Moreover, empirical studies have demonstrated that raising the minimum wage may not always have a detrimental impact on employment. Several publications stand out in this field, such as the groundbreaking work by Card and Krueger (1994) and more recent studies like Dustmann et al. (2022) in Germany and Cengiz et al. (2019, 2022) in the US example. Overall, as demonstrated by Neumark (2024), the majority of MW publications indicate notable adverse employment consequences, especially for low-skilled workers.

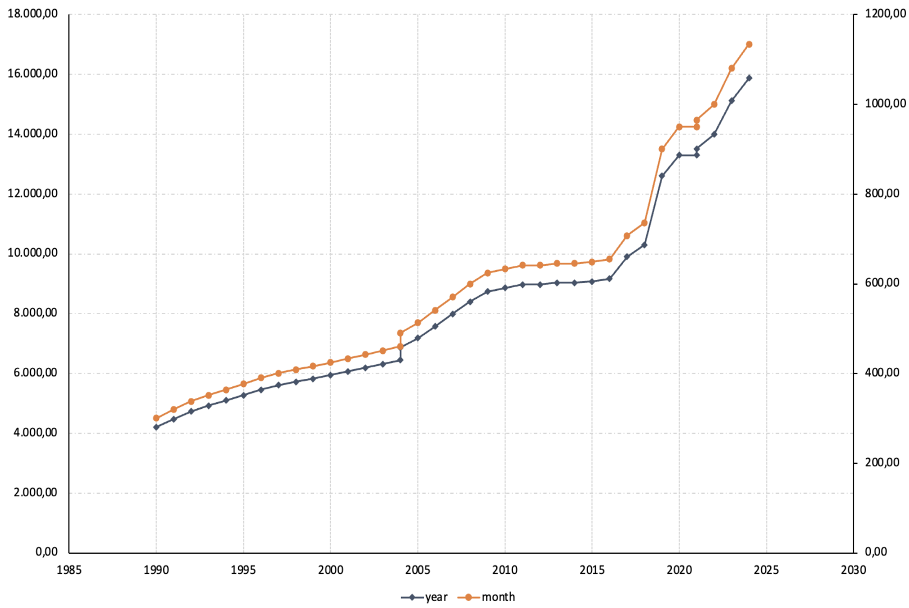
Unlike other countries like China (Liu et al., 2024) and the US (Averett et al., 2018; Buszkiewicz et al., 2021) where different provinces or states can set their wages depending on the prevailing labour conditions, in Spain, this decision is set annually by the central government through negotiations with relevant employers' bodies and representative unions. This decision is usually made in January each year and remains binding until the next annual revision (Salario Mínimo Interprofesional, SMI). Factors such as the average productivity, the growth in labour's share of the country's national income and the consumer price index (CPI) influence the determination of this minimum wage. Currently, the set rate defines the least remuneration a worker may receive for a legal working day without discrimination based on age, gender, the type of contract and the duration of the employment or region of residence (Galán and Puente, 2015). The minimum wage is defined in monthly wage terms, but it's also prorated based on the number of days and hours worked. On February 6th 2024, the Ministerial Council through Royal Decree 145/2024 fixed the current minimum wage which is €1,134 per month and €37.80 per day.

This idea of establishing a mandatory minimum wage in Spain dates back to 1964, with a strong emphasis on addressing regional inequalities. Until 1980, minimum wages varied according to age and region of residence. However, since 1980, regional differences have been abolished. Between 1980 and 1990, there were three age-related minimum wages: one for workers under 17 years old, another for those at aged 17 and finally another for workers over 17. Currently, minimum wages are established without taking into account the sector of employment, age or region.

Focusing on the historical trajectory, the MW increased nominally by 22.3%, or 5.6% annually, from €490.8 to €600 between 2004 and 2008 (see Figure 2.3.1). Following a slower growth during the Great Recession and the early phases of the recovery stage, largely due to the impact of the economic downturns, the MW rose to €655.2 by 2016. Even though the annual rise was only 1.2%

on average, the MW maintained workers' purchasing power in line with the terms of collective bargaining agreements (Barceló et al., 2021). The MW began to increase more quickly after 2017, following initiative by successive governments. Initially, the Popular Party (PP)'s centreright coalition - implemented a 8% increase, raising the MW from €655.2 to €707.7. Subsequently, in 2019 a coalition between left-wing parties and the Spanish Socialist Workers Party (PSOE) enacted a substantial 22% increase in the minimum wage, raising it to €900 per month 22.3% (€12,600 per year). This marked one of the largest increases among OECD countries and the largest in Spain since 1977 (Barceló et al., 2021; OECD, 2023).

Figure 2.3.1: *Evolution of Minimum wage*



Notes: Source: Labour Statistics Bulletin from the Ministry of Labor and Social Economy.

This study explores the health related consequences of the observed increase in MW after 2016. On average, this increase is about 6.6% which is attributed to economic recovery, job creation and economic expansion. The World Bank estimates that the Spanish economy grew by about 2.4% before 2020 and about 5.2% after 2020 even though 2020 saw a drastic decline in growth due to covid 19. Over the entire period (2017 - 2023), the growth of the Spanish economy was about 1.7% while the share of wage and salaried workers increased by only approximately 0.25% (World Bank, 2024).

Various studies have explored how minimum wages have affected labour market outcomes in Spain. For instance, drawing on the Continuous Sample of Working Lives (CSWL), Gorjón et al. (2024) investigated how the increase in minimum wage in Spain in 2019 affected employment and work intensity. They established that this rise in MW significantly increased the probability of experiencing unemployment after one year (by 1.7%) and reduced the intensity of work (by 0.8%). Morever, they found considerable regional and age-related differences with the southern regions experienced larger job losses younger workers were more likely to get reduced working hours, and older workers were more likely to get unemployed. No substantial gender differences were found. Similarly, drawing on the same dataset -Continuous Sample of Working Lives (CSWL)- Lacuesta et al. (2019), Barceló et al. (2021) and Fernández-Baldor Laporta (2022) also found employment losses associated with the 2019 increase in the MW, estimating somewhat larger effects (about 3-10%, 8-9% and 6-11%, respectively). The study by López-Tamayo et al. (2017) explores the regional impact of the minimum wage on youth employment also finding a negative relationship between both variables (between 0.8% and 1.8%). According to Nolla Sabater et al. (2022), the minimum wage have has detrimental effects on employment when it is not accompanied by proportional increases in average wages. Similarly, leveraging on the 2004-2010 increase in the minimum wage in Spain, Galán and Puente (2015) found that in comparison to other age groups, older people had a higher probability of losing their employment. Antón and Muñoz de Bustillo (2011) examined a policy that equalized minimum wages of young workers over the period 1995-1998, and found increased unemployment and a reduction in the probability of them remaining in formal education. Cengiz et al. (2019) used a difference-in-difference method comparing excess jobs at or above the new minimum wage with missing jobs below it to assess the employment impact of minimum wage rises. Examining U.S. state-level minimum wages from 1979 to 2016, they found low-wage job totals stayed mostly constant over five years, with minor wage spillovers increasing the minimum wage's effect on average wages. These studies do not address workers' health outcomes.

2.4 Methods

2.4.1 Data and Descriptive Statistics

The empirical analysis draws on the Spanish Survey of Living Conditions (ES-SILC), which is a part of the European Statistics on Income and Living Conditions (EU-SILC) - harmonized set of statistical data across European Union countries. The data used spans the years 2012 to 2023, a period marked by significant changes in minimum wage. This survey collects both cross-sectional and longitudinal information with follow-ups conducted every four years. This information is mainly collected between April and July[1] and published in May of the following year using computer-assisted personal interviews (CAPI) focusing on households, persons (adults), and children. This

[1]However, during some years where the data was collected after the summer period.

study relies mainly on adults aged 16 to 67 as its primary aim to investigate the impact of the minimum wage for the working-age population. The information collected in the dataset include social participation, housing conditions, material deprivation, intra-household sharing of resources, material deprivation, social participation, access to services, health, well-being, intergenerational transmission of disadvantages, over-indebtedness, consumption, and wealth.

Self-perceived health measure is the key health outcome in this study. The ES-SILC respondents are asked to answer a question which centered on their general health. More specifically, they responded to the question: "How is your health in general?" The possible answer categories were very good (1), good (2), fair (3), bad (4) or very bad (5).[2] This metric is likely to reflect a person's overall assessment of their health (Lenhart, 2017a, Chen, 2021). Following the previous studies in this field (Lenhart, 2017a; Horn et al., 2017; Hafner and Lochner, 2022), we constructed three binary indicators for self-rated health; the first variable equals one if the individual reported to be in very good or good health and zero otherwise. The second one takes the value one for those reporting satisfactory health and zero otherwise. Finally, the third variable equals one for those who reported very bad or bad health or zero otherwise.

2.4.2 Treatment identification

We focus on the yearly income levels of all employed workers. This is to enable us define the treatment cohort in this study. That is, our treated cohort is defined as individuals with wage income levels in 2016 below €9907.80 the minimum wage in 2017, while the comparison cohort consists of individuals with income levels in 2016 between this minimum wage and 140% of the MW. There was about 8% increase in MW from 2016 to 2017. In Figure 2.3.1, there was a sharp increase in the minimum wage policy in 2016 and this means a substantial increase, however this increase was fairly stable from 2012 to 2016. Therefore, just like Bai et al. (2023), this design relies on comparison over time and across various treatment groups.

There have been various ways earlier studies have employed alternative identification strategies to categorize individuals into treatment groups and control groups. Research such as that conducted by, Allegretto and Nadler (2020), Huang et al. (2021) and Kaufman et al. (2020) have examined college educational qualifications as an identification strategy to classify individuals into treatment groups, specifically targeting those whose education does not reach the college degree level and

[2] The first question in the Minimum European Health Module (MEHM) is the one that corresponds to this variable. By its very nature, self-perceived health measurement is subjective. The idea is limited to an evaluation made by the person themselves, without assistance from an interviewer, medical expert, or family member. Although thoughts or impressions from others can have an impact on one's self-perceived health, this is the outcome of the individual's processing of these impressions in light of their own attitudes and beliefs.

individuals possessing at least some college-level education designated as the control group. In this vein, we employ this strategy as a robustness check in our analysis.

Other identification strategies focus on geographical or state level minimum wages where the treatment is based on states or locations that have change their minimum wage policies and those that have not as the control groups. Studies like Liu et al. (2024), Horn et al. (2017) and Kuroki (2021) have employed this strategy as their source of identification. However, this strategy does not apply in the Spain case, since the minimum wage policy is not subject to the provincial level. These definitions serve as a way of identifying respondents who are more likely to be affected by minimum wage (Dube et al., 2010). Following other studies (Lenhart, 2017a; Reeves et al., 2017) which most of them follow the UK setting, we also employ income as an identification strategy for the treatment assignment.

Table 2.B.1 in the Appendix outlines the baseline characteristics of the study populations and the distribution of the sample in the treatment and comparison groups. On average, individuals in this sample are about 40 years old, with those who are likely to be affected by the minimum wage policy being about 5 years older than those in the comparison groups who are about 37 years old. We also find that there are more females (58%) than males receiving minimum wages. The treated group possesses a greater proportion of females. On average, about 45% of these workers have secondary (medium) education and most of them are married (60%) with an average household size of about 3. The household income is about €788 (9451) on average monthly (yearly). Regarding health status, about 36% of them have a chronic health condition. The treated group has a larger percentage of married individuals, are more likely to work in production, construction and heavy industries, have a permanent contract, higher income, and have chronic disease, relative to the comparison group.

2.4.3 Control variables

We control for time variant covariates like marital status, education level, household size, household income, and an indicator for chronic illness. Additionally, we adjusted for other employment characteristics, that is the type of job contract and the type of employment. Also, including individual-level fixed effects controls for all time-invariant confounders (Quintana, 2021; Brüderl and Ludwig, 2015).

2.4.4 Empirical strategy

To estimate the causal effect of the minimum wage policy change on our health outcomes of interest, we rely on the Difference-in-Difference estimator with multiple timing developed by Callaway and Sant'Anna (2021). This method is particularly useful for our study setting since it relaxes the constant treatment effect's assumption of the conventional Differences-in-Differences (DiD) estimator (Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Sun and Abraham, 2021). Moreover, the CSDID estimator can be viewed as more efficient relative to the TWFE under some conditions, more specifically, when working with small samples or a limited number of groups in panel data. Also, CSDID assumes heterogeneity in treatment effects and staggered adoption settings and can be used both in panel data or repeated cross-sectional data. TWFE produces a weighted average of heterogeneous treatment effects where some weights can be negative, meaning the estimator can yield a negative coefficient even when the true effect is positive for all units, CSDID avoids this by separately identifying $ATT(g,t)$ for each cohort and time period and aggregating them with strictly non-negative, chosen weights, while also allowing for covariate-adjusted parallel trends and valid simultaneous inference. In this framework, a treated subject remains treated in an absorbing conditions that is once the individual receives treatment, they continue to be treated with no possibility of reversal (Callaway and Sant'Anna, 2021). That is estimating average treatment effect from the treated subpopulation by comparing the average change in health outcomes experiences by the control group. In this framework, in terms of assumptions, the DiD setups such that once subjects are treated, they stay treated in the following periods (irreversible treatment). That is once an individual starts receiving minimum wage, it is not reversed. This method provides average treatment effects in DiD with multiple time periods, variation in treatment timing, and the parallel trends assumption potentially holds only after conditioning on observed covariates. Also, the common support assumption (Abadie, 2005) must hold. That is for some range, it must be the case that the treatment and comparison groups have units with the same approximate propensity score.

Estimating the causal effect using this method is not without challenges. First, common trends assumption needs to be validated. It is the state of the effect in the absence of the treatment, intervention and control group would evolve. Although it is impossible to verify this premise directly, there are a number of methods to assess its plausibility. We can apply a causality test in the vein of Granger (1969) because our data includes several pre- and post-treatment periods. The idea behind this test is that it would cast doubt on the identification technique if effects started to appear before the policy instead of the other way around. As a result, we add anticipatory effects (leads) and post-treatment effects (lags) to Equation (2.1). However, recent work by Roth et al. (2023) highlights that relying on unconditional mean outcomes may be problematic in the presence of confounders, as the parallel trends assumption is more likely to hold only after accounting for certain observable factors.

That is, exploring the dynamics of minimum wage policy effect:

$$y_{it} = \alpha + \sum_{p=-\underline{P}}^{\overline{P}} \phi_p MW_{it}^{p} + \Gamma_{it}^{'}\eta + \rho_i + \gamma_t + \nu_{it} \tag{2.1}$$

our variable of interest, MW_{it}^{p}, is a binary variable which signifies that the respective individual - time observation ($p = -\underline{P}, \ldots, \bar{P}$) for which the event occurred in this settings when individuals are affected by minimum wages. Specifically, we control for indicator variables for periods before ($p < 0$, leads) and after ($p \geq 0$, lags) when there were minimum wage policy. Period $p = 0$ signifies the year for which this increase in the minimum wage policy is being evaluated. Urbanization and regional fixed effects are represented as ρ_i and γ_t respectively and the set of controls which comprises of demographics, economic, health and employment factors are represented in Γ. The error term is indicated by ν_{it}. Our variable of interest is ϕ. This estimation is clustered at the regional level. We rely on linear probability models to estimate this model since this model is the commonly used model for difference-in-differences strategies with binary outcomes like self-perceived health (Leigh et al., 2019).

2.4.5 Entropy Matching

We used matching techniques to build a counterfactual control cohort of individuals who were not affected by minimum wages in 2017, that is, attributes in the pre-treatment period are not statistically different from those that are treated (receiving minimum wages). Specifically, we use pre-treatment features to balance treated workers in a 1:1 ratio to controls using an entropy matching strategy suggested by Hainmueller (2012) since King et al. (2011) and King and Nielsen (2019) have criticized propensity score matching techniques.[3] Entropy balancing relies on a maximum entropy reweighting method that calibrates unit weights so that the treatment and reweighted control groups achieve exact balance across the first, second, and potentially higher moments of

[3]Critics have alluded that matching or propensity score methods can be cumbersome to apply and frequently yield low covariate balance. These techniques involve repeated cycles of estimating propensity scores, matching, and checking balance to find appropriate weighting for covariate balance. This iterative process often does not achieve overall covariate balance and can even exacerbate bias when balancing one covariate negatively impacts another (Diamond and Sekhon, 2006; Iacus et al., 2009).

covariates.[4] That is, incorporating information about known sample moments into the reweighting scheme, eliminating the need for any distributional assumptions. Entropy balancing identifies a set of unit weights that satisfy the balance constraints while remaining as close as possible to uniform base weights in an entropy sense. By minimizing the entropy distance, this approach preserves information and maintains efficiency for subsequent analyses. Consequently, explicit balance checks are generally unnecessary for the covariates included in the balance constraints. It employs a maximum entropy reweighting scheme, which enables the preprocessing of data with binary treatments. Unlike nearest-neighbour matching, which restricts unit weights to zero or one, entropy balancing assigns weights that vary smoothly across units, thereby preserving more information in the data. With regard to the following parameters, our matching process precisely matches workers below and over the 2017 threshold: gender, education, marital status, household size, employment sector, the type of job contract, income and chronic diseases. That is to choose a partner at random, since the same person may have several partners. As a result, the same number of people are matched with each member of the treatment group. The distributions of the treatment and control groups, as well as the quantity of observations in each group, are therefore the same when this approach is used. Those unmatched units are not included in the analysis. Using this matching strategy, we successfully identified one control unit for 32,328 units, representing 94.8% of the total 34,110 units. Table 2.4.1 reports the first-moment covariate balance, with the second- and third-moment balances for the eleven covariates shown in Table 2.B.2, illustrating the effects of entropy balancing. By construction, we find that there are no statistically significant differences in observable characteristics between the treatment and control group as seen in Figure 2.A.4 and also in Table 2.4.1. From this we find that about 56% of the treated sample are females, they are about 42 years old. As compared to those in the secondary education level, 41% of them were in the tertiary level and about 14% are in the primary education level. About 24% of these treated individual are never married. The average household size of these treated individuals was about 2.9 and their income level is about 27,000. Just about 22% of them have temporal jobs with about 23% working in the trade and services and about 15% in the public service jobs. Only about 33% of them have chronic illness.

This balancing method uses a selection-on-observables identification strategy, which considers the health transitions of control units to closely approximate the counterfactual situation for the treated cohorts in the absence of the policy. In assessing the impact of the 2017 minimum wage increase, it is crucial to condition on observed characteristics, as treatment identification is not reliant

[4]Entropy balancing extends the propensity score weighting method by calculating weights directly from an extensive set of balance constraints, leveraging the understanding of sample moments.

Table 2.4.1: Balancing test

	Means		
		Controls	
Covariates	Treated	Pre	Post
Age	41.548	37.402	41.537
Female	0.559	0.563	0.559
Primary	0.144	0.242	0.144
Tertiary	0.407	0.296	0.407
Never married	0.237	0.216	0.237
Separated	0.022	0.023	0.022
Widow	0.049	0.066	0.049
Divorce	0.064	0.050	0.064
Household size	2.853	2.840	2.853
Trade and Services	0.227	0.275	0.228
Public services	0.146	0.186	0.146
Temporal job	0.222	0.311	0.222
Chronic illnes	0.329	0.348	0.329

on possible health transitions without treatment. This balancing approach improves conventional modelling methods while controlling for covariates is a good strategy.

2.4.6 Sensitivity Analyses

Additionally, we conducted various sensitivity analyses to further re-affirm the robustness of these findings. To begin with, we evaluate the effect of minimum wage across age groups, gender, type of sector, type of job contract and educational level. We also consider changes in the treatment group to address some spillover effects related to the minimum wage increase. That is, the potential of the minimum wage policy is more likely to affect individuals whose earnings slightly exceed the updated minimum wage (Cengiz et al., 2019; de Paz-Báñez et al., 2024; Garcia-Louzao and Tarasonis, 2023). Therefore, we performed the robustness of the policy effects by repeating the analysis with an adjusted definition of the treatment group, aside from using 140% of minimum wage, we consider definition treatment based on individuals, 130% and 120% of the minimum wage to better capture the sizeable influence of minimum wage changes addressing spillover effects. We also consider other definitions of the health outcome as other sensitivity test. In doing this, the study focuses on self-reported health as a continuous variable and also a binary outcome measuring those reporting very bad, bad or regular health state.

2.5 Results

The average treatment effect of the treated from the csdid regression models have been presented in Table 2.5.1 and Figure 2.5.1 shows the period by period treatment effects between 5 period lags and 6 leading periods.

From Table 2.5.1, the minimum wage policy affects those who reported bad/poor health states negatively and it has a positive effect on the health state of those reporting very good or good health status. In terms of magnitude for the model without controls, the increase in minimum wage has on average decreased the treated individuals' probability of assessing their health as bad/poor by 0.044 points whilst it increased the probability of reporting health as very good/good by 0.141 points and they are highly statistically significant at 1% level of significance and we also find that these effects are much smaller and statistically significant. When control variables are included, the share of individuals reporting bad/poor health decreased by about 66% relative to the baseline. Also as compared to the effect of those reporting very good/good health in the baseline, there is about 70% reduction in v/good health.

However focusing on the entire sample in Table 2.B.3, there is about 0.065 less likely to report bad/poor health but then this marginal increase in wages increase the probability of reporting very good or good health by 0.187 points in the matched sample in Table 2.B.3. Concerntrating on the model with controls, the effect for bad or poor health is much lower of about 0.018 and about 0.046 for those reporting very good or good health state. These estimates rely on the doubly robust DiD estimator method under the csdid command, which is based on stabilized inverse probability weighting and ordinary least squares.[5]

That is, increases in minimum wage can have measurable health consequences. For instance, there could be diminishing returns to health improvements as wages increase. More so, health could be evaluated as a form of human capital that individuals invest in over time. An increase in minimum wage raises workers' income, allowing them to spend more on healthcare, nutritious food, housing, and other health-promoting goods and services. Consequently, this reduces the likelihood of reporting poor health (Grossman, 1972). Studies that concluded in the same way include Lenhart (2017a), Averett et al. (2018), Du and Leigh (2015) and Chen (2021).

While some studies indicate minimal job displacement, the theoretical possibility of employers reducing staff or work hours in response to increased labour costs remains (Buszkiewicz et al., 2021). This could lead to reduced earnings and heightened stress, both of which are detrimental

[5]We also results estimates based on ordinary least squares in the appendix are not different from the main results.

to health, particularly for those already in a vulnerable state.[6] Research has also shown that significant minimum wage increases can lead to reduced employment and labour force participation among individuals with severe disabilities, a group likely to report poorer health (Clemens et al., 2025). Conversely, individuals reporting good or very good health might experience positive effects from minimum wage policies in various ways. With more financial resources, these individuals may have greater access to health-improving goods and services, such as nutritious food, preventative healthcare, and better housing options. The increased financial stability can also lead to a reduction in financial stress, which is known to have a positive impact on mental and physical well-being (Buszkiewicz et al., 2021; Blavin and Gangopadhyaya, 2022; Leigh et al., 2019). Beyond these additional financial benefits, higher minimum wages can contribute to improved job satisfaction (Leigh and Du, 2018; Leigh et al., 2019). Individuals who feel adequately compensated for their work may experience higher morale and lower stress levels, which can positively influence their overall health. The concept of increased opportunity costs of unhealthy behaviours also comes into play (Leigh and Du, 2018, Lenhart, 2017a). With a higher wage, individuals might be more inclined to prioritise activities that further enhance their well-being, such as exercise and healthy eating, rather than engaging in detrimental habits. Furthermore, increased income can facilitate greater social participation (Buszkiewicz et al., 2021; Blavin and Gangopadhyaya, 2022), allowing individuals to engage more actively in their communities, which can have positive effects on mental and social health. For those in good or very good health, these increased resources might simply reinforce their existing healthy lifestyles and provide a buffer against potential health challenges in the future.

The lag coefficients of almost all the periods (pre-treatment average) for all the outcomes are insignificant, indicating that these estimations do not violate the parallel trend assumption. The minimum wage policy in Spain appears to have statistical significance at $t = 1$ for those who reported very good or good health. At $t = 4$, we find that significance for those reporting that their health is bad or poor and very good or good health state for the entire sample. But then under the matched sample, $t = 3$ shows noticeable significant effect when minimum wage increase that is a decrease in those likely to be reporting bad or poor health and an increase in reporting very good or good health.

From the event studies, we investigate the effect dynamics and also evaluate the validity of the common trends assumption. To do this, we use equation (2.1) to depict the leads and lags

[6]Studies that have included unemployed individuals in their analysis have often reported more negative health outcomes, suggesting that job loss associated with minimum wage increases could disproportionately affect those with pre-existing health issues (Buszkiewicz et al., 2021).

Table 2.5.1: *Effect of Minimum wage on health*

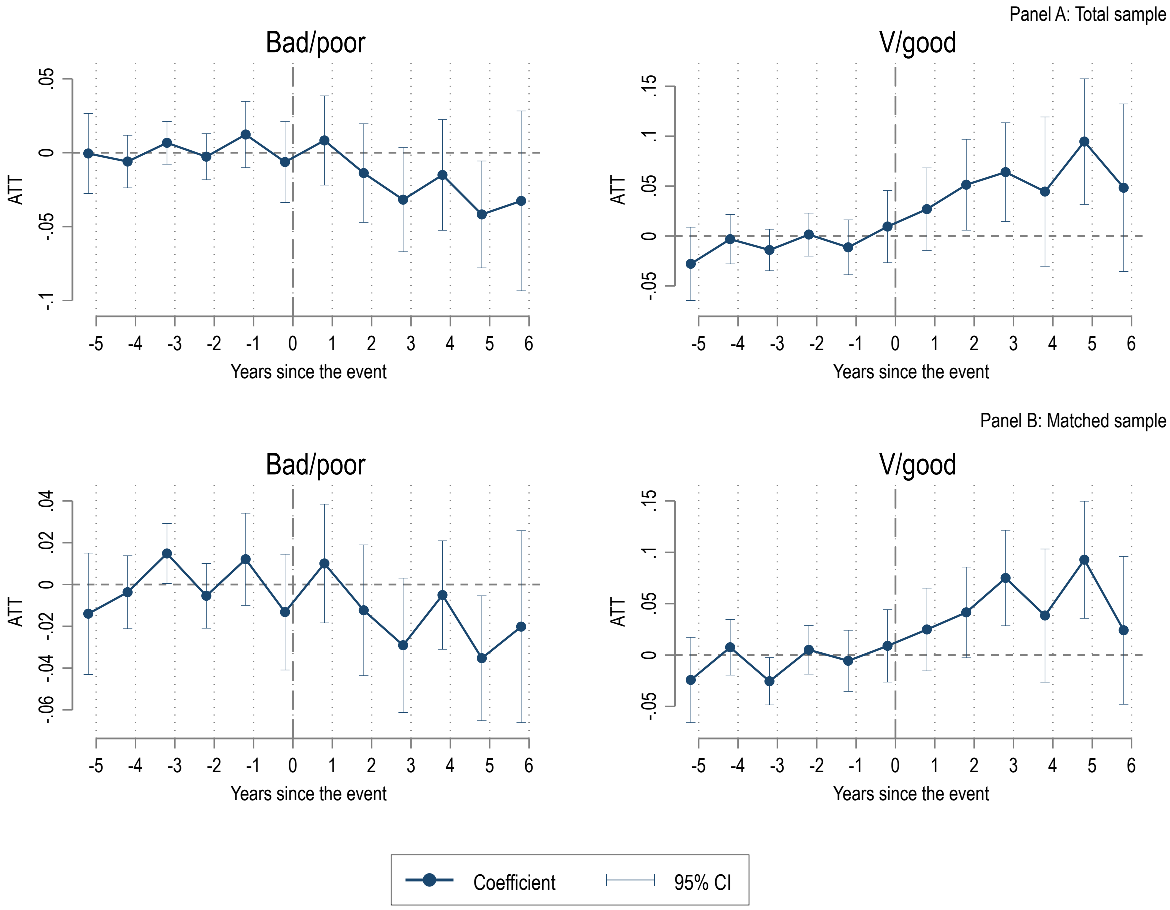
	Bad/poor (1)	V/Good (2)	Bad/poor (3)	V/Good (4)
ATT	-0.044***	0.141***	-0.015*	0.042***
	(0.008)	(0.015)	(0.008)	(0.014)
Pre average	0.010***	-0.037***	0.001	-0.009
	(0.003)	(0.005)	(0.004)	(0.005)
Post average	-0.045***	0.148***	-0.015*	0.044***
	(0.008)	(0.015)	(0.008)	(0.014)
$\hat{\phi}_{es}(-5)$	-0.000	-0.060***	-0.014	-0.024
	(0.013)	(0.023)	(0.015)	(0.021)
$\hat{\phi}_{es}(-4)$	0.001	-0.007	-0.004	0.007
	(0.008)	(0.015)	(0.009)	(0.014)
$\hat{\phi}_{es}(-3)$	0.013*	-0.029**	0.015**	-0.026**
	(0.007)	(0.014)	(0.007)	(0.012)
$\hat{\phi}_{es}(-2)$	0.004	-0.024*	-0.005	0.005
	(0.008)	(0.014)	(0.008)	(0.012)
$\hat{\phi}_{es}(-1)$	0.032***	-0.067***	0.012	-0.006
	(0.010)	(0.017)	(0.011)	(0.015)
$\hat{\phi}_{es}(0)$	-0.022*	0.032	-0.013	0.009
	(0.013)	(0.021)	(0.014)	(0.018)
$\hat{\phi}_{es}(1)$	-0.013	0.087***	0.010	0.025
	(0.012)	(0.024)	(0.015)	(0.021)
$\hat{\phi}_{es}(2)$	-0.041***	0.133***	-0.012	0.041*
	(0.013)	(0.025)	(0.016)	(0.023)
$\hat{\phi}_{es}(3)$	-0.068***	0.196***	-0.029*	0.075***
	(0.016)	(0.027)	(0.016)	(0.024)
$\hat{\phi}_{es}(4)$	-0.045***	0.167***	-0.005	0.038
	(0.008)	(0.026)	(0.013)	(0.033)
$\hat{\phi}_{es}(5)$	-0.065***	0.238***	-0.035**	0.093***
	(0.011)	(0.030)	(0.015)	(0.029)
$\hat{\phi}_{es}(6)$	-0.061***	0.179***	-0.020	0.024
	(0.013)	(0.028)	(0.023)	(0.037)
Controls	No	No	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes
N	55706	55706	55678	55678
Pretrend χ^2 (df)	62.04 (28)	124.15 (28)	24.26 (28)	34.78 (28)
Pretrend p-value	0.000	0.000	0.668	0.176

* *p<.1, ** p<.05, *** p<.01*

Note: ATT is the coefficient of minimum wage. This table depicts the event study estimate of the ATT (ϕ_{es}). ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications. Estimation is clustered at the regional level. Using not treated as control group. Sample is the matched sample.

coefficients together with the appropriate 95% confidence interval across relative time. The dynamic effect on bad/poor and very good/good self-reported health has been displayed in Figure 2.5.1

Figure 2.5.1: *Dynamic effect of minimum wage and health*



Notes: This figure illustrates the dynamic Average Treatment on the Treated (ATT) of very bad/bad health and very good/good health (self-reported health). The time window is restricted to five periods before and six after treatment due to a drastic decrease in statistical precision outside this range. The time of treatment is denoted as $e = 0$, depicted with a vertical dashed line. Whiskers depict the 95% confidence interval based on Wild Bootstrap standard errors clustered at the regional level. This panel is a visual representation of the eight models as displayed in Table 2.5.1. Panel A depicts models for very bad/bad and very good/good health focusing on the entire sample and Panel B depicts the matched sample results.

respectively for the entire sample in Panel A and Panel B depicts models with matched sample. It appears that there is no significant effect before the policy year, suggesting the validity of the common trends assumption. To be more precise, almost all the pre-treatment coefficients are extremely close to zero. On the other hand, at the 5% level of significance, almost all the post-treatment periods are statistically significant with the exception of very good/good where it is not significant for some periods. Further, the negative effect after the treatment exhibits decreasing development over time for bad/poor and satisfactory health and a positive effect after treatment for very good/good health state shows increasing development over time.

2.5.1 Heterogenous Effects

This section investigates some heterogeneous effects focusing on the effects on gender, age groups, the type of employment sector, the type of contract and educational status. With regard to gender focusing on the matched sample, we find different effects for the male and female samples presented in Table 2.B.8. Although we do not find any significant effect on males reporting bad/poor health on the matched sample, however, we find about 2.1 percentage points decrease in females reporting bad/poor health significantly as a result of an increase in minimum wage. Reporting very good or good health state is about 4.3 and 4.2 percentage points increase in females and males, respectively, when the minimum wage increases in the matched sample. Overall, it appears that the effect of minimum wage is more pronounced on females' health relative to males. These results are consistent with previous findings from Sigaud et al. (2022) and Horn et al. (2017). Females in the poorest health might be particularly sensitive to income fluctuations because their existing health conditions require resources. The minimum wage increase could have provided the necessary financial buffer. Women could be faced with more profound and obvious health challenges that might not have been captured by the marginal increase in income. In addition to socioeconomic factors, constrained access to comprehensive healthcare, or chronic inherent conditions which extend beyond the direct effects of the minimum wage increase could be a reason.

Age was grouped into those between the ages of 16-24, 25-34, 35-44 and 45-67 years old and the results are outlined in Table 2.B.8. For those below age 25 years old, we do not effects of minimum wage. However, the effects are statistically significant amongst 25-34 years old. We find that based on the direction of the effect, there is an inverse relationship between minimum wage and reporting bad or poor health. This effect is significant for those reporting very good or good health in the matched sample. Notably, there is a significant effect of this marginal increase in income increases the probability of reporting very good or good health among 35 to 44 year olds. Also, we do not find effects on the bad/poor health on those between the ages of 45 and 67, however, there is an increasing effect for those reporting very good/good health. These workers could those who have been working for a while have gained much experience and expertise and that minimum wage might not be affecting them. We observe more effects for those who are between 25 and 34 years.

This could be that employers are cutting jobs or hours for young, low-skilled workers when wages rise, leading to income instability (if hours are reduced) and unemployment stress, which is strongly linked to poorer mental and physical health. Some studies (Neumark and Wascher, 2008) find that minimum wage hikes reduce teen employment. Young workers might use extra income on unhealthy coping mechanisms (fast food, substance use) due to stress and also risk-taking behaviours (less sleep, overwork). Those between the ages of 16 and 25 years may have present bias that is the young workers may prioritise short-term consumption over health investments. Workers aged 25-34 are more likely to hold steady jobs (less turnover than teens). Gain from employer retention efforts (better schedules, safety measures) when wages rise marginally. Similarly, higher wages may allow workers to leave toxic or hazardous jobs that harm health.

These analyses were also performed on the type of employment sector in which the workers fall also in Table 2.B.8. In doing this, we characterized these various sectors into those working in production, construction and heavy industry, as one group, the other one is trade and services, and finally, those working in public services. The result indicates that the minimum wage affects those working in the trade and services, and production/construction/heavy industries sectors. That is, we observe a negative effect of minimum wage on those reporting bad or poor health and working in the both the production, construction, heavy industries sector and trade and services sector. In addition, among those reporting very good or good health, the effect is positive for both the production, construction, heavy industries sector and trade and services sector (Lebihan, 2023; Kim et al., 2025). However, we find that minimum wage increases the probability of reporting very good or good health for those working in the public services.

Trade and services jobs (retail, hospitality, cleaning) are often low-paying, high-stress, and physically demanding. A retail worker earning more may face fewer understaffed shift crises, reducing stress-related health complaints. Trade and service jobs often lack benefits (health insurance, paid sick leave) so extra earnings helps workers self-insure against health risks. Also, public sector jobs typically have fixed pay structure due to union contracts and government budgets. Raising the minimum wage could narrow the pay differences between junior and senior workers, known as wage compression. However, this could demotivate workers with higher qualifications as their relative earnings decrease, potentially leading to increased stress and dissatisfaction, negatively impacting their self-reported health. On the positive side, it could improve conditions for the lowest-paid workers, transitioning them from poor to satisfactory health. Additionally, production sector employers might compensate for higher wage expenses by reducing non-wage benefits like healthcare subsidies and wellness programs or by increasing workloads. As a result, while workers may feel better than poor, they might not feel as good as before, leading to an increase in satisfactory health reports but a decrease in very good or good health reports. Production sector workers often benefit from job stability and superior benefits, which generally results in better-than-average health. However, the higher minimum wage may attract less healthy individuals who previously couldn't afford lower-paying public jobs, potentially lowering the average of very good or good health reports.

We also performed a heterogeneous effect focusing on the type of contract, that is, whether they were working with a permanent or temporary contract. The results presented in Table 2.B.8 suggest that minimum wage affects those reporting bad or poor health in permanent contracts negatively, while the likelihood of those reporting very good or good is positive. With regard to temporal employment, we find that an increase in minimum wage increases the probability of reporting good or very good health but reduces the probability of reporting bad or poor and satisfactory health. The effect is more pronounced for temporal workers.

Permanent workers enjoy stable employment, which allows higher wages to significantly contribute to long-term health investments such as preventive care and better nutrition. This stability reduces financial stress by eliminating the fear of sudden job loss. Moreover, permanent employees are more likely to receive employer-provided health benefits, which enhances the positive impact of wage increases. To mitigate the impact of higher wage costs, companies can focus on improving workplace safety, thereby retaining permanent staff. Additionally, offering flexible schedules or wellness programs can enhance the general health of permanent workers. Nevertheless, since permanent workers often undergo stringent hiring processes, they might already be healthier, and wage increases further enhance their well-being.

Furthermore, the sample was also segregated into three cohorts: those who achieved primary, secondary and tertiary education and similar analysis were done in Table 2.B.8. On average, those who had primary education had less likelihood of reporting very bad/bad health, whilst those who had tertiary education were more likely to report very good or good health when minimum wages increase. As was confirmed by Lebihan (2023). But then we do not find effect of minimum wage increase on those who had secondary education and reported bad/poor health. Minimum wage policies may act as a protective measure for the most economically vulnerable, leading to better health outcomes. The positive effect on educated individuals who reported very good or good health suggests broader economic benefits beyond just low-wage workers, possibly reflecting macroeconomic improvements.

In Table 2.B.7, we present the effect of the minimum wage on employment and unemployment to check the effect on the labour market. Among employed individuals, we find that the minimum wage increases the likelihood of reporting very good health in the matched sample. This effect is not significant for those reporting bad or poor health. The effect of minimum wage on the health of the unemployed sample was also presented in this table. When controlling for individual characteristics amongst the matched sample, we find only a significant effect on those reporting bad or poor health. That is, a less likelihood of reporting bad or poor health. That is, the probability of reporting bad/poor health increases by about 8.2 percentage points when the minimum wage increases. This aligns with Lenhart (2019) indicate no effect on improved health of unemployed individuals.

2.5.2 Results of Sensitivity analyses

We constructed outcomes in different ways to also investigate the stability of the results. First based on the 5-point scale response of self reported health, binary outcomes for each response were created. These outcomes are those reporting very bad, bad, regular, good and very good health, which were coded 1 if respondents reported their respective health state and 0 otherwise. Focusing on the results presented in Table 2.5.2 and the model without controls in this case, we find a decreasing effect on very bad, bad and regular health states when minimum wage increases; however this increase in minimum wage increases those reporting good and very good health state. Similarly, regarding the models with controls, we observe a negative and significant effect on those reporting very bad and regular health, but then there is a higher probability of reporting very good health. These results reaffirm the effects we observe from the main results. This result has been confirmed by studies like Lenhart (2017a), Averett et al. (2018) and Du and Leigh (2018).

In another sensitivity test, we focus on another outcome to measure poor health. This binary variable which is 1 for respondents whose health state are very bad, bad or regular. Correspondingly, the average treatment effect of minimum wage on those reporting very bad, bad or regular health states is negative and significant. As presented in Table 2.B.4 in the Appendix. The probability of reporting very bad, bad or regular health is about 0.141 less likely when minimum wage increases marginally in the matched sample with no control characteristics. When comparing with the model with controls, this effect is much lower of about 0.042. This effect aligns with what we observe in the main results in Table 2.5.1, that is we find the minimum wage negatively results in people reporting worse health outcomes.

2.5.3 Robustness analysis

The study investigated some robustness analysis to support the results and the conclusion from the analysis. First, we constructed another treatment status using the educational status. Similarly, we find a statistically significant effect of minimum wage on health presented in Table 2.B.10. More specifically, this effect improves health. Those reporting poor health indicate that the minimum wage reduces their probability of bad or poor health by about 5.8 percentage points (larger effect compared to the main results in Table 2.5.1) and there is a higher likelihood of reporting very good or good health by about 16.5 percentage points (larger effect than compared to Table 2.5.1). This suggests that our results are consistent when we rely on the educational status of those who are more likely to be affected by the minimum wage.

Also, another robustness check of this policy effect was performed by replicating the analysis, defining different variants of the treatment group. To do this, we consider defining treatment based on individuals' wages around 130% and 120% of the minimum wage. The results have been presented in Table 2.B.11. These findings are similar to results found in the main results in Table 2.5.1. However, the results are marginally smaller as compared to the one observed in the main table. We find that an increase in minimum wage increases the likelihood of reporting very good or good health in the model with controls. But then we do not find significant effect on bad or poor health.

Table 2.5.2: Effect of Minimum wage on Health

Variables	Very bad	Bad	Regular	Good	Very good	Very bad	Bad	Regular	Good	Very good
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
ATT	-0.014***	-0.030***	-0.097***	0.108***	0.033***	-0.009***	-0.006	-0.027**	0.041**	0.001
	(0.003)	(0.007)	(0.014)	(0.017)	(0.013)	(0.003)	(0.008)	(0.014)	(0.018)	(0.013)
Pre average	0.004***	0.006**	0.027***	-0.027***	-0.010**	0.002	-0.001	0.008	-0.007	-0.002
	(0.001)	(0.003)	(0.005)	(0.006)	(0.005)	(0.002)	(0.004)	(0.005)	(0.007)	(0.005)
Post average	-0.014***	-0.031***	-0.103***	0.112***	0.036***	-0.009***	-0.006	-0.029**	0.042**	0.001
	(0.003)	(0.007)	(0.014)	(0.017)	(0.013)	(0.003)	(0.008)	(0.014)	(0.018)	(0.014)
$\hat{\phi}_{es}(-5)$	0.004	-0.004	0.060***	-0.025	-0.035	-0.003	-0.011	0.038*	-0.002	-0.022
	(0.006)	(0.012)	(0.020)	(0.028)	(0.022)	(0.008)	(0.013)	(0.021)	(0.029)	(0.022)
$\hat{\phi}_{es}(-4)$	-0.004	0.005	0.006	-0.022	0.016	-0.005	0.002	-0.004	-0.012	0.020
	(0.004)	(0.007)	(0.014)	(0.019)	(0.015)	(0.005)	(0.008)	(0.014)	(0.019)	(0.014)
$\hat{\phi}_{es}(-3)$	0.007*	0.007	0.016	-0.010	-0.019*	0.007*	0.008	0.011	-0.007	-0.018
	(0.004)	(0.006)	(0.012)	(0.016)	(0.012)	(0.004)	(0.007)	(0.012)	(0.015)	(0.012)
$\hat{\phi}_{es}(-2)$	-0.001	0.005	0.020	-0.025	0.001	-0.003	-0.002	0.000	-0.002	0.007
	(0.004)	(0.007)	(0.013)	(0.016)	(0.012)	(0.004)	(0.007)	(0.012)	(0.016)	(0.011)
$\hat{\phi}_{es}(-1)$	0.017***	0.015*	0.035**	-0.054***	-0.014	0.014**	-0.002	-0.006	-0.010	0.004
	(0.005)	(0.008)	(0.015)	(0.019)	(0.013)	(0.007)	(0.010)	(0.016)	(0.018)	(0.012)
$\hat{\phi}_{es}(0)$	-0.005	-0.017	-0.011	0.031	0.001	-0.001	-0.012	0.004	0.005	0.004
	(0.005)	(0.012)	(0.019)	(0.025)	(0.020)	(0.007)	(0.013)	(0.019)	(0.023)	(0.016)
$\hat{\phi}_{es}(1)$	-0.008	-0.005	-0.073***	0.088***	-0.002	-0.006	0.016	-0.035	0.046*	-0.021
	(0.006)	(0.011)	(0.022)	(0.027)	(0.021)	(0.008)	(0.012)	(0.021)	(0.025)	(0.018)
$\hat{\phi}_{es}(2)$	-0.013***	-0.028**	-0.092***	0.141***	-0.008	-0.006	-0.006	-0.029	0.060**	-0.019
	(0.005)	(0.013)	(0.022)	(0.030)	(0.024)	(0.006)	(0.015)	(0.023)	(0.028)	(0.020)
$\hat{\phi}_{es}(3)$	-0.017***	-0.051***	-0.128***	0.130***	0.066***	-0.012**	-0.017	-0.046*	0.038	0.037*
	(0.006)	(0.015)	(0.025)	(0.031)	(0.023)	(0.006)	(0.016)	(0.024)	(0.030)	(0.021)
$\hat{\phi}_{es}(4)$	-0.019***	-0.026***	-0.122***	0.079**	0.089***	-0.014***	0.009	-0.034	0.013	0.026
	(0.003)	(0.008)	(0.025)	(0.033)	(0.026)	(0.003)	(0.013)	(0.033)	(0.041)	(0.030)
$\hat{\phi}_{es}(5)$	-0.021***	-0.045***	-0.173***	0.183***	0.056**	-0.017***	-0.018	-0.057*	0.095**	-0.002
	(0.004)	(0.010)	(0.028)	(0.033)	(0.025)	(0.004)	(0.015)	(0.030)	(0.037)	(0.027)
$\hat{\phi}_{es}(6)$	-0.017***	-0.044***	-0.119***	0.130***	0.049**	-0.007*	-0.013	-0.004	0.040	-0.015
	(0.003)	(0.012)	(0.027)	(0.033)	(0.025)	(0.004)	(0.023)	(0.034)	(0.044)	(0.030)
Controls	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	55704	55704	55704	55704	55704	55676	55676	55676	55676	55676
Pretrend χ^2 (df)	63.12 (28)	31.84 (28)	80.67 (28)	56.42 (28)	26.04 (28)	27.66 (28)	20.94 (28)	25.31 (28)	27.37 (28)	24.86 (28)
Pretrend p-value	0.0002	0.281	0.000	0.001	0.571	0.483	0.828	0.611	0.498	0.636

* $p<.1$, ** $p<.05$, *** $p<.01$

Note: ATT is the coefficient of minimum wage. This table depicts the event study estimate of the ATT (ϕ_{es}). ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications and clustered at the regional level. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group.

Another concern was the COVID-19 period. This period could have lead to both economic conditions and changes in health outcomes. That is, the pandemic could have resulted in differential effects of wage on health outcomes. And to address this potential confounding effects of our results, we dropped the COVID-19 years of 2020 and 2021 from the analysis and re-estimated the model. The results have been presented in Table 2.B.12 in the Appendix. The results slightly differs in terms of magnitude. We find that the effects are relatively lesser than compared to the main results in Table 2.5.1. The share of those reporting bad health fell by about 1.4 percentage points (1.5 p.p in Table 2.5.1) whilst those reporting very good or good health rose by 3.6 percentage points (4.2 p.p in Table 2.5.1).

Presenting results also from a difference-in-difference model is consistent with the main results. The post treatment period is equal to 1 for years from 2017 - 2023 and otherwise equal to 0. The variable of interest in this model is the interaction of the period and the treatment status. Table 2.B.13 shows the results of the effect of minimum wage on health outcomes using DiD strategy. We find that minimum wage just like in the main results increases the share of individuals reporting very good/good health and it reduces those reporting bad/poor health. The effect on those reporting very/good is about 1.5 percentage points (4.4 p.p. in Table 2.5.1) but then we do not find significant effects on bad/poor health. In terms of magnitude, the effect under the DiD strategy is much lower compared to the main results.

As a placebo, we also run the staggered treatment effects, considering a sample of those who are close to their retirement age (more specifically, 60 years and above) and are still in the labor force. Individuals around retirement age (67+) are generally not impacted by changes in the minimum wage since they are less likely to be part of the labor force. If increases in the minimum wage truly enhance health outcomes by raising earnings and reducing financial stress among working individuals, then we should not observe the same effect among retirees who are unaffected by these wage changes. If a similar health improvement is noted among the elderly, it suggests that other unobserved factors (such as broader economic trends or improved healthcare access) may be influencing the results rather than the minimum wage policy. The results have been presented in Table 2.B.9. We find that when controlling for some characteristics, we do not find effects of the minimum wage increase on the probability of reporting bad or poor, and very good or good health status for individuals who are above 60 years old. Similarly, this has been confirmed in the even study figure depicted in Figure 2.A.7. The effect on bad/poor, satisfactory and very good/good self-reported health has been displayed respectively for models without controls in Panel A and Panel B depicts models with controls in this figure. We see no significant effect before and after this increased minimum wage for all the outcomes considered.

2.5.4 Potential Pathways

We considered addressing some channels through which minimum wage affects health outcomes. Doing this, we estimated the effect of minimum wage on limited activities due to health problems and unmet need for medical and dental examination. The variable 'limited in activities due to health problems' is binary (yes/no), characterized by respondents indicating a restriction in participation caused by prolonged health-related limitations lasting 6 months or more, in comparison to others.[7] In addition, the unmet need for medical examination and/or the unmet need for dental examination was also constructed as a binary outcome, which captures the restricted access to medical care according to the person's own assessment of whether he or she needed medical examination/ treatment and/or dental examination/treatment, but did not get it, experienced a delay in getting it or did not seek for it.[8] Table 2.B.5 presents results of the effect of minimum wage on other outcomes (limited in activities due to health problems, unmet need for medication examination and unmet need for dental care). We find that there is less likelihood that individuals are limited in activities due to health problems. This could imply that earning a better wage allows individuals to afford better healthcare, reduce stress, improve nutrition, or work under less harmful conditions, of which can reduce health-related limitations in everyday life. Higher minimum wages might enable individuals to afford better healthcare, nutrition, or living conditions, which can reduce the severity or frequency of health problems.

In addition, this study included other possible transmission mechanism. This section of the study relied on data from the European Health Survey in Spain (Encuesta Europea de Salud en España, EESE)[9] in Spain for 2014 and 2020 and the (Encuesta Nacional de Salud de España,

[7]It describes a measure for assessing an individual's self-perceived limitations in performing usual activities due to physical, mental, or emotional health issues, including diseases, impairments, aging, injuries, accidents, and congenital conditions. Only limitations directly related to health problems are considered; those caused by financial, cultural, or non-health-related factors are excluded (Eurostat (2024).

[8]Delays in accessing healthcare can be considered unmet needs when deemed significant by individuals. The measurement of delays varies due to differing time references needed for various health conditions. It is subjective for respondents to determine if the delay constitutes an unmet need. Medical care includes services provided by medical doctors, traditional, and complementary medical professionals, but excludes self-medication and dental care. Preventive care is included if respondents see it as vital, such as when they struggle to book appointments for guaranteed preventive check-ups, perceiving it as a health risk. Dental care encompasses personal healthcare services delivered by, or under the supervision of, licensed dentists (classified under ISCO-08 code 2261), including treatments provided by orthodontists.

[9]The ENSE is the European Health Survey in Spain (EESE), which forms part of the broader European Health Interview Survey (EHIS) coordinated by Eurostat. This survey is also conducted by the Ministry of Health and INE and aims to ensure harmonised and comparable health data across EU member states. The EESE targets individuals aged 15 and older and excludes children, focusing instead on adult health and behaviours. Like the ENSE, it is conducted every five years, with its most recent wave in 2020. The survey consists of four standardised modules: demographic and socio-economic characteristics, health status (including chronic diseases and mental health), health care use, and health determinants such as smoking, alcohol consumption, and physical activity. The EESE is particularly valuable for international comparisons and tracking progress on EU-wide health indicators.

ENSE)[10] for 2011, 2017 and 2023 which are national health surveys provide essential data for public health monitoring, research, and policy evaluation. Focusing on this data, we estimate the effect on minimum wage on some possible transmission mechanisms using other dimension of health behaviours. These include access to health care, alcohol consumption, obesity, smoking, and exercise. Lack of access to medical care, dental care, drug access and mental health care was measured as a binary variable which 1 when respondents answered yes to the lack of healthcare due to financial problems in the past 12 months or 0 otherwise. The other outcome used in this section is alcohol consumption. That is, weekly (daily) alcohol intake which is the average daily alcohol consumption per week (Monday to Sunday) (during the week, Monday to Friday) measured in grams of pure alcohol. Other outcomes include obesity, smoking, which was measured by those who responded that they currently smoke, and the other one was measured by the number of cigarettes they smoked per day. Moreover, we considered frequency of exercises as another one, it was constructed by those who responded how often they sometimes do physical activities. This is a binary variable which is 1 if respondents responded that they exercise several times a month or several times a week or 0 otherwise.

These results have been presented in Table 2.B.6 using a differences-in-differences model. Treatment is calculated based on the educational level since those who are at the high school level and below are more likely to be affected by minimum wage. Therefore, treatment is 1 if individuals had high school or below level of education or 0 otherwise from 2016. The post period was also defined as 1 from 2017 and below that as the pre-period. In these models, we also controlled for some household characteristics here. We find statistically significant effects for these results. More specifically, when minimum wage increases, it reduces the lack of health care (medical, dental, drug access, mental health care). However, it increases some unhealthy behaviours such alcohol consumption. Even though, smokers do not stop smoking, they reduce their cigarettes smoked per day. Whilst they tend not to exercise even at their free time. This implies that medical, dental, drug and mental health services behave like normal goods for low-wage workers. With higher wages, families can better afford care, so the share lacking insurance or skipping care falls (Narain and Zimmerman, 2019). This implies an income effect: increased earnings translate into greater

[10]The ENSE, conducted by the Spanish Ministry of Health in collaboration with the National Statistics Institute (INE), is a comprehensive survey that offers detailed information on the health status, health determinants, and healthcare utilization of the Spanish population. It covers both adults and children, making it one of the most inclusive health surveys in the country. The survey is carried out approximately every five years, with the latest edition published in 2021 (ENSE 2020). It uses a combination of face-to-face interviews and self-completed questionnaires, sampling over 23,000 households nationwide. The ENSE includes modules on self-rated health, chronic conditions, mental health, lifestyle behaviours (such as smoking, diet, and physical activity), and use of healthcare services. Its child component captures data on growth, development, nutrition, and pediatric healthcare utilisation, making it a key source for evaluating child health in Spain.

health care spending and reduced unmet needs. Alcohol and other leisure goods also tend to be normal goods. An income rise gives workers more disposable income to spend on consumables like alcohol. This can explain the rise in drinking even as healthcare access improves. In other words, the extra wage is partly spent on riskier consumption, that is higher wages have been linked to increases in drinking (and smoking) (Hoke and Cotti, 2016). Similarly, evidence is mixed, but some studies find smoking prevalence up with higher wages (Palazzolo and Pattabhiramaiah, 2021). In our case, smokers did not quit but did smoke fewer cigarettes per day. Economically, this suggests cigarettes are an inelastic or necessity type good; smokers still buy them, but with more income they moderate consumption. They may reallocate part of their budget (and perhaps use better cessation aids) rather than increase smoking intensity. A higher wage raises the opportunity cost of time. Each hour of leisure or exercise now means forgoing more wage income, so workers tend to allocate extra time differently. Higher wages have been shown to reduce time spent exercising (Palazzolo and Pattabhiramaiah, 2021). In our data, we find that minimum wage leads to lower probability of frequent exercise. As documented by Neumark (2024). This may reflect a change in time allocation or lifestyle choices rather than a direct improvement in health behavior, implying that higher wages do not necessarily lead people to exercise more.

2.6 Conclusion

This study explores the effect of a consistent minimum wage increase on the health of workers in Spain using these established minimum wage policy changes as a natural experiment. Economists and policymakers are keenly interested in studying health impacts, as changes in the labour market can lead to effects extending beyond just employment outcomes.

We employ an estimation method that difference-in-differences analysis with multiple treatments, integrating it with entropy matching. Changes in self-rated health are assessed among individuals most likely impacted by the minimum wage reform - those whose prior hourly wage fell below the set minimum in 2017 -and they are compared with individuals presumably unaffected by the reform. In light of this, our analysis utilises the Spanish Survey of Living Conditions (ES-SILC) from 2012 to 2023. This study highlights that the minimum wage policy implementation by the Spanish government has nonmonetary advantages in addition to its primary objectives of protecting worker wages and reversing earlier trends towards greater income disparity. And elaborating some potential underlying mechanisms. The identification approach compares health transitions between a group of workers who earned less than the established minimum wage prior to 2017 and those who made more beyond the minimum wage threshold.

The study reveals that overall there is a positive effect of minimum wage on health outcomes in Spain. Specifically, we find that the likelihood of reporting bad or very bad health reduces whilst the probability of reporting good or very good health increase when minimum wages increases. There is evidence that women are more likely to report better health relative to men and they are also less likely to report bad /poor health. We find that those between the ages of 25 and 34 are more likely to report very good or good health relative the other age cohorts. Other heterogeneous effects analysis on the type of employment sector and the type of contract indicated that there is a lesser probability of reporting bad or very bad and are more likely to report very good or good health among those working in the trade and services sector compared to the production and public sectors. We also find that minimum wage increased the probability of reporting good or very health and reduced the likelihood of reporting bad or poor health for permanent works as compared with temporal workers. The health of tertiary educated individuals are improved. Similarly, focusing on the 5 point scale of self-reported health, we find results confirming conclusion from the main results. Also, another treatment based on educational status concluded on similar effect that is minimum wage improves health.

In conclusion, the evidence suggests that raising the minimum wage can be an effective policy tool not only for improving economic conditions but also for enhancing public health. By addressing income inequality and its associated health disparities, minimum wage policies have the potential to contribute to healthier, more productive societies. Spain's experience provides valuable lessons for other countries considering similar interventions, highlighting the importance of integrating economic and public health perspectives in policy design. Our findings align with previous research indicating that increasing the minimum wage serves as an effective policy lever, beneficial not just for improving working conditions and narrowing income gaps - its usual targets - but also for boosting public health and addressing health inequities. This implies that assessments of minimum wage policies should encompass considerations beyond employment or poverty to include crucial factors like population health. Furthermore, a significant takeaway from these results is that the advantages linked to this policy, such as enhanced productivity or decreased healthcare usage, might counterbalance the economic costs involved. The case of Spain offers insightful lessons for other nations contemplating similar measures, underscoring the necessity of intertwining economic and public health perspectives in policy formulation.

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Appendix

Appendix 2.A Figures

Figure 2.A.1: Self-reported health status by age group

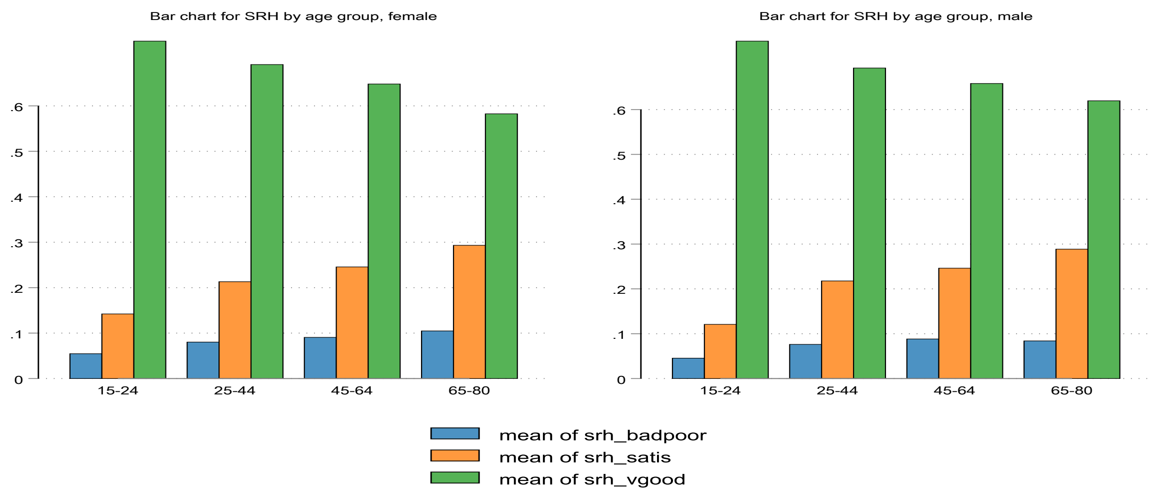


Figure 2.A.2: Empirical CDFs of mean income by self-reported health status

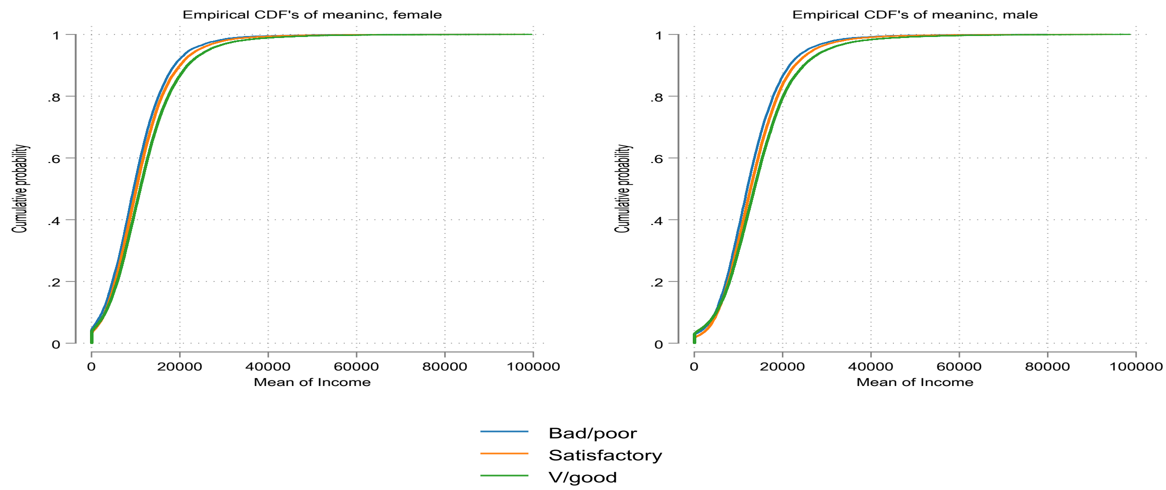


Figure 2.A.3: Intensity

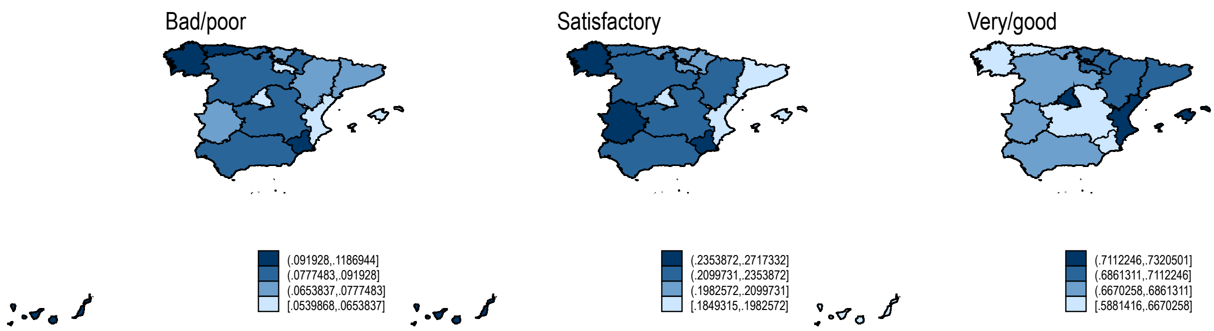


Figure 2.A.4: Covariate Balance: Standardised Difference between post and pre-treatment periods

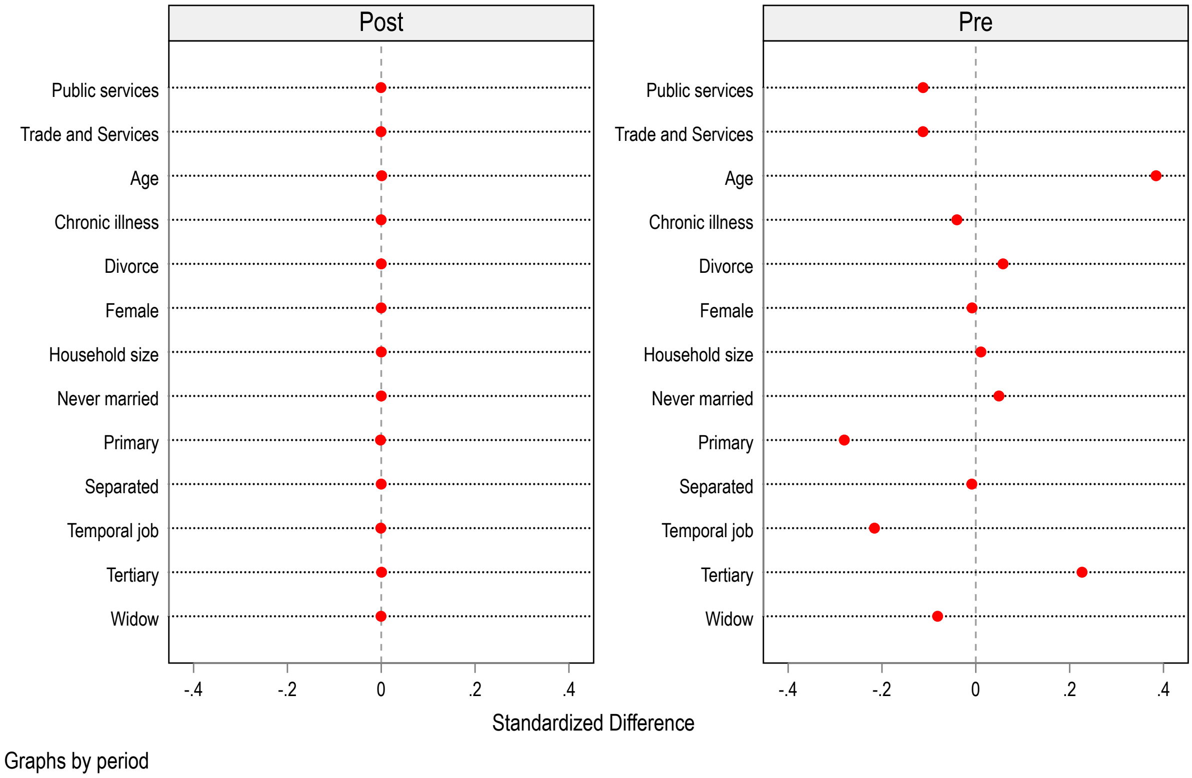
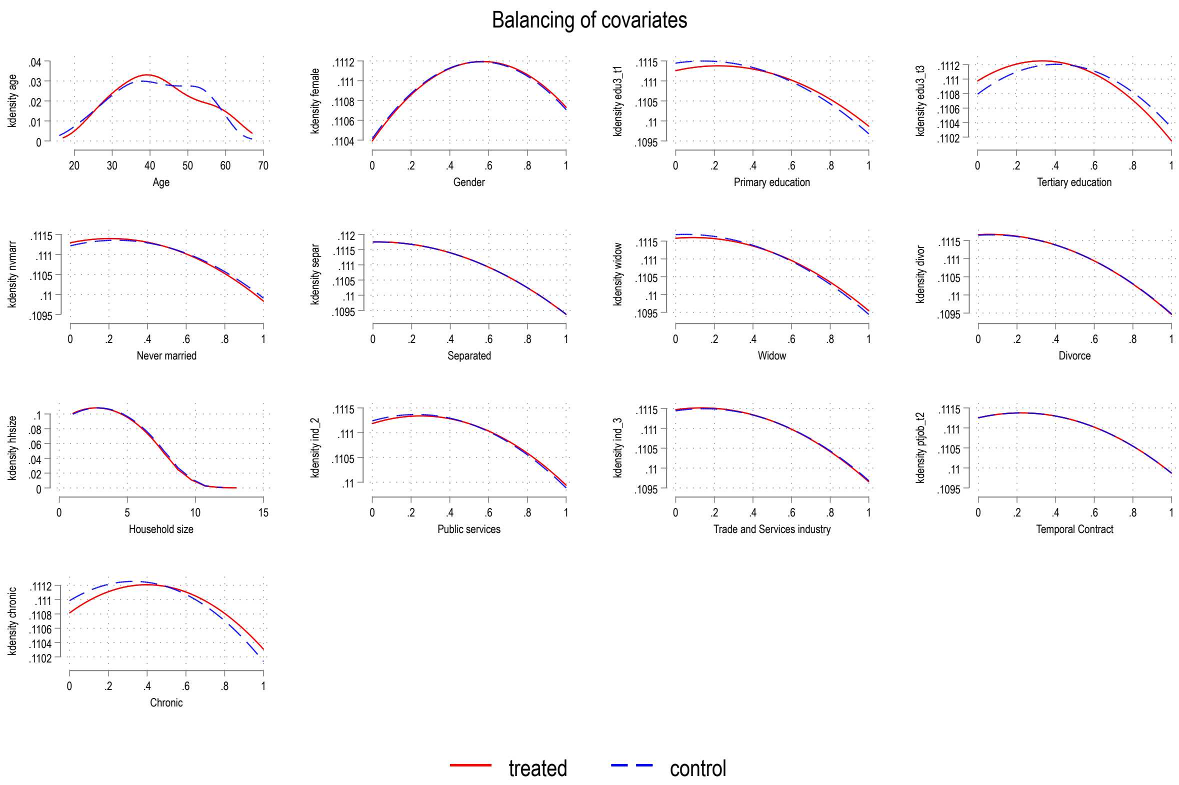
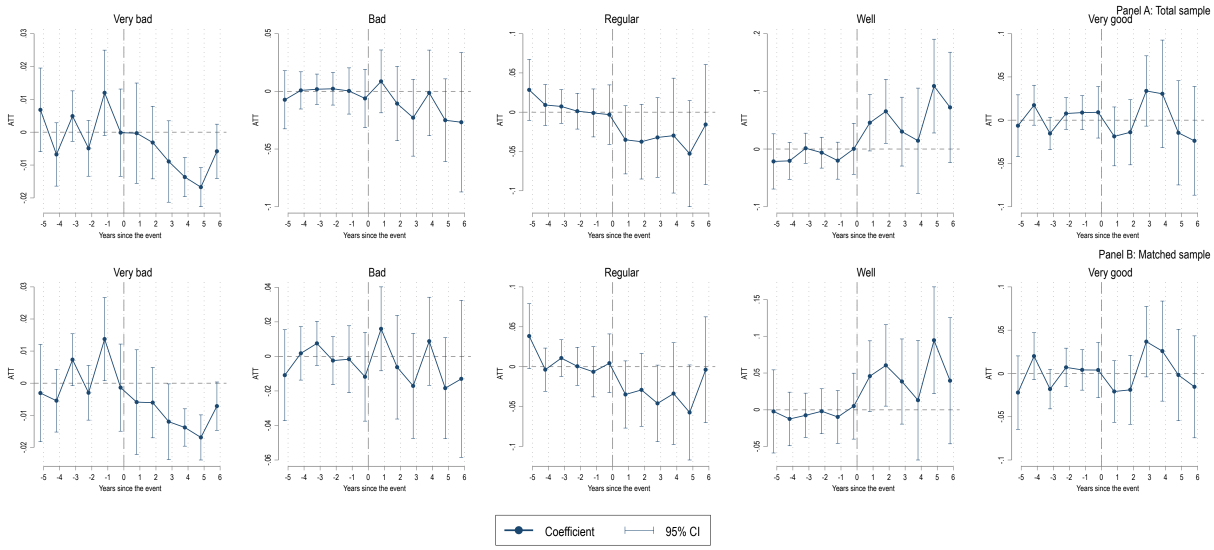


Figure 2.A.5: Covariate Balance: Standardised Difference between post and pre-treatment periods



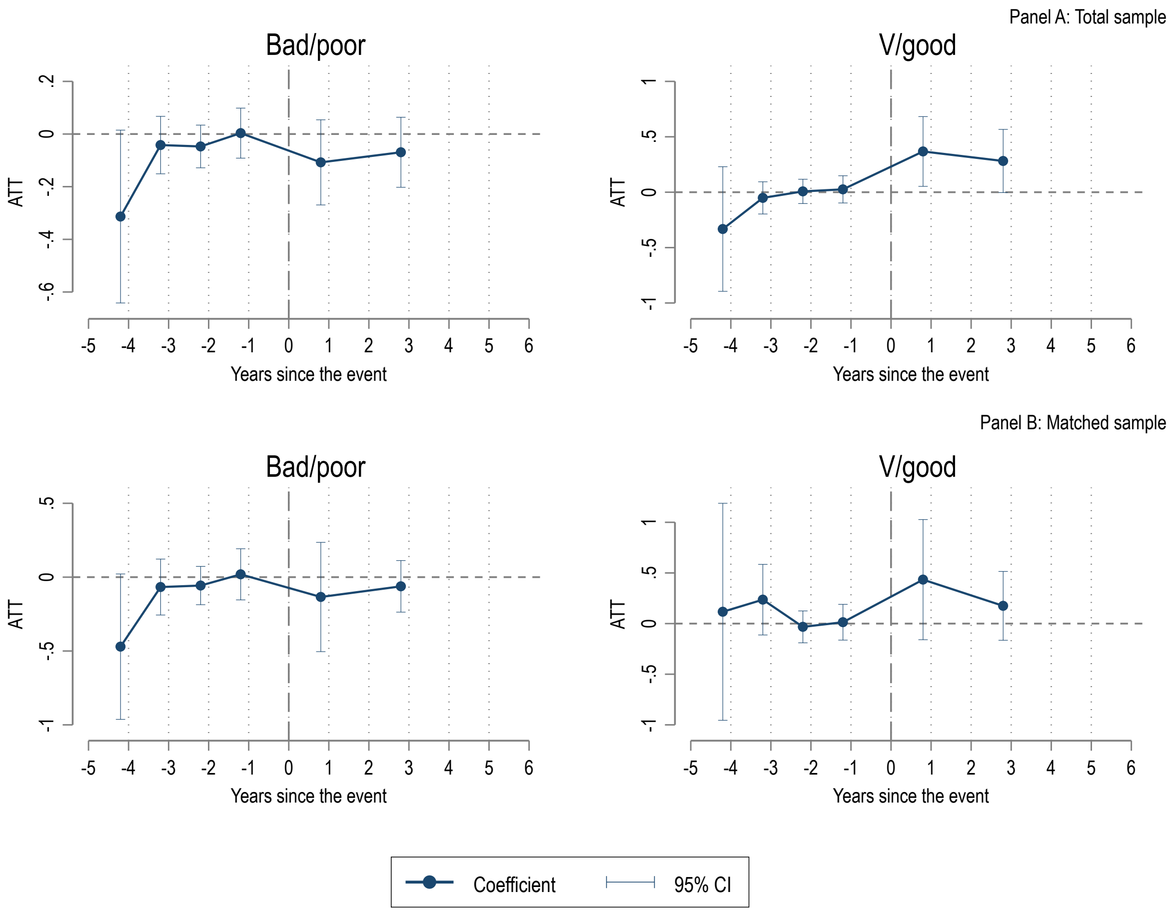
Notes:

Figure 2.A.6: Dynamic effect of minimum wage on health



Notes: This figure illustrates the dynamic Average Treatment on the Treated (ATT) of all the 5 categories of self-reported health (very bad, bad, regular, good, very good). The time window is restricted to five periods before and six after treatment due to a drastic decrease in statistical precision outside this range. The time of treatment is denoted as $e = 0$, depicted with a vertical dashed line. Whiskers depict the 95% confidence interval based on Wild Bootstrap standard errors clustered at the regional level. This panel is a visual representation of the models as displayed in Table 2.5.2. Panel A depicts models for very bad/bad and very good/good health focusing on the entire sample and Panel B depicts the matched sample results.

Figure 2.A.7: Dynamic effect of minimum wage on health



Notes: This figure illustrates the dynamic Average Treatment on the Treated (ATT) of self-reported health (very bad/bad and very good/good). The sample here are those aged 60 and above. The time window is restricted to five periods before and six after treatment due to a drastic decrease in statistical precision outside this range. The time of treatment is denoted as $e = 0$, depicted with a vertical dashed line. Whiskers depict the 95% confidence interval based on Wild Bootstrap standard errors clustered at the regional level. This panel is a visual representation of the models as displayed in Table 2.B.9. Panel A depicts models for very bad/bad and very good/good health focusing on the entire sample and Panel B depicts the matched sample results.

Appendix 2.B Additional Tables

2.B.1 Descriptive Statistics

Table 2.B.1: Descriptive statistics

	(1) Total	(2) Treated	(3) Control
$SRH_{badpoor}$	0.08	0.08	0.10
	(0.268)	(0.271)	(0.296)
SRH_{vgood}	0.69	0.68	0.65
	(0.463)	(0.468)	(0.478)
Controls			
Age	39.70	42.13	37.22
	(11.224)	(11.012)	(11.022)
Male	0.42	0.43	0.42
	(0.494)	(0.495)	(0.494)
Female	0.58	0.57	0.58
	(0.494)	(0.495)	(0.494)
Primary	0.23	0.22	0.30
	(0.419)	(0.415)	(0.460)
Secondary	0.45	0.45	0.45
	(0.498)	(0.497)	(0.497)
Tertiary	0.32	0.33	0.25
	(0.466)	(0.471)	(0.432)
Never Married	0.23	0.21	0.20
	(0.422)	(0.405)	(0.404)
Married	0.60	0.61	0.61
	(0.490)	(0.487)	(0.488)
Separated	0.02	0.02	0.02
	(0.140)	(0.142)	(0.141)
Widow	0.08	0.09	0.10
	(0.274)	(0.286)	(0.306)
Divorce	0.05	0.06	0.04
	(0.223)	(0.233)	(0.202)
Number of household members	2.84	2.73	2.80
	(1.261)	(1.214)	(1.247)
Production, Construction, Heavy Ind.	0.60	0.62	0.53
	(0.490)	(0.486)	(0.499)
Trade and Services	0.26	0.25	0.29
	(0.438)	(0.433)	(0.454)
Public services	0.14	0.13	0.18
	(0.348)	(0.342)	(0.383)
Permanent	0.75	0.78	0.69
	(0.430)	(0.415)	(0.464)
Temporal	0.25	0.22	0.31
	(0.430)	(0.415)	(0.464)
Income (Monetary, year)	9450.98	9707.28	6052.85
	(1.3e+04)	(1.3e+04)	(1.0e+04)
Income (Monetary, month)	787.58	808.94	504.40
	(1092.817)	(1124.409)	(870.714)
Chronic Health Condition	0.36	0.40	0.38
	(0.481)	(0.489)	(0.486)
N	287239	57644	49365

Standard deviations in parentheses

Table 2.B.2: Balancing test

	Means			*Variances*			*Skewness*		
		Controls			*Controls*			*Controls*	
Covariates	Treated	Pre	Post	Treated	Pre	Post	Treated	Pre	Post
Age	41.548	37.402	41.537	116.376	115.918	119.094	0.208	0.215	-0.107
Female	0.559	0.563	0.559	0.247	0.246	0.247	-0.237	-0.253	-0.237
Primary	0.144	0.242	0.144	0.123	0.183	0.123	2.031	1.204	2.025
Tertiary	0.407	0.296	0.407	0.241	0.208	0.241	0.378	0.895	0.379
Never married	0.237	0.216	0.237	0.181	0.169	0.181	1.235	1.378	1.236
Separated	0.022	0.023	0.022	0.022	0.023	0.022	6.487	6.300	6.486
Widow	0.049	0.066	0.049	0.047	0.062	0.047	4.182	3.480	4.177
Divorce	0.064	0.050	0.064	0.060	0.047	0.060	3.571	4.151	3.572
Household size	2.853	2.840	2.853	1.449	1.496	1.500	0.433	0.650	0.584
Trade and Services	0.227	0.275	0.228	0.176	0.199	0.176	1.300	1.010	1.299
Public services	0.146	0.186	0.146	0.125	0.151	0.125	2.004	1.615	2.002
Temporal job	0.222	0.311	0.222	0.173	0.214	0.173	1.340	0.815	1.338
Chronic illnes	0.329	0.348	0.329	0.221	0.227	0.221	0.728	0.639	0.728

Table 2.B.3: Effect of minimum wage on health

	Bad/poor (1)	V/Good (2)	Bad/poor (3)	V/Good (4)
ATT	-0.065***	0.187***	-0.018*	0.046***
	(0.006)	(0.012)	(0.009)	(0.015)
Pre average	0.015***	-0.043***	0.002	-0.011**
	(0.003)	(0.004)	(0.004)	(0.005)
Post average	-0.066***	0.189***	-0.019**	0.048***
	(0.007)	(0.012)	(0.010)	(0.015)
$\hat{\phi}_{es}$(-5)	0.029**	-0.071***	-0.001	-0.028
	(0.011)	(0.019)	(0.014)	(0.019)
$\hat{\phi}_{es}$(-4)	-0.001	-0.016	-0.006	-0.003
	(0.008)	(0.013)	(0.009)	(0.013)
$\hat{\phi}_{es}$(-3)	0.002	-0.021*	0.007	-0.014
	(0.007)	(0.011)	(0.007)	(0.011)
$\hat{\phi}_{es}$(-2)	0.009	-0.025**	-0.003	0.001
	(0.007)	(0.012)	(0.008)	(0.011)
$\hat{\phi}_{es}$(-1)	0.037***	-0.083***	0.012	-0.011
	(0.008)	(0.013)	(0.011)	(0.014)
$\hat{\phi}_{es}$(0)	-0.024**	0.096***	-0.006	0.009
	(0.011)	(0.019)	(0.014)	(0.018)
$\hat{\phi}_{es}$(1)	-0.032***	0.117***	0.008	0.027
	(0.012)	(0.020)	(0.015)	(0.021)
$\hat{\phi}_{es}$(2)	-0.066***	0.188***	-0.014	0.051**
	(0.013)	(0.021)	(0.017)	(0.023)
$\hat{\phi}_{es}$(3)	-0.093***	0.232***	-0.032*	0.064**
	(0.013)	(0.023)	(0.018)	(0.025)
$\hat{\phi}_{es}$(4)	-0.080***	0.211***	-0.015	0.044
	(0.012)	(0.021)	(0.019)	(0.038)
$\hat{\phi}_{es}$(5)	-0.084***	0.256***	-0.042**	0.095***
	(0.011)	(0.021)	(0.018)	(0.032)
$\hat{\phi}_{es}$(6)	-0.084***	0.227***	-0.033	0.048
	(0.011)	(0.021)	(0.031)	(0.043)
Controls	No	No	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes
N	88072	88072	55678	55678
Pretrend χ^2 (df)	122.40 (28)	221.15 (28)	15.92 (28)	29.31 (28)
Pretrend p-value	0.000	0.000	0.967	0.397

** p<.1, ** p<.05, *** p<.01*

Note: These results focus on the entire sample. ATT is the coefficient of minimum wage. This table depicts the event study estimate of the ATT (ϕ_{es}). ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications. Using not treated as control group.

Table 2.B.4: Effect of minimum health on self-reported health

	$SRH_{cont.}$ (1)	SRH_{dum} (2)	$SRH_{cont.}$ (1)	SRH_{dum} (2)
ATT	0.231***	-0.141***	0.066***	-0.042***
	(0.026)	(0.015)	(0.024)	(0.014)
Pre average	-0.062***	0.037***	-0.013	0.009
	(0.010)	(0.005)	(0.010)	(0.005)
Post average	0.243***	-0.148***	0.069***	-0.044***
	(0.026)	(0.015)	(0.025)	(0.014)
$\hat{\phi}_{es}(-5)$	-0.098**	0.060***	-0.029	0.024
	(0.044)	(0.023)	(0.041)	(0.021)
$\hat{\phi}_{es}(-4)$	0.012	0.007	0.037	-0.007
	(0.029)	(0.015)	(0.026)	(0.014)
$\hat{\phi}_{es}(-3)$	-0.068***	0.029**	-0.066***	0.026**
	(0.025)	(0.014)	(0.022)	(0.012)
$\hat{\phi}_{es}(-2)$	-0.025	0.024*	0.020	-0.005
	(0.026)	(0.014)	(0.022)	(0.012)
$\hat{\phi}_{es}(-1)$	-0.130***	0.067***	-0.027	0.006
	(0.031)	(0.017)	(0.028)	(0.015)
$\hat{\phi}_{es}(0)$	0.059	-0.032	0.027	-0.009
	(0.041)	(0.021)	(0.035)	(0.018)
$\hat{\phi}_{es}(1)$	0.106**	-0.087***	-0.000	-0.025
	(0.043)	(0.024)	(0.040)	(0.021)
$\hat{\phi}_{es}(2)$	0.179***	-0.133***	0.041	-0.041*
	(0.047)	(0.025)	(0.041)	(0.023)
$\hat{\phi}_{es}(3)$	0.348***	-0.196***	0.153***	-0.075***
	(0.049)	(0.027)	(0.042)	(0.024)
$\hat{\phi}_{es}(4)$	0.320***	-0.168***	0.083	-0.039
	(0.043)	(0.026)	(0.051)	(0.033)
$\hat{\phi}_{es}(5)$	0.380***	-0.238***	0.143***	-0.093***
	(0.048)	(0.030)	(0.048)	(0.029)
$\hat{\phi}_{es}(6)$	0.306***	-0.179***	0.036	-0.024
	(0.047)	(0.028)	(0.063)	(0.037)
Controls	No	No	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes
N	55704	55706	55676	55678
Pretrend χ^2 (df)	120.59 (28)	124.15 (28)	34.73 (28)	34.78 (28)
Pretrend p-value	0.000	0.000	0.178	0.176

** p<.1, ** p<.05, *** p<.01*

Note: The outcomes here are self-reported health as continuous variable (SRH_{cont}) and a binary outcome for self-reported health (SRH_{dum} - 1 is individuals' report very bad, bad or regular or 0 otherwise). ATT is the coefficient of minimum wage. This table depicts the event study estimate of the ATT (ϕ_{es}). ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group. Sample here is the matched sample.

2.B.2 Potential pathways

Table 2.B.5: Potential pathways: effects of minimum wage on some health behaviours

	Total sample			*Matched sample*		
	(1) Limited in activities due to health problems	(2) Unmet need for medical exam.	(3) Unmet need for dental exam.	(1) limited in activities due to health problems	(2) Unmet need for medical exam.	(3) Unmet need for dental exam.
	Panel A: Without controls					
ATT	-0.174***	-0.002	-0.019***	-0.118***	-0.008*	-0.010
	(0.011)	(0.003)	(0.006)	(0.014)	(0.005)	(0.008)
Pre_avg	-0.002	-0.009	0.007	0.013	-0.009	0.014
	(0.018)	(0.008)	(0.010)	(0.027)	(0.016)	(0.022)
Post_avg	-0.176***	-0.002	-0.019***	-0.123***	-0.009*	-0.010
	(0.011)	(0.003)	(0.006)	(0.014)	(0.005)	(0.008)
Region & urban FE	Yes	Yes	Yes	Yes	Yes	Yes
N	86831	88072	88072	55703	55706	55706
Pretrend χ^2 (df)	253.67 (28)	32.76 (28)	42.34 (28)	123.87 (28)	36.59 (28)	36.89 (28)
Pretrend p-value	0.000	0.245	0.040	0.000	0.128	0.121
	Panel B: With controls					
ATT	-0.051***	0.002	-0.004	-0.047***	-0.003	-0.001
	(0.014)	(0.005)	(0.009)	(0.013)	(0.005)	(0.009)
Pre_avg	0.037***	-0.044***	-0.009	0.066**	-0.047*	0.018
	(0.011)	(0.012)	(0.008)	(0.033)	(0.027)	(0.018)
Post_avg	-0.055***	0.002	-0.004	-0.050***	-0.003	-0.001
	(0.015)	(0.005)	(0.010)	(0.014)	(0.005)	(0.009)
Region & urban FE	Yes	Yes	Yes	Yes	Yes	Yes
N	55675	55678	55678	55675	55678	55678
Pretrend χ^2 (df)	38.56 (28)	42.68 (28)	47.00 (28)	39.06 (28)	40.69 (28)	47.60 (28)
Pretrend p-value	0.088	0.037	0.014	0.080	0.057	0.012

** p<.1, ** p<.05, *** p<.01*

Note: ATT is the coefficient of minimum wage. ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Standard errors shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group.

Table 2.B.6: Potential pathways: effect of minimum wage on other health behaviours

Variables	(1) lack of medical care	(2) lack of dental care	(3) lack of drug access	(4) lack of access to mental health	(5) Weekly alcohol intake	(6) Daily alcohol intake	(7) Obesity	(8) Smoker	(9) No of cigarettes smoked per day	(10) frequency of exercise
treated*reform	-0.009*	-0.026**	-0.012**	-0.016***	1.863*	1.835*	-0.009**	0.017*	-0.655*	-0.040***
	(0.004)	(0.011)	(0.005)	(0.004)	(1.018)	(0.975)	(0.003)	(0.009)	(0.362)	(0.010)
treated	0.008***	0.075***	0.011***	0.004	-2.571**	-2.047**	0.060***	0.091***	1.931***	-0.112***
	(0.003)	(0.008)	(0.003)	(0.003)	(0.904)	(0.910)	(0.003)	(0.007)	(0.346)	(0.010)
y2011	-0.031				17.035***	15.435***	0.015	0.089***	2.258***	0.044***
	(0.023)				(4.454)	(4.424)	(0.009)	(0.006)	(0.462)	(0.014)
y2014	-0.010	0.028*		0.006	1.803**	1.283*	-0.007	0.044***	0.574	0.077***
	(0.007)	(0.014)		(0.005)	(0.731)	(0.697)	(0.006)	(0.010)	(0.398)	(0.020)
y2017	-0.021***	-0.007	-0.005		4.770***	3.818***	0.022**	0.054***	1.380***	0.085***
	(0.006)	(0.013)	(0.004)		(0.968)	(0.902)	(0.009)	(0.004)	(0.243)	(0.027)
y2020	-0.013*	0.003	-0.003	0.018***						
	(0.006)	(0.020)	(0.003)	(0.006)						
y2023			0.006	0.037***	4.773***	3.512***	0.012	0.010	1.013***	0.123***
			(0.004)	(0.007)	(0.734)	(0.548)	(0.007)	(0.009)	(0.203)	(0.016)
N	55,916	54,397	53,428	36,941	74,259	74,259	71,684	74,101	18,363	74,023
R-squared	0.0342	0.075	0.0281	0.0451	0.0156	0.0137	0.038	0.039	0.069	0.060
dep. var. mean	0.0287	0.125	0.0234	0.0270	7.320	4.994	0.142	0.282	12.79	0.848

** p<.1, ** p<.05, *** p<.01*

DID results have been illustrated in this table. Treatment is 1 if individuals had high school or below level of education or 0 otherwise from 2016. The post period was also defined as 1 from 2017 and below that as the pre-period. Some individual characteristics have been controlled for. Robust standard errors are in parentheses.

2.B.3 Heterogeneous Effects

Table 2.B.7: Effect of minimum wage on health, Employment and Unemployment sample

	Total sample				*Matching sample*			
	(1) Bad/poor	(2) V/good	(3) Bad/poor	(4) V/good	(1) Bad/poor	(2) V/good	(3) Bad/poor	(4) V/good
	Employed							
ATT	-0.053***	0.159***	-0.011	0.084***	-0.002	0.058***	0.005	0.055***
	(0.009)	(0.016)	(0.010)	(0.018)	(0.008)	(0.019)	(0.010)	(0.019)
Pre average	-0.008	-0.002	-0.006	-0.041**	-0.008	-0.021	-0.009	-0.036*
	(0.008)	(0.018)	(0.007)	(0.018)	(0.006)	(0.020)	(0.006)	(0.021)
Post average	-0.054***	0.160***	-0.011	0.085***	-0.002	0.060***	0.005	0.056***
	(0.009)	(0.017)	(0.010)	(0.019)	(0.008)	(0.019)	(0.010)	(0.019)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Region & urban FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	46966	46966	34359	34359	34377	34377	34359	34359
Pretrend χ^2 (df)	74.82 (28)	95.00 (28)	32.85 (28)	67.33 (28)	27.19 (28)	30.38 (28)	32.79 (28)	51.34 (28)
Pretrend p-value	0.000	0.000	0.242	0.000	0.508	0.345	0.244	0.005
	Unemployed							
ATT	-0.042***	0.107***	-0.088***	0.032	-0.040*	0.079**	-0.082***	0.001
	(0.014)	(0.027)	(0.026)	(0.043)	(0.021)	(0.036)	(0.026)	(0.042)
Pre average	0.005	-0.020	0.003	-0.050**	0.014	-0.041	0.013	-0.048*
	(0.006)	(0.018)	(0.018)	(0.025)	(0.010)	(0.025)	(0.019)	(0.026)
Post average	-0.046***	0.115***	-0.091***	0.032	-0.038*	0.082**	-0.083***	0.0001
	(0.015)	(0.028)	(0.028)	(0.044)	(0.021)	(0.036)	(0.027)	(0.043)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Region & urban FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	10827	10827	7934	7934	7941	7934	7934	7934
Pretrend χ^2 (df)	23.65 (27)	59.05 (27)	32.15 (27)	79.82 (27)	35.87 (27)	56.33 (27)	33.47 (27)	71.01 (27)
Pretrend p-value	0.650	0.0004	0.227	0.000	0.118	0.001	0.182	0.000

** p<.1, ** p<.05, *** p<.01*

Note: ATT is the coefficient of minimum wage. ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group.

Table 2.B.8: Heterogenous effects of minimum wage on health

	Total sample		*Matching sample*	
	(1)	(2)	(3)	(4)
	Bad/poor	V/good	Bad/poor	V/good
		Gender		
Females	-0.027**	0.044**	-0.021*	0.043***
	(0.012)	(0.017)	(0.011)	(0.017)
N	30,722	30,722	30,722	30,722
Males	-0.011	0.052**	-0.011	0.042*
	(0.013)	(0.024)	(0.012)	(0.023)
N	24,956	24,956	24,956	24,956
		Age		
<= 24	0.029	-0.022	0.031	-0.020
	(0.027)	(0.044)	(0.025)	(0.043)
N	4,902	4,902	4,902	4,902
25 - 34	-0.022	0.086***	-0.024*	0.085***
	(0.015)	(0.026)	(0.014)	(0.023)
N	15,546	15,546	15,546	15,546
35 - 44	-0.025	0.062**	-0.013	0.047*
	(0.017)	(0.026)	(0.016)	(0.025)
N	17,607	17,607	17,607	17,607
45+	-0.008	0.040	-0.019	0.053**
	(0.015)	(0.027)	(0.015)	(0.025)
N	17,623	17,623	17,623	17,623
		Type of employment sector		
Prod., Const., Heavy Ind	-0.032***	0.125***	-0.031***	0.110***
	(0.011)	(0.020)	(0.012)	(0.021)
N	31,957	31,957	31,957	31,957
Trade & Services	-0.108***	0.206***	-0.088***	0.190***
	(0.020)	(0.033)	(0.019)	(0.034)
N	14,295	14,295	14,295	14,295
Public services	-0.033	0.067**	-0.021	0.051
	(0.027)	(0.032)	(0.026)	(0.033)
N	9,426	9,426	9,426	9,426
		Type of contract		
Permanent	-0.075***	0.182***	-0.057***	0.147***
	(0.014)	(0.020)	(0.013)	(0.020)
N	40,512	40,512	40,512	40,512
Temporal	0.006	0.095***	0.017	0.030
	(0.015)	(0.027)	(0.014)	(0.027)
N	15,166	15,166	15,166	15,166
		Education		
Primary	-0.154***	0.102***	-0.115***	0.107***
	(0.032)	(0.035)	(0.031)	(0.034)
N	11,342	11,342	11,342	11,342
Secondary	-0.008	0.064***	-0.015	0.070***
	(0.012)	(0.021)	(0.013)	(0.022)
N	25,378	25,378	25,378	25,378
Tertiary	-0.014	0.087***	-0.024	0.110***
	(0.016)	(0.026)	(0.017)	(0.028)
N	18,958	18,958	18,958	18,958

** p<.1, ** p<.05, *** p<.01*

Note: ATT is the coefficient of minimum wage. ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group.

2.B.4 Placebo Test

Table 2.B.9: Placebo Estimates

	Bad/poor (1)	V/Good (2)	Bad/poor (3)	V/Good (4)
ATT	-0.075***	0.112**	-0.006	-0.119*
	(0.020)	(0.052)	(0.032)	(0.070)
Pre average	0.018	0.011	0.063	-0.046
	(0.019)	(0.034)	(0.047)	(0.063)
Post average	-0.075***	0.113**	0.001	-0.135*
	(0.020)	(0.052)	(0.036)	(0.077)
Controls	No	No	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes
N	2990	6920	6918	6918
Pretrend χ^2 (df)	11.34 (12)	9.86 (12)	7.80 (12)	17.48 (12)
Pretrend p-value	0.500	0.628	0.801	0.132

** p<.1, ** p<.05, *** p<.01*

Note: Sample is those who 60 years and above focusing matched individuals. ATT is the coefficient of minimum wage. This table depicts the event study estimate of the ATT. ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications and clustered at the regional level. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group.

2.B.5 Robustness checks

Table 2.B.10: Effect of minimum wage on health using education as treatment variable

	(1) Bad/poor	(2) V/Good	(3) Bad/poor	(4) V/Good
ATT	-0.068***	0.195***	-0.058***	0.162***
	(0.008)	(0.013)	(0.010)	(0.016)
Controls	No	No	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes
N	58990	58990	58962	58962
Pretrend χ^2 (df)	126.33 (28)	285.38 (28)	130.12 (28)	21.98 (28)
Pretrend p-value	0.000	0.000	0.000	0.000

** p<.1, ** p<.05, *** p<.01*

Note: ATT is the coefficient of minimum wage. ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each see Equation (2.1). One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications and clustered at the regional level. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group. The sample here are those in the matched sample. Treatment is defined by those who have high school education.

Table 2.B.11: Effect of MW on health using other treatment groups

	Bad/poor (1)	V/Good (2)	Bad/poor (3)	V/Good (4)
	Treatment 1			
ATT	-0.037***	0.127***	-0.010	0.031**
	(0.008)	(0.016)	(0.009)	(0.015)
N	54133	54133	54106	54106
Pretrend χ^2 (df)	41.93 (28)	94.53 (28)	23.10 (28)	29.87 (28)
Pretrend p-value	0.044	0.000	0.728	0.370
	Treatment 2			
ATT	-0.032***	0.097***	-0.003	0.012
	(0.009)	(0.018)	(0.011)	(0.018)
N	52291	52291	52265	52265
Pretrend χ^2 (df)	30.30 (28)	67.15 (28)	24.37 (28)	28.27 (28)
Pretrend p-value	0.349	0.000	0.662	0.450
Controls	No	No	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes

** p<.1, ** p<.05, *** p<.01*

Note: ATT is the coefficient of minimum wage. This table depicts the estimate of the ATT. ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each see Equation (2.1). One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications and clustered at the regional level. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group. The sample here are those in the matched sample. Treatment 1 is defined by those whose wages are around 130% of the minimum wage, Treatment 2 is based on wages around 120% of the minimum wage.

Table 2.B.12: Effect of MW on health outcomes dropping COVID-19 period

	Bad/poor (1)	V/Good (2)	Bad/poor (3)	V/Good (4)
ATT	-0.039***	0.126***	-0.014	0.036**
	(0.008)	(0.015)	(0.009)	(0.014)
Pre average	0.010***	-0.037***	0.001	-0.009
	(0.003)	(0.005)	(0.004)	(0.005)
Post average	-0.040***	0.134***	-0.014	0.038***
	(0.008)	(0.016)	(0.009)	(0.015)
$\hat{\phi}_{es}(-5)$	-0.000	-0.060***	-0.014	-0.024
	(0.013)	(0.023)	(0.015)	(0.021)
$\hat{\phi}_{es}(-4)$	0.001	-0.007	-0.004	0.007
	(0.008)	(0.015)	(0.009)	(0.014)
$\hat{\phi}_{es}(-3)$	0.013*	-0.029**	0.015**	-0.026**
	(0.007)	(0.014)	(0.007)	(0.012)
$\hat{\phi}_{es}(-2)$	0.004	-0.024*	-0.005	0.005
	(0.008)	(0.014)	(0.008)	(0.012)
$\hat{\phi}_{es}(-1)$	0.032***	-0.067***	0.012	-0.006
	(0.010)	(0.017)	(0.011)	(0.015)
$\hat{\phi}_{es}(0)$	-0.022*	0.032	-0.013	0.009
	(0.013)	(0.021)	(0.014)	(0.018)
$\hat{\phi}_{es}(1)$	-0.013	0.087***	0.010	0.025
	(0.012)	(0.024)	(0.015)	(0.021)
$\hat{\phi}_{es}(2)$	-0.041***	0.133***	-0.012	0.041*
	(0.013)	(0.025)	(0.016)	(0.023)
$\hat{\phi}_{es}(5)$	-0.065***	0.238***	-0.035**	0.093***
	(0.011)	(0.030)	(0.015)	(0.029)
$\hat{\phi}_{es}(6)$	-0.061***	0.179***	-0.020	0.024
	(0.013)	(0.028)	(0.023)	(0.037)
Controls	No	No	Yes	Yes
Region & Urban FE	Yes	Yes	Yes	Yes
N	49342	49342	49315	49315
Pretrend χ^2 (df)	62.04 (28)	124.15 (28)	24.26 (28)	34.78 (28)
Pretrend p-value	0.000	0.000	0.668	0.176

** p<.1, ** p<.05, *** p<.01*

Note: ATT is the coefficient of minimum wage. This table depicts the event study estimate of the ATT (ϕ_{es}). ATT depicts the average of all ATT(g,t)'s weighted by group size (Equation 2.1). Pre average and Post average are the average pre - and post - treatment effects with equal weights for each. One can evaluate the pre-trends by looking at the pretrend test, the coefficients of Pre average or at each ATT for $e < 0$. Standard error shown in parenthesis are estimated via multiplicative Wild Bootstrap with 999 replications and clustered at the regional level. Covariates used for doubly robust procedure was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. Using not treated as control group.

Table 2.B.13: Effect of minimum wage on health: DiD

	(1) Bad/poor	(2) Bad/poor	(3) V/Good	(4) V/Good
	Total sample			
post	0.014*	-0.018**	-0.108***	-0.020
	(0.008)	(0.008)	(0.013)	(0.013)
treat	0.027***	0.004	-0.071***	-0.017**
	(0.005)	(0.005)	(0.008)	(0.007)
post#treat	-0.024***	-0.001	0.071***	0.016*
	(0.006)	(0.006)	(0.010)	(0.009)
N	106,980	66,418	106,980	66,418
R-squared	0.005	0.137	0.013	0.370
	Matched sample			
post	-0.009	-0.017**	-0.053***	-0.026**
	(0.008)	(0.008)	(0.015)	(0.012)
treat	0.017***	0.003	-0.058***	-0.017**
	(0.005)	(0.004)	(0.008)	(0.007)
post#treat	-0.009	-0.001	0.039***	0.015*
	(0.006)	(0.005)	(0.011)	(0.009)
N	66,448	66,418	66,448	66,418
R-squared	0.010	0.129	0.018	0.357
Controls	No	Yes	No	Yes
Region & Urban FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Note: This table depicts the difference-in-difference estimates. Standard error shown in parenthesis and clustered at the regional level. Covariates was age, educational level, marital status, gender, and household size, type of employment sector, type of contract, income, chronic diseases. The post period was also defined as 1 from 2017 and below that as the pre-period. * p<.1, ** p<.05, *** p<.01

Table 2.B.14: Statistics of household income for treatment and control groups after 2019

	(1) Total	(2) Treated	(3) Control
Income (Monetary, year, gross)	13685.89	13079.27	12600.19
	(2.0e+04)	(2.0e+04)	(1.8e+04)
Income (Monetary, month, gross)	1140.49	1089.94	1050.02
	(1639.945)	(1627.714)	(1495.110)
N	153411	41842	4303

3

Media Utilization and Vaccine Hesitancy: Evidence from the European Union

3.1 Introduction

This study contributes to the existing economic literature by examining the relationship between online health information and healthcare utilisation. That is, it investigates the effect of media utilisation on the vaccination hesitancy attitudes of adults in Europe applying instrumental variable (IV) approach to identify the causal link between vaccine information from the internet (social networks and other websites on vaccine hesitancy). The emergence of major coronaviruses such as MERS, SARS and COVID-19 has highlighted the vital role of vaccination, with COVID-19 vaccines alone estimated to have prevented 1.4 million deaths in the WHO European Region between 2020 and 2023 (WHO, 2024). Routine immunisation programmes in the EU/EEA against diseases like tuberculosis, polio, measles, tetanus, pertussis, diphtheria and hepatitis B are similarly crucial for protecting child health. Vaccination is also a highly cost-effective public health tool that reduces antimicrobial use and helps combat antimicrobial resistance, which costs the EU around €1.5 billion annually (EU, 2017), while improved vaccine uptake could avert up to 2.5 billion antibiotic doses globally each year (WHO, 2014). Nevertheless, declining or insufficient coverage has led to major resurgences of vaccine-preventable diseases, between 2024 and 2025, measles cases in 30 EU/EEA countries rose to 28,791 (over ten times the 3,973 cases in 2023), and pertussis notifications increased nearly ten-fold compared with 2021-2022. These outbreaks are linked to immunity gaps, with only a minority of EU/EEA countries achieving the WHO target of 95% coverage for two doses of measles-containing vaccine and DTP3 in 2023, and several hundred thousand children in the wider European Region missing their first measles dose (WHO, 2024). These trends have contributed to significant outbreaks of preventable diseases in several European Union (EU) countries and neighbouring regions.

Public health experts continue to face challenges such as declining trust in vaccines, disparities in vaccine accessibility across regions, and the rapid spread of misinformation (Nogara et al., 2024; EU, 2024). Research demonstrates that misinformation, especially via social media, has contributed to vaccine hesitancy and the resurgence of preventable diseases, with polarisation evident in discussions around vaccine safety and efficacy (Vaccines, 2024). In response, the European Commission and EU Member States have taken coordinated actions to promote confidence in vaccination, combat misinformation, and ensure equitable vaccine distribution, supported by strict regulatory frameworks governing vaccine approval (ECDC, 2024; EU, 2024) and by initiatives to monitor vaccine confidence, tailor communication strategies, and address barriers among underserved populations (Vaccines, 2024). Nevertheless, vaccine rollout in Europe has been a strenuous task. Several EU countries have experienced restrictions in vaccine uptake due to challenges related to production, distribution, acceptance, and public confidence. This hesitancy attitude caused by the problem aforementioned is likely to be addressed with effective information and communication geared toward the safety and efficiency of vaccines. The World Health Organization explains vaccine hesitancy as the non-acceptance or delay in accepting vaccines irrespective of the availability of vaccination services (WHO, 2014) and this has therefore emerged as a critical concern. Although vaccine hesitancy has existed for decades (Stern and Markel, 2005), it has recently gained prominence as a serious threat to scientific progress and public health (Petrelli et al., 2024). The COVID-19 pandemic, in particular, has highlighted how hesitancy can impede the attainment of herd immunity, prolonging widespread suffering and avoidable deaths (Wiysonge et al., 2022). Vaccine attitudes exist along a spectrum, ranging from total refusal to full acceptance, and are shaped by a complex and dynamic set of factors.

Research examining vaccine hesitancy has identified a wide range of determinants (Cadeddu et al., 2021; Vuolanto et al., 2024; Recio-Román et al., 2023; Mascherini and Nivakoski, 2022; Burns et al., 2024b,a). More recently, information sources particularly media and online platforms have been recognised as potentially significant contributors to vaccine hesitancy. The influence of information sources on vaccine attitudes cannot be overstated. In 2022, daily internet use in the EU was almost universal among 16-29 year olds (96%), compared with 84% of adults overall. In 2019, 77% of Europeans used the internet daily, rising to 95% among 16-24 year olds (Figure 3.A.1). In every EU country at least 94% of young people were daily users, with Italy and Bulgaria at the lower end and several countries (Ireland, Malta, Luxembourg, Portugal, Czechia, Lithuania, Slovenia, and Latvia) nearing full coverage. Individuals obtain vaccination-related information from a variety of sources, including healthcare professionals, traditional media, and online platforms.

Healthcare professionals can strongly influence vaccination decisions by addressing concerns and providing tailored advice. Media sources such as television, radio, and online news may offer valuable information but can also facilitate the spread of misinformation, thereby contributing to vaccine hesitancy (Patelarou et al., 2021), particularly in emergency contexts such as the COVID-19 pandemic (Brilli et al., 2020a). While the internet and social media have become prominent sources of health information, they also enable the dissemination of false or misleading content and pessimist narratives (Benecke and DeYoung, 2019; Witteman and Zikmund-Fisher, 2012). As a result, vaccination uptake can be influenced both positively and negatively depending on the nature and credibility of information encountered. Dispelling misinformation while promoting trustworthy information is therefore critical.

Much of the existing research on vaccine information and hesitancy is mostly found in non-economics fields, particularly in medicine, communication studies, and epidemiology. Economic analyses remain relatively limited. Among the literature are Carrieri et al. (2019) and Brilli et al. (2020a,b). Carrieri et al. (2019) indicate that repeated exposure to negative vaccine-related information through reading, hearing, or viewing misinformation, rumours, and myths in mainstream media is a significant factor shaping vaccine attitudes. In subsequent work, they document that trust in science is inversely related to vaccine hesitancy, while reliance on social media as a primary information source is positively associated with hesitancy. Other studies highlight how fear of advanced vaccine technologies can disrupt vaccine diffusion (Saleska and Choi, 2021). In many cases, reports of adverse reactions circulated through social and mass media before medical experts could establish causal links, contributing to heightened perceived risks. Misinformation including claims that vaccines contain toxins, microchips, or cause long term reproductive harm has flooded online spaces (Offit and Jew, 2003; Smith et al., 2017; Flaherty et al., 2022; Cherkaev, 2022). Empirical evidence suggests that such media coverage can lead to significant and sustained declines in vaccine uptake, driven largely by increased perceived risks. Information has been shown to affect vaccination behaviour across different contexts. Studies on the MMR-autism controversy (Anderberg et al., 2011; Carrieri et al., 2019; Chang, 2018; Qian et al., 2020) illustrate how misinformation can alter parental decisions. For influenza vaccines, positive news coverage is associated with increased uptake, whereas reports of adverse events lead to declines (Brilli et al., 2020a; Yoo et al., 2010). Similarly, research on COVID-19 vaccines indicates that temporary suspensions and exposure to conservative media reduced vaccination rates (Deiana et al., 2022; Motta and Stecula, 2023; Pinna et al., 2022).

This chapter extends the economic literature by examining the causal relationship between online health information and vaccine hesitancy among adults in Europe. Using instrumental variable (IV) estimation and the Eurobarometer 2019 data, it identifies the effect of vaccine related information obtained from the internet including social networks and other websites on hesitancy attitudes. Unlike previous studies (Brilli et al., 2020a; Recio-Román et al., 2023; Mascherini and Nivakoski, 2022), this analysis explicitly addresses endogeneity concerns arising from reverse causality and self - selection into media sources. These concerns are particularly relevant because vaccine hesitant individuals may actively seek out information that confirms their prior beliefs, while exposure to online misinformation may itself increase hesitancy. In addition to media utilisation, the analysis controls for a comprehensive set of covariates, including socio demographic characteristics and underlying health conditions. We also consider the links between vaccine hesitancy and a comprehensive range of covariates comprising individual socio-demographic characteristics, underlying health conditions and vaccination information sources (internet). We find that vaccination information from the internet is positively related to the probability of being vaccine hesitant. This study contributes by explicitly addressing the potential endogeneity of online information-seeking behaviour emanating from media utilisation and its effects on vaccine hesitancy. The findings in this area remain inconclusive. For instance, Suenaga and Vicente (2022) along with Wagner and Jimison (2003) find no evidence of a link between seeking health information online and the use of physician services. In contrast, Suziedelyte (2012), employing an instrumental variable approach, shows that searching for health information online has a positive and substantial effect on individuals' demand for healthcare.

The paper's remaining sections are arranged as follows. An overview of relevant literature on the main topics of vaccine information sources from the internet, and vaccine hesitancy is presented in Section 2. In Section 3, vaccination in Europe is explained. In Section 4, the data used for the empirical study and some descriptive statistics are described. Section 5 presents the empirical model and estimation approach; Section 6 elaborates on the findings and discussion. In conclusion, Section 7 provides some final thoughts as concluding remarks.

3.2 Related Literature

This study advances the understanding of the literature on media diffusion and vaccination outcomes by bridging two related strands: descriptive evidence on how media use, politics, and social structure correlate with vaccine attitudes and uptake, and a smaller set of studies that leverage experimental or quasi-experimental designs to make stronger causal claims about information environments. Vaccination is widely regarded as the most secure and recommended method to mitigate epidemics (WHO, 2017). While research on vaccine hesitancy long predates COVID-19, the pandemic has generated substantial renewed interest in explaining why some individuals remain reluctant to vaccinate and in clarifying the role of media in shaping these attitudes.

Descriptive studies link vaccine attitudes to political ideology, institutional trust, and social cleavages. A strand of the literature shows that political ideology and trust in government shape vaccine uptake, hesitancy, acceptance, and confidence. Baumgaertner et al. (2018) documents that trust in government medical experts, filtered through political ideologies, influences attitudes towards pertussis, measles, and flu vaccination in the U.S. Suryadevara et al. (2019) find lower HPV vaccination rates in Republican-leaning states than in Democratic-leaning states during the 2016 U.S. election, while meningococcal and Tdap vaccination rates remain relatively similar across these cohorts.[1] Estep (2018) discusses the policy implications of vaccine opposition in California, showing that resistance to compulsory kindergarten immunisation increased the risk of disease outbreaks, particularly in conservative regions. Trust is also structured along racial and social lines. In Australia, Rozbroj et al. (2019) identify trust in healthcare and alternative medicine, trust in government, and conspiratorial beliefs as key correlates of vaccine attitudes.

European research broadly confirms the salience of institutional trust while highlighting contextual variation. Sabat et al. (2023) associate vaccine hesitancy with trust in government information, risk perceptions, and vaccine confidence. In a comparative perspective, Lazarus et al. (2021) report COVID-19 vaccine acceptance rates ranging from 55% in Russia to 90% in China, with higher trust in government information correlating strongly with willingness to vaccinate. Using Eurobarometer data, Vulpe (2020) identifies four distinct forms of vaccine hesitancy: price hesitation (when vaccines are perceived as expensive), effort hesitation (when vaccination is seen as complex or burdensome), unexercised pro-vaccination (individuals who trust scientific authority to manage health risks but remain unvaccinated), and consistent anti-vaccination (highly reflexive individuals who reject expert authority due to perceived scientifically derived risks). These categories illustrate how access barriers, trust in science, and risk perceptions interact to shape vaccination attitudes and inform more targeted public health policies in the European Union.

The evidence on the political roots of vaccine attitudes is mixed. Stoeckel et al. (2022) find no strong association between political orientation and vaccine attitudes in Europe, whereas other work emphasizes the role of populism. Recio-Román et al. (2023) show that populist actors mobilize vaccine hesitancy to deepen broader distrust in institutions, and Kennedy (2019) document a

[1] HPV - human papillomavirus; Tdap - tetanus-diphtheria-acellular pertussis vaccine

significant influence of populist beliefs among individuals who question the necessity of vaccination. Country-specific studies further underscore heterogeneity. In Italy, the introduction of compulsory vaccination was followed by declining coverage and a measles outbreak; examining beliefs, Cadeddu et al. (2020) find higher scepticism among older, male, less educated, and right-wing individuals, and show that low cultural engagement and weak political participation are also associated with hesitancy. In Poland, right-wing populist actors have supported the removal of mandatory vaccination, reflecting a broader anti-enlightenment sentiment in parts of Eastern Europe (Żuk et al., 2019).

Research has also examined the role of media exposure and misinformation in shaping vaccination attitudes and behaviours. A large body of work treats social media misinformation and fake news as risk factors for vaccine hesitancy (e.g. Aquino et al., 2017; Dubé et al., 2015; Jolley and Douglas, 2014; Smith and Marshall, 2010). Not all media effects are negative, however. Yoo et al. (2010) show that U.S. media coverage during vaccination campaigns is associated with earlier and higher vaccination rates. Chen and Stoecker (2020) estimate that among individuals aged 65+, every additional 100 media reports is associated with a 0.3 percentage point increase in vaccine uptake, though these estimates remain primarily correlational.

Platform-specific studies refine these descriptive patterns. In the European context, Recio-Román et al. (2023) find that media use is generally mediated through vaccine hesitancy, with television constituting a notable exception, suggesting that algorithmic recommendation systems and peer networks on social media versus editorial standards in broadcast media create distinct information environments. Mascherini and Nivakoski (2022) emphasize the contribution of social media use to explaining COVID-19 vaccine hesitancy within the EU, while Sasse et al. (2024) report similar associations for the U.S., stressing the need for tailored interventions that account for platform-specific dynamics. Evidence from Italy further illustrates these links. Carrieri et al. (2019) argue that misinformation about autism and the MMR vaccine contributed to reduced immunisation rates. Brilli et al. (2020a) conclude that media coverage contributed to declining influenza vaccination uptake; however, a free flu vaccination program for those 65+ yielded coverage rates between 70% and 90%, indicating that improved access and reduced cost can offset negative media influences.

A second, smaller strand of the literature makes more explicit causal claims by leveraging experimental or quasi-experimental designs to address endogeneity in media exposure and information acquisition. Using National Health Survey data for Italy, Amaral-Garcia et al. (2024) show that, once endogeneity is addressed, the estimated effect of internet penetration on vaccination rates becomes much smaller, underscoring the importance of identification strategies in this area. Using social media data, Giaccherini et al. (2022) apply natural language processing and an instrumental variable strategy to Italian vaccine-related tweets from 2013-2018 and find that increases in anti-vaccine sentiment causally reduce MMR coverage and increase hospitalisations. From a more explicitly causal angle, Principe and Weber (2023) use SHARE data and an instrumental variable strategy, instrumenting health information with workplace computerisation, and find that improved access to health information reduces vaccine hesitancy, highlighting the importance of the broader information environment in shaping vaccination decisions in Europe. Experimental work complements these quasi-experimental designs: Featherstone and Zhang (2020) use an online experiment with a convenience sample of 609 U.S. adults and show that short-term exposure to uncertainty and conspiracy-framed misinformation messages significantly decreases pro-vaccination attitudes, reinforcing the centrality of message framing and content.

Beyond media and politics, a broad descriptive literature documents general and psychosocial determinants of hesitancy, often in interaction with media and institutional factors. Sociodemographic correlates include age, gender, education, and income (Nagase, 2024; Troiano and Nardi, 2021; Schmitz and Wübker, 2011), as well as ethnicity, online misinformation exposure (Pierri et al., 2021), and moral values (Amin et al., 2017). Psychological factors such as conspiratorial thinking, reactance, and specific worldviews are consistently associated with anti-vaccination attitudes (Hornsey et al., 2020). Cultural and religious factors also matter: Christian nationalism in the U.S. is linked to anti-vaccine attitudes (Whitehead and Perry, 2020); in Australia, Rozbroj et al. (2019) report that being a religious male, having children, and not voting are associated with more negative vaccine attitudes; and in Canada, Burns et al. (2024b) find that age, ethnicity, political orientation, and conspiracy beliefs correlate with hesitancy. Within the EU, Nagase (2024) show that younger individuals, manual workers, early school leavers, individuals with children at home, residents of small towns, and those holding specific beliefs are more likely to be hesitant. In Italy, Bertoncello et al. (2020) conclude that lower education predicts outright refusal, whereas economic hardship is more closely associated with hesitancy. Using the Flash Eurobarometer, Toshkov (2023) identifies complex relationships between vaccine refusal, hesitancy, and demographic variables, with trust in health-related factors and scepticism towards the internet emerging as significant predictors. Makarovs and Achterberg (2017) suggest that education is crucial for vaccination acceptance and that in highly integrated countries, more educated individuals are sometimes more likely to object to flu vaccination, underscoring the contextual nature of acceptance. In addition, a smaller but more policy-relevant literature uses experimental designs to test whether specific message frames can causally shift vaccine intentions and uptake. Galasso et al. (2023) presents a randomized experiment across nine high-income countries comparing egoistic and altruistic public health messages on COVID-19 vaccine outcomes and shows that self-protection framing had no effect, whereas altruistic messages with emphasis on protection of others, population health, and the economy increased vaccine intentions and were associated with higher uptake at follow-up.

Finally, studies combining single-country designs and cross-national surveys examine hesitancy in relation to mandates, perceived adverse health effects, limited awareness of vaccine-preventable diseases, and mistrust in institutions (Dubé et al., 2013; MacDonald, 2015; Larson et al., 2016). Taken together, descriptive analysis and the smaller set of causal studies converge on the conclusion that the internet and social media play a central role in disseminating (mis)information and shaping vaccine hesitancy (Jolley and Douglas, 2014; Dubé et al., 2015; Nuwarda et al., 2022; Marco-Franco et al., 2021). This has made vaccine hesitancy a major challenge for national immunisation programmes and public health more broadly, and has prompted social media platforms to introduce measures aimed at curbing misinformation.

3.3 Vaccinations in Europe

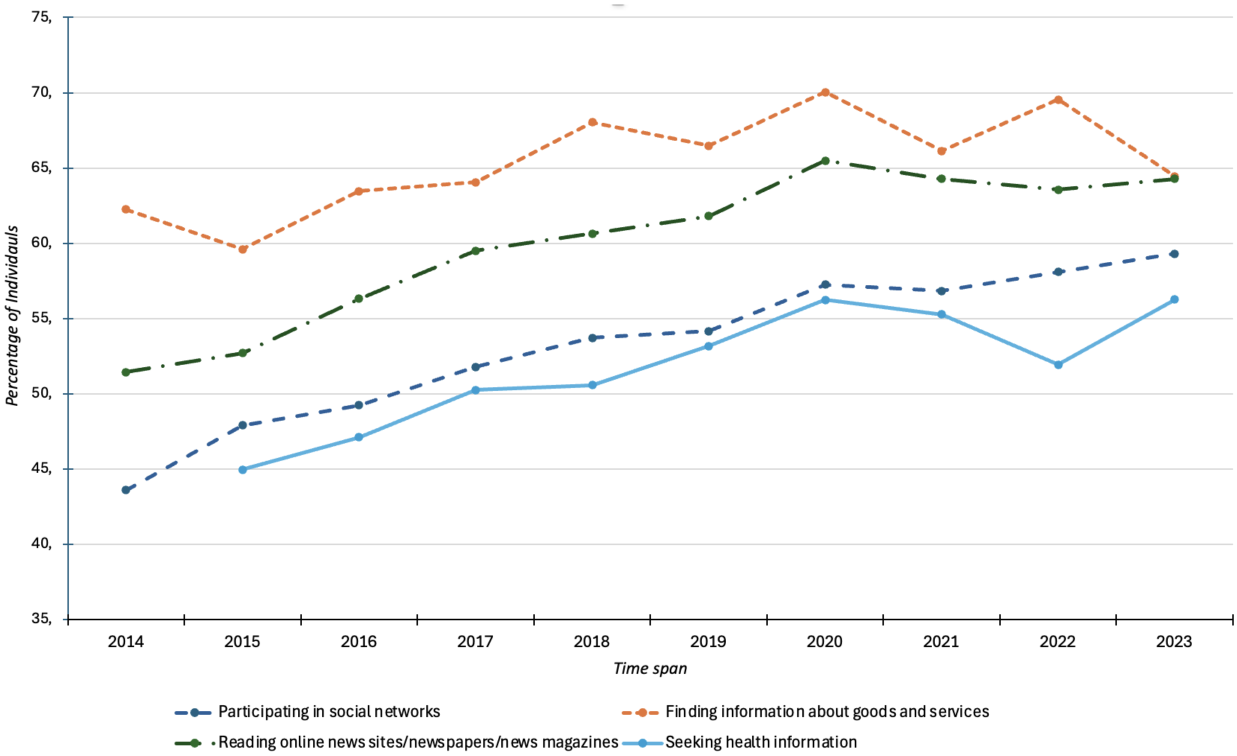
Vaccination policies vary across EU countries: some vaccines are mandatory in some countries, while others are recommended. Most of these countries operate under heterogeneous vaccination systems, with differing recommendations and administration schedules. As a result, immunisation is not uniformly approached, and for some antigens, vaccination coverage does not always align with evolving medical needs. Due to widespread vaccination, smallpox has been eradicated, Europe has become polio-free, and numerous other diseases have been nearly eliminated. The vaccination programmes in the EU are generally publicly financed, although their administration and delivery remain largely decentralized across Member States. Parents and legal guardians are provided with comprehensive information on vaccines and are required to give informed consent, after their children receive vaccinations at no cost through designated times and locations. The European Medicines Agency (EMA) is responsible for evaluating and monitoring vaccines after their development and rigorous testing. For other EU states, the degree of centralisation is generally lower. Italy for instance, mandates by law to be vaccinated against diphtheria, tetanus, polio, hepatitis B, measles, mumps, rubella and varicella , which are administered at regional centres at no cost; for other vaccines, the National Health System on immunization and vaccination suggests recommendation on which vaccines should be administered and advice on the appropriate timing for offering them to children and infants at all cost (Bertoncello et al., 2021; Bozzola et al., 2018). Centralised vaccination policies can be costly, as transactional savings may not fully offset expenses. Introducing new vaccines is challenging unless deemed essential, and access is often limited to the less expensive options procured by health authorities.

France and Germany have more decentralised systems, with no government involvement in vaccine administration. In Germany, vaccines are funded by insurance companies, sometimes physicians in public health facilities or individuals, as indicated by Schmitt (2001). The administration is typically determined by a vaccination physician. However, the National Advisory Committee is responsible for the national vaccination plan, and they adjudicate which vaccines satisfy public importance. Most centralised systems grant greater vaccination coverage since they enable the implementation of detailed plans regarding immunisation schedules, targets, uptake and deadlines. In Germany, limited adherence to vaccination programs results in low coverage, and this has led to vaccine-preventable diseases. There could also be inefficiencies in decentralised systems.

According to the European Commission report on the State of Vaccine Confidence (2022) (de Figueiredo et al., 2022), Portugal (92.4%), Finland (90.4%), and Spain (88.6%) have the largest percentage of respondents who agree that vaccines are vital in 2022, while Slovakia (62.1%), Croatia (61.7%), and Latvia (60.3%) have the lowest percentage. Compared to 2020, this report argues that there is less agreement that vaccines are necessary, safe, effective, and consistent with personal beliefs. While opinions on the importance and efficacy of vaccines are likewise lower than in 2018, opinions on their safety and compatibility with beliefs are higher.

Access hurdles prevent people from getting vaccinated, in addition to things like confidence, hesitancy, or complacency. Economic disadvantages make up the majority of these access hurdles (Peretti-Watel et al., 2019; Bedford et al., 2018). Figure 3.3.1 presents the percentage of internet usage by individuals in the European area. Noticeably, it is observed that generally, internet usage has been increasing over the years. People use the internet the most to find information about goods and services, while finding health information appears as the least relevant activity among the internet activities shown in Figure 3.3.1. This indicates that around 45% of individuals used the internet to obtain health information in 2015, and although this share has risen over time, searching for health information remains one of the least common activities among those shown.

Figure 3.3.1: Percentage of Individuals Internet Activities



Note: The data plotted on this figure was sourced from Eurostat, 2023. In 2018, data on the proportion of people who read online news websites, newspapers, or news magazines was unavailable. As a result, the value for that year was estimated using interpolation. Figure 3.A.1 in the Appendix indicates the percentage of people using the internet daily in 2019.

3.4 Data

3.4.1 Data and Descriptive Statistics

Our empirical analysis is based on individual-level data from Eurobarometer 91.2 (European Commission, 2019):*Europeans in 2019, The General Data Protection Regulation, Awareness of the Charter of Fundamental Rights of the European Union, and Europeans' Attitudes Towards Vaccination.* It includes inhabitants of European states between the ages 15 and 98 years, and we focus on all individuals for the analysis. The dataset is derived from face-to-face interviews in all EU member states and some additional countries on key trends and relevant information on citizens' beliefs and attitudes toward vaccination.[2]

This survey relies on a multi-stage stratified randomly selected sample of at least 1000 individuals for each country or territory reported. However, for the population of countries or territories with less than one million residents, a sample of 500 individuals is used. The total sample is

[2]European Union. Eurobarometer. Information on Eurobarometer, https://europa.eu/eurobarometer/about/eurobarometer

weighted to allow for geographical and demographic representativeness. Stratification by individual unit and area type was conducted for the countries of the survey. Subsequently, to further check the representativeness of the European Union countries, in tandem with the NUTS II standards (European Commission, 2019), the sampling units were systematically extracted commensurate with the administrative regional units. These random selections are based on computer-assisted personal interviews (CAPI) from citizens' home countries in the national languages.

3.4.2 Outcome measures

Our primary outcome is the variable "vaccine hesitancy", which is a proxy variable derived from the question "*Have you had any vaccinations in the last five years?*." We define vaccine hesitancy as a binary variable equal to 1 if the respondent reports not having received any vaccination in the past five years, and 0 otherwise. This measure should be interpreted as a behavioural proxy for vaccine hesitancy rather than a direct attitudinal measure. This outcome variable "vaccine hesitancy" does not directly measure a hesitant attitude. Vaccine hesitancy is therefore measured using this question. To deal with spillovers, we accounted for reason why they might not have vaccinated in the last five years due to factors like: *You are still covered by vaccines you received earlier*; *You do not see the need to be vaccinated*; *You think that vaccines are not safe and they can have side-effects*; *Vaccines are only necessary for children*; *You have not been offered any vaccine by your general practitioner, a doctor, or a paediatrician*; *It is expensive*; *It is complicated and requires a lot of effort* and *others or no reason at all or do not know.* We do not focus on results on vaccine hesitancy children and others in the household, we present results in the appendix since as a deficiency of the data, we are not able to account for reasons why children or other household members would have have vaccinated.

3.4.3 Main explanatory variable of interest

The main explanatory variable is "information on vaccinations from internet sources" that aggregates information from social networks and other internet websites. This relies on the survey question, "*If you were looking for information about vaccination, which of the following sources would you consult?*" The options were Family; Friends; Your general practitioner, a doctor, or a paediatrician; Other health care workers (nurses, specialist doctors, etc); Pharmacists; Online social networks; Other Internet sites; The health authorities; Other; None; and Do not know. From this, a binary variable (internet) was constructed taking a value of 1 for those responding to seeking vaccine information from online social network and other internet sites or 0 otherwise. However, this internet variable measures respondents' stated propensity to consult online sources for vaccination information, not necessarily actual exposure. It also combines social networks and other websites, which may differ in credibility, intensity of use, and informational direction. Similarly, we estimated an index using principal component analysis from these social networks and other internet sites.[3] We performed robustness checks using this variable.

3.4.4 Socio-economic controls variables

We control for a set of socio-demographic characteristics of survey respondents. Specifically, we include controls for gender (male as the reference category), marital status (unmarried as the reference), and the presence of children in the household (having children below age 10, with households with children aged 10 and above serving as the omitted category). Place of residence is captured by indicators for rural areas, small or medium-sized towns, and large towns, with rural residence as the reference group. We further control for occupation (self-employed, employed, and not working, with the not-working category as the reference), age at completion of full-time education (primary, secondary, and higher education, with primary education as the reference), and financial constraints (difficulty paying bills, with no difficulty as the reference). Social class is also included, with categories for working class, lower middle class, middle class, upper middle class, and higher class, using the middle class as the reference category. In addition, we account for respondents' health-related characteristics by including dummy variables indicating whether the individual reports having a weak immune system and whether they believe vaccines are ineffective (based on responses of "no" to the question: "Do you think that vaccines can be effective in preventing them?").

Table 3.4.1 below gives an overview of the characteristics of the respondents considered in this study. The sample size used in this study is 22,624. The sample is predominantly female, with women representing roughly 55% of all respondents. Access to health care services for females makes it likely for them to be vaccinated, however, males could have risk-loving attitudes and focus on short-term concepts, resulting in them being more vaccine-hesitant (Toshkov, 2023). Age has been established as an important determinant of vaccine attitudes. Age has been identified as a key demographic determinant of vaccine attitudes (Nagase, 2024). The average age of these respondents is about 51 years, with most of them having at least a secondary school level education. Because they are more susceptible to illnesses, older adults are generally expected to have higher

[3]This estimate had a Kaiser-Meyer-Olkin (KMO) of 0.50. Although the KMO value is low, it meets the minimum threshold commonly considered acceptable (Kaiser, 1974; Yong et al., 2013). The Bartlett's test of sphericity was significant ($\chi^2 = 100.18$, $p < 0.000$), indicating that the correlation matrix was factorable and that PCA was appropriate.

vaccination uptake and lower vaccine hesitancy compared to younger people. Most respondents in the sample are married (54%), and they are less likely to be vaccine-hesitant than unmarried individuals, which is consistent with evidence that spousal dynamics can support higher vaccination uptake, as partners influence each other's vaccination decisions so that one partner's vaccination can encourage the other to vaccinate as well (Schmaling, 2022; Liu et al., 2023). The high share of married respondents suggests that interventions targeting couples or households (messages or information framed around protecting the family, or involving both partners in decision making on their health) may be especially effective at shifting hesitancy.

Households with children are more likely to be vaccinated relative to those without children at home. That is, since guardians and parents are responsible for their wards and know the importance of vaccines, they may be less hesitant to accept vaccination. Previous studies (Borga et al., 2022; Ozdenerol and Seboly, 2022) have argued that parents are conventionally more likely to take vaccination as compared to individuals with no children since these parents could have more confidence in the health care system and would be in support of vaccination. The number of children living at home below the age of 10 is about 18%. Also, using difficulty in paying bills as a proxy for the financial capacity of respondents, we found that respondents who had difficulty in paying bills are about 31% of the respondents. Taking into account this factor is necessary since people with economic constraints appear to be more hesitant about vaccines (Paul et al., 2021; Sowa et al., 2021). They could be faced with health insurance varies greatly across Europe, and this reduces their awareness of health outcomes. Their acceptance of vaccination is derailed since they are more concerned about financing their basic needs, and these burdens could prevent them from accessing vaccination services. The respondents were mostly residents in small/medium towns (38%) and those who resided in large towns were about 29%. Those who resided in rural areas were 33% of the sample. Studies indicate that individuals residing in rural areas/villages are more vaccine hesitant than those in large towns or small/middle towns (Sun et al., 2024; Zhai et al., 2024). They may be more susceptible to be faced with several impediments to vaccination, including transportation as a result of being a rural dweller. Occupation is also relevant for vaccination. That is, there are varying vaccination attitudes associated with specific professions, particularly healthcare employees (Baniak et al., 2021). We categorised occupation into self-employed, employed and not working, with not working as the reference group. We found that about 47% of the respondents are not working, about 46% of them were employed, and only approximately 7% of them were self-employed. This group of not-working individuals comprises students, the unemployed or temporarily out of work, retirees or those unable to work due to illness,

Table 3.4.1: Descriptive Statistics

	Mean	SD	Min	Max	*N*
Outcomes					
Vaccine hesitancy	0.22	0.41	0.00	1.00	22624
Social network	0.06	0.24	0.00	1.00	22624
Other internet sites	0.14	0.34	0.00	1.00	22624
Internet	0.18	0.39	0.00	1.00	22624
Controls					
Gender:					
Male	0.45	0.50	0.00	1.00	22624
Female	0.55	0.50	0.00	1.00	22624
Age	51.29	17.82	15.00	98.00	22624
Age2	2947.83	1833.58	225.00	9604.00	22624
Married	0.54	0.50	0.00	1.00	22624
Child under age 9	0.18	0.39	0.00	1.00	22624
Difficulty to pay bill	0.31	0.46	0.00	1.00	22624
Residence:					
Rural	0.33	0.47	0.00	1.00	22624
Small town	0.38	0.48	0.00	1.00	22624
Large town	0.29	0.45	0.00	1.00	22624
Occupation					
Self-employed	0.07	0.26	0.00	1.00	22624
Employed	0.46	0.50	0.00	1.00	22624
Not working	0.47	0.50	0.00	1.00	22624
Social class					
Working	0.25	0.43	0.00	1.00	22624
Lower middle	0.16	0.37	0.00	1.00	22624
Middle	0.50	0.50	0.00	1.00	22624
Upper middle	0.08	0.27	0.00	1.00	22624
Higher	0.01	0.08	0.00	1.00	22624
Education					
Primary	0.13	0.34	0.00	1.00	22624
Secondary	0.45	0.50	0.00	1.00	22624
Higher	0.37	0.48	0.00	1.00	22624
Weak immune system	0.38	0.48	0.00	1.00	22624
Believes vaccines are not effective	0.10	0.29	0.00	1.00	22624

Note: SD is the Standard deviation, Min represents is the minimum value of the variable, Max is the maximum value and the number of observations for each variable is indicated in column *N*

and individuals engaged in household duties, such as shopping and home care, as well as those with no current occupation. However, this category is heterogeneous and therefore difficult to interpret. Studies have argued that people who are manual labourers or self-employed could be less aligned to get vaccinated (Beale et al., 2022).

Studies find that wealthier people tend to have higher vaccination rates and lower hesitancy because they face fewer access barriers (Lamot and Kirbiš, 2024). However, others shows that in some affluent and educated groups, skepticism toward vaccines can actually be more common, suggesting that privilege can also contribute to hesitancy (Vlasak et al., 2023). Another reason could be financial constraints. Resultantly, low social classes could be more vaccine-hesitant. In this study, we observed that the majority (50%) of these respondents are found in the middle class of society, only about 1% for those in the higher class of society and those in the working class of the society were only about 25% of the sample. Education is also another factor that influences vaccine hesitancy. Studies have indicated that the less educated tend to be hesitant towards vaccines and may have lower vaccination rates as compared to those highly educated (Schwarzinger et al., 2021; Wu et al., 2021; Brownstein et al., 2022). These lowly educated could have less access to information about vaccines, trusting vaccinations and could have less healthcare access. We use the age at which respondents completed their full-time education as an indicator of education. Those who completed full-time education at the primary level were 13% of the respondents, a majority (45%) of them were found at the secondary school level and about 37% of them completed at the tertiary level. Also, we find that about 38% of these individuals have weak immune systems. People who see themselves as immunocompromised often may worry more about side effects, interactions with existing conditions, or vaccines overloading their already weak immune system, which could increase hesitancy even when they are at higher risk from the disease itself. Some also indicated that they thought vaccines were not effective and these people formed about 10% of the sample.

3.4.5 Instrumental variables

This analysis relies on *broadband coverage* and *lightning frequency* as instrumental variables for information sources on vaccination from social networks and other internet sites. The data on broadband coverage was extracted from the Broadband Coverage in Europe report (2019) of the EU (2020). Bhuller et al. (2013) and Kearney and Levine (2015) have already employed a similar instrument. Overall fixed broadband coverage reflects progress in household broadband availability, indicating the share of homes that can access fixed networks offering minimum download speeds of at least 2 Mbps.[4] The penetration of fixed broadband coverage provides households with reliable

[4]This is extracted from the European Commission DG Communications Networks, Content & Technology by OMDIA, IHS Markit, and Point Topic, monitors progress toward EU broadband goals of universal coverage of at least 30 Mbps and 50% household subscriptions of 100 Mbps or more by 2020. It covers 31 European countries, including the EU27 plus Norway, Iceland, Switzerland, and the UK, and analyzes broadband availability at both national and rural levels. The study examines major technologies such as DSL, VDSL, VDSL2 Vectoring, cable modem DOCSIS 3.0 and 3.1, FTTP, FWA, LTE, and 5G, while also reporting combined measures such as overall fixed broadband and next-generation access availability. It includes a Europe-wide overview, country comparisons, year-on-year trends, and individual country chapters, with the fixed-line analysis focused on the main access technologies and excluding satellite.

internet access, allowing them to access rich information about vaccines from social networks, government websites, health organisations, and news sites. Broadband or mobile signal coverage is a more direct supply-side instrument: areas physically covered by signal infrastructure have access to the internet and therefore to online vaccine information, while uncovered areas do not (Manacorda and Tesei, 2020). Poor broadband coverage results in higher cost for this quality of internet access, and this could reduce access to online health information, including vaccines. This information is collected at the regional NUTS II level of the European area. That is, individuals could be more likely to have access to information on vaccination when broadband coverage in the area where they live is high. Broadband signal coverage is a more direct supply factor that areas physically covered by broadband infrastructure have access to the internet and, therefore, to online vaccine information, while uncovered areas do not. It constitutes a strong predictor of individuals' access to online information. The expansion of mobile and broadband internet infrastructure has been shown to substantially increase exposure to digital content, including news, social media, and other information channels. In particular, the diffusion of mobile broadband technologies enables individuals to access a wide range of information sources in real time, thereby shaping beliefs, attitudes, and perceptions. Manacorda and Tesei (2020), Guriev et al. (2021) and Andersen et al. (2012) demonstrate that increased availability of mobile internet significantly affects individuals' information environments and subsequent attitudes toward public institutions and policies. Given that vaccine-related information could be accurate and misleading, when it is widely distributed online, broadband coverage is expected to be strongly correlated with exposure to such information. Therefore, the relevance condition for the instrument is satisfied, areas with greater broadband coverage exhibit higher levels of internet usage and, consequently, greater exposure to vaccine-related content. The rollout of broadband infrastructure is primarily determined by technological, geographic, and economic factors, such as installation costs, terrain, and expected returns on investment, rather than by local attitudes towards vaccines. Conditional on appropriate controls and fixed effects, there is no reason to expect broadband coverage to directly influence vaccine hesitancy except through increased access to online information.

The other instrument used is *lightning frequency* which was sourced from the Global Hydrology Resource Center. More specifically, we employed the incidence of lightning from the National Aeronautics and Space Administration (NASA) satellite-generated data. The study utilises the average lightning frequency intensity for 2014 in $0.5\times$ 0.5cells resolution, where each lightning frequency is recorded along with its spatial location, with a level of resolution of 5-10 km on the ground.[5] Storm-related frequent electrostatic discharges have been shown to impair connection and harm cellular phone infrastructures, affecting supply and demand (Andersen et al., 2012) and this affects information sources. Studies by Manacorda and Tesei (2020) and Guriev et al. (2021) have focused on this instrument as well. Lightning can emit electromagnetic interference, and that could affect the quality of wireless signals like Wi-Fi, leading to slower internet speeds, dropped connection or increased latency. This may cause delays or disruptions in accessing information online or through social networks. The intensity, colour, or flicker of ambient lightning can interfere with Visible Light Communication (VLC), potentially leading to errors in data transmission. For instance, if the lightning frequency changes rapidly, it could cause signal degradation, affecting the speed or reliability of the internet connection. lightning frequency could result in power surges and outages, which could also lead to frequent or longer internet disruptions, leading to ineffective access to online health information. Lightning frequency is used as an instrument for exposure to vaccine-related information online because adverse atmospheric conditions may affect the quality and reliability of internet connectivity, thereby influencing access to online sources of information. For this instrument to be valid, however, lightning intensity must affect vaccine hesitancy only through this channel. A potential concern is that lightning frequency may also be correlated with broader regional characteristics, such as geography, infrastructure, or remoteness, which could themselves influence health behaviour and access to care. In our specification, this concern is partly addressed by the inclusion of a rich set of individual controls and NUTS II regional fixed effects, which absorb persistent regional heterogeneity. Under this assumption, remaining variation in lightning frequency is interpreted as affecting vaccine-information exposure primarily through internet connectivity rather than through other direct channels.

Figure 3.A.2 in the Appendix presents the intensity of lightning frequency and broadband coverage in the Europe area. On these maps, darker shaded areas correspond to regions where the instrument records a high frequency of events (high intensity), whereas lighter or faintly coloured areas denote regions with a low frequency of recorded events. We find that there is a high intensity of lightning frequency in Eastern Europe, however, there is a high intensity of broadband coverage in Western Europe.

[5]LIS/OTD 0.5 Degree High Resolution Annual Climatology (HRAC) V2.3.2015: The LIS/OTD 0.5 Degree High Resolution Annual Climatology (HRAC) contains a variety of gridded climatologies of total lightning flash rates obtained from two lightning detection sensors - the spaceborne Optical Transient Detector (OTD) on Orbview-1 and the Lightning Imaging Sensor (LIS) onboard the Tropical Rainfall Measuring Mission (TRMM) satellite. The long LIS (equatorward of about 38 degrees) record makes the merged climatology most robust in the tropics and subtropics, while the high latitude data is entirely from OTD. The HRAC dataset includes annual flash rate climatology data on a 0.5 degree grid in HDF and netCDF-4 format. The associated year was selected early enough to be clearly exogenous to the 5 year period vaccination behaviour window.

3.5 Empirical strategy

Our baseline model is a linear probability model (LPM). We address the potential endogeneity issues that may arise when investigating the role of information on vaccination from internet sources in vaccination attitudes by estimating a causal effect model using a two-stage least squares estimation (2SLS). However, there could be reasons why there may be a correlation between vaccination information sources and the error term, making the LPM estimates inconsistent. The first concern is reverse causality, which suggests that individuals could be prone to hesitancy may actively seek online vaccine content that confirms their prior beliefs. Beyond this, unobservable individual characteristics simultaneously drive both vaccine information sources and attitudes, suggestive evidence of omitted variable bias. Observable characteristics through socioeconomic status, age, education and other factors could be further confounding channels, as these characteristics determine both media use and vaccine attitudes (Greyling and Rossouw, 2022; Principe and Weber, 2023). Another source of endogeneity is from the non-random selection into different media use platforms. Individuals do not receive vaccine information directly but resort to online platforms and content providers that align with their pre-existing beliefs, giving an indication of implicit heterogeneity and endogeneity (Greyling and Rossouw, 2022). And the measurement of vaccination information sources could also be another reason to drive the LPM estimates towards zero.

From the LPM models, we present the average treatment effect of media utilisation vaccine hesitancy on the entire sample of the analysis.
The analysis relies on the following model:

$$vh_{ir} = \alpha + \beta M_{ir} + \Gamma X'_{ir} + \nu_r + \epsilon_{ir} \tag{3.1}$$

where vh_{ir} indicates a binary variable for vaccine hesitancy of respondents, information sources on vaccination from media (social networks and other internet sites) that is a stated intention to consult the internet is represented by M_{ir}, and the set of confounding factors are indicated by vector X'. We also control for regional-level fixed effects [NUTS II (ν_r)], and the error terms capturing the unobserved characteristics that cannot be defined in this model is indicated by ϵ_{ir}. The inclusion of NUTS II fixed effects may pose a potential identification concern, as the instrument may be absorbed by these fixed effects.

The instrumental approach identifies a local average treatment effect (LATE), which is the weighted causal effect of media utilisation on vaccine hesitancy for subgroups of compliers (Imbens and Angrist, 1994). These compliers are those individuals who use this information from social networks and other internet sources when there is instrument inducement (Harris and Remler, 1998). Comparing the LPM and IV estimates, if the LPM is downward biased, IV can correct this by providing a large estimate, which means LPM underestimates the true effect. Similarly, IV could produce smaller estimates when LPM is biased upward, that is, LPM overestimates the true effect. Information sources on vaccination are likely to be endogenous and the estimated coefficient from the LPM estimation could be biased. To control for this bias, we estimate a 2SLS model using potential instrument (broadband coverage and lightning frequency). For these instruments to be suitable, their validity needs to be tested by using the relevance condition and exclusion restriction. The first-stage regression of media utilisation on the exogenous variables in the model:

$$M_{ir} = \eta + \rho Z_{ir} + \gamma X'_{ir} + \xi_{ir} \tag{3.2}$$

here X' contains all the individual's characteristics including regional fixed effects. Standard errors are clustered at the regional NUTS II level and Z_{ir} represents the instruments considered. Now, we turn our attention to the second stage to determine the factors that influence vaccine hesitancy when media utilisation is instrumented with broadband coverage and lightning frequency as instruments. We estimate the empirical specification below;

$$vh_{ir} = \alpha + \beta \hat{M}_{ir} + \Gamma X'_{ir} + \nu_r + \epsilon_{ir} \tag{3.3}$$

To check for the robustness of these models, we also use another variable that defines media utilisation for vaccination information differently. Respondents were also asked if, in the past six months, they had read or heard any information on vaccination in the media. The responses were "no", "yes" (on TV, on the radio, in newspapers or magazines, on online social networks, on other internet sites), "other" and "don't know". To be able to identify information on vaccination from internet, we created a binary variable which is 1 if response was "yes" from "online social networks" and "other internet sites (internet)" and 0 otherwise.

To perform additional sensitivity analyses, we specifically addressed the potential confounding effects of age trends in our models. This was necessary due to the strong association between age and health outcomes, as individuals generally experience a decline in health as they grow older. To mitigate this issue, our models incorporated second-order polynomial terms of age, ensuring that both the first-stage and second-stage regression models appropriately controlled for these age-related effects (Carrieri et al., 2023; Bartram, 2021).

3.6 Empirical Results

We start this section by discussing the results under the LPM models by evaluating the effect of internet use on vaccine hesitancy of respondents. This outcome variable is a proxy variable for vaccine hesitancy measured by whether the respondent has not been vaccinated in the past five years. Therefore not a direct measure of hesitant attitude. Table 3.6.1 reports in Column (1) the effects of relying on information sources from internet, while, in Column (2) we focus on the internet index as defined in Section 3.4.3. It is observed that vaccination information from the internet has a direct effect on vaccine hesitancy for the respondents. Significantly, information from internet sites sites increases the likelihood of being vaccine hesitant by about 2.1 percentage points. This effect suggests that information on the internet can shift beliefs and perceived risks enough to reduce demand for vaccination, which is consistent with evidence that online misinformation can raise hesitancy and lower uptake (Pierri et al., 2021).

In particular, age, being married, working class, having weak immune system, and the belief that vaccines are ineffective of vaccines are other determinants that appear to affect vaccine hesitancy. Vaccine hesitancy appears to increase by about 1 percentage point when respondents become older by one year. Age can be seen to have diminishing effects on the probability of the respondent being vaccine hesitant. Prior research suggests that, age has an impact on vaccine reluctance (Halilova et al., 2024; Wang et al., 2024). Also, being married is less likely to lead to vaccine hesitancy. This result is in line with previous literature which shows that marriage offers special economic, psychological, and social resources that are good for health and could encourage vaccination uptake. That is these married individuals who tend to have access to internet could possess valuable health promotion information, including those on vaccines (Liu et al., 2023).

Compared with the "middle class", "upper middle" class status is associated with a reduced probability. More pro-vaccine sentiments are predicted by acknowledging one's own intellectual fallibility, indicating that people with greater "social standing may be less inclined to vaccines (Vlasak et al., 2023; Peretti-Watel et al., 2019). We also find that highly educated individuals are less likely to be hesitant to receive the vaccine, although not significant. Higher education levels are linked to better access to and understanding of scientific information. College students and graduates are more likely to have the skills to critically evaluate vaccine-related information and distinguish between credible and non-credible sources (Jaffe et al., 2022; Pogue et al., 2023).

Those who believe that vaccines are ineffective are more likely to be vaccine hesitant. Individuals with compromised immune systems may worry about potential adverse reactions to vaccines, leading to hesitancy. Hesitancy may increase if certain individuals with immunological disorders think their illness makes it unsafe for them to get vaccinations. In addition, individuals with complex health conditions, such as immune disorders, may be reluctant to vaccinate in the absence of clear guidance from healthcare providers and may underestimate their susceptibility to vaccine-preventable diseases, thereby contributing to vaccine hesitancy (Zhang et al., 2021). Concerns regarding vaccine ineffectiveness, particularly those arising from the accelerated vaccine development process are associated with increased vaccine hesitancy (Pourrazavi et al., 2023; Pouliasi et al., 2023) that is mistrust in vaccine benefits is seen as a reason for hesitancy, suggesting that perceived ineffectiveness contributes to scepticism about vaccination.

Turning to the IV estimates in Table 3.6.2, we present instrumental variable models that examine how exposure to vaccination-related information on the internet affects vaccine hesitancy. Here, we estimate the causal relationship between information sources on vaccination and vaccine hesitancy. The IV model suggested an estimated effect of about 0.65 points for vaccine hesitancy using broadband coverage as instrument, this estimate is much higher of about 0.5 when instrumented with lightning frequency and using both instruments, vaccine hesitancy increases by about 0.83. Also this is consistent with the results from the linear probability model. That is seeking vaccination information from the internet provides suggestive evidence that of an increase the probability of being vaccine hesitant. Determinants which suggests the likelihood of vaccine hesitancy in this case include age, class, weak immune system, ineffective vaccine, and education are significant. The relevance assumption of these instruments hold in all our models, as elaborated by formal tests based Kleibergen-Paap and the Cragg Donald Wald F statistics which are test for under or weak identification. However, since we have more instrument than the endogenous variable, we estimated a joint over-identification tests for all instruments, which could not reject the null hypothesis of instrument validity based on the Sargan-Hansen J statistic.[6] The overidentification test does not reject the null, although this should not be interpreted as definitive proof of instrument validity. That is there is some evidence that the instruments are exogenous. Considering the Panel B in Table 3.6.2, we observed that the instruments (broadband coverage and lightning frequency) have a negative and significant effect on internet sourced vaccine information.

We observed that LPM underestimates the effects of media use. This could be a result of un-

[6]That is, in these models, excluded instruments' first-stage F-statistic ranges approximately between 11 and 15, which satisfies the conventional criterion for instrumental relevance, which suggests a first-stage F-statistic of 10 or above. Similarly, more formal tests for weak identification and under-identification based on the Cragg-Donald Wald F statistic and the Kleibergen-Paap *rk* LM statistic readily reject the null hypotheses at any traditional critical levels. The null hypothesis of instrument validity is based on the Hansen or Sargan J statistic of the overidentification test of all instruments, which is exactly identified since we had the same number of endogenous variables.

Table 3.6.1: Effect of Media Utilisation on Vaccine Hesitancy using LPM

	Vaccine Hesitancy$_{adult}$	
	(1)	(2)
Internet	0.021***	
	(0.007)	
Internet index		0.008***
		(0.003)
Female	-0.007	-0.007
	(0.005)	(0.005)
Age	0.008***	0.008***
	(0.001)	(0.001)
Age2	-0.000***	-0.000***
	(0.000)	(0.000)
Married	-0.012**	-0.012**
	(0.006)	(0.006)
children under age 10	0.016**	0.016**
	(0.008)	(0.008)
Difficulty in paying bill	0.005	0.005
	(0.007)	(0.007)
Rural	-0.005	-0.005
	(0.007)	(0.007)
Large town	-0.006	-0.006
	(0.007)	(0.007)
Self employed	-0.016	-0.016
	(0.011)	(0.011)
Employed	-0.001	-0.001
	(0.007)	(0.007)
Working class	0.008	0.008
	(0.007)	(0.007)
Lower middle class	-0.001	-0.001
	(0.008)	(0.008)
Upper middle class	-0.019*	-0.019*
	(0.010)	(0.010)
Higher middle class	0.033	0.033
	(0.032)	(0.032)
Secondary	0.009	0.009
	(0.008)	(0.008)
Higher	-0.012	-0.012
	(0.009)	(0.009)
Weak immune system	0.113***	0.112***
	(0.006)	(0.006)
Believes vaccine are not effective	0.200***	0.200***
	(0.009)	(0.009)
N	22,624	22,624
R-squared	0.127	0.127
Region - NUTS II	Yes	Yes
AIC	21509	21508
BIC	23652	23651

Note: Models are estimated using linear probability regression. Columns differ in their specifications. Columns 1 and 2 vary by the variable of interest. Column 1 uses information from internet (social networks and other websites), while Column 2 uses information from the internet constructed by a PCA. NUTS II regional fixed effects are controlled for. AIC and BIC information criteria are presented, which are important metrics for model selection. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

observable traits of less hesitant individuals, making them less likely to use the internet to obtain information on vaccines conditional on other covariates. Also, internet algorithms selectively expose users to content aligned with their preexisting beliefs. The LPM could fail to account for this endogenous exposure, where vaccine-hesitant individuals are disproportionately shown anti-vaccine content. The IV approach could better isolate the exogenous variation in exposure (via platform-wide policy changes or instrumented shocks). If the IV model employs a more precise instrument (broadband coverage, lightning frequency), it may capture the true intensity of exposure, which the LPM underestimates due to noisy proxies. Vaccine hesitancy may also spread through social networks via peer influence. The LPM typically measures individual-level exposure, and the IV estimate may additionally capture indirect (spillover) effects if the instrument shifts exposure at the group or network level, for example, through friends' exposure that in turn influences the respondent's hesitancy. This could explain the larger IV coefficient if misinformation has multiplicative social effects. Finally, the LPM assumes a linear relationship, but misinformation exposure might have a tipping-point effect (no impact until a critical volume of exposure is reached). The IV estimate could proved suggestive evidence that reflect a local average treatment effect (LATE) for individuals highly responsive to the instrument, while the LPM averages over both affected and unaffected groups.

In sum, just like Dambadarjaa et al. (2021), Wilson and Wiysonge (2020), Allington et al. (2023), Reno et al. (2021), we found that the reliance on information on vaccination from social networks and other online sources is related to a high level of vaccine hesitancy. That is, information found on internet sites could largely be interpreted as suggesting that vaccinations are unsafe, with these views mainly originating from social networks and similar sources. This occurs against the background of a marked increase in the use of social networks and other websites, which enable individuals to freely share, produce, and exchange information on virtual platforms (Al-Surimi et al., 2017). These debates have been dominated by anti-vaccination voices, with most vaccination-related topics reflecting negative attitudes and the spread of misleading information (Blankenship et al., 2018; Basch et al., 2022). The result reflects the previously noted advantage that hesitant views enjoy in the current information environment: misinformation is easily disseminated, which amplifies vaccine-hesitant narratives and fuels further discussion. The IV estimates are substantially larger than the corresponding LPM coefficients, which is consistent with 2SLS identifying a local average treatment effect for compliers whose exposure to online vaccine-related information is shifted by the instruments, rather than an average effect for the full sample.

Even though we do not focus on vaccine hesitancy of children and other members in the house-

Table 3.6.2: Effect of Media Utilisation on Vaccine Hesitancy

	LPM (1)	$2SLS_b$ (2)	$2SLS_l$ (3)	$2SLS_{bl}$ (4)
	Panel A: *Vaccine Hesitancy*			
Internet	0.021***	0.650**	1.149**	0.830***
	(0.007)	(0.317)	(0.468)	(0.312)
N	22624	22624	22624	22624
KP. Wald F stat.		14.573	10.631	8.834
CD. F stat.		14.573	10.631	8.834
F	13.565	8.946	5.628	7.622
Sargan (p-value)				1.576 (0.209)
Mean dep. var	0.216	0.216	0.216	0.216
Instruments		broadband_b	lightning_l	Both_{bl}
	Panel B: *First-stage regression*			
Dep. var (*Internet*)				
broadband coverage		-0.182***		-0.141***
		(0.048)		(0.053)
lightning frequency			-16.838***	-10.116*
			(5.164)	(5.752)
N		22624	22624	22624
Mean dep. var		0.185	0.185	0.185
Controls	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes

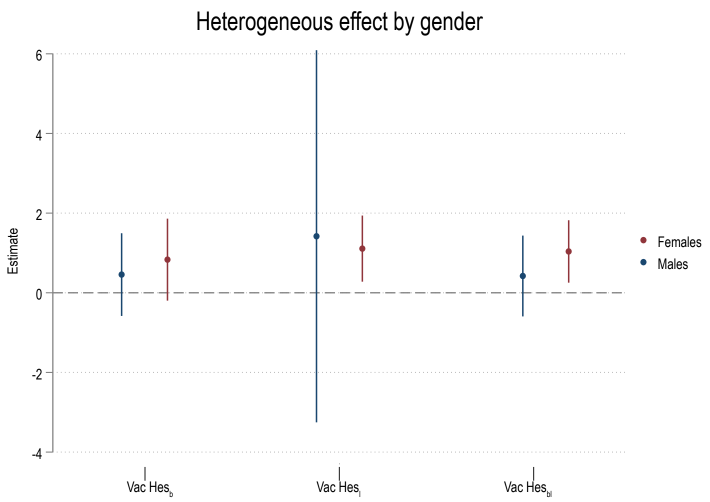
Note: Outcomes are vaccine hesitancy of respondents. LPM is a linear probability regression (Column 1), 2SLS are the two-stage least square models with broadband coverage (Column 2) and lightning frequency (Column 3) as instruments and in Column (4) is a 2SLS using both instruments. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. Controlled for NUTS II regional fixed effects. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

hold, we have presented its results in the appendix in Tables 3.C.1 and 3.C.3. While we do not find significant effects for vaccine hesitancy of children, we find that vaccine information from the internet suggests a reduction in vaccine hesitancy of other members in the household in only some models.

3.6.1 Heterogeneous effects

We also perform sensitive analysis based on heterogenous effects on gender, age groups, education level and the type of residence and using the two-stage least square models. When focusing on gender, it is observed that vaccine hesitancy suggests increases for both women and men cohorts as seen in Figure 3.6.1. This effect is more pronounced for women as compared to men. Vaccination information from the internet is more likely to lead to vaccine hesitancy in terms of magnitude amongst women, even though the effect is smaller, it is significant in most cases and the effect for men is much smaller and insignificant. This finding suggests that online information appears to have a higher estimated effect on hesitancy among women relatively to men, although the result is statistically significant. For men, the estimated effect is smaller and statistically insignificant. Substantively, this implies that policy and communication efforts should acknowledge that internet-based information can provide suggestive evidence of heighten hesitancy in both men and women, but this effect is more relevant for women (Principe and Weber, 2023).

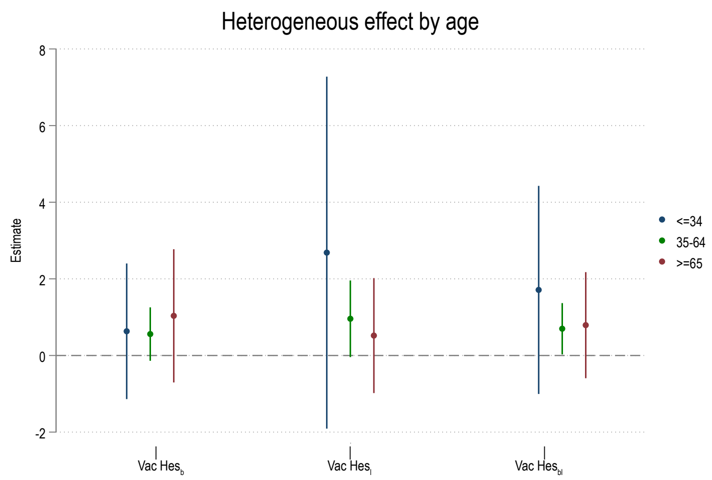
Figure 3.6.1: Effect of media utilisation on Vaccine Hesitancy: Gender



Notes: Outcome is vaccine hesitancy of respondents (Vac Hes). Estimates from IV estimations for male and female samples. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

We also performed heterogenous analysis on age groups. We grouped age into a different cohorts, that is those between ages 15 and 34, 35 to 64 and those above 64 years. The results of this exercise is reported the Figure 3.6.2. Even though, these effects are not statistically significant, we find that vaccination information sources increases the probability being vaccine hesitant. This suggests that in this age group this information source may be facilitating exposure to misinformation or distrustful content that affects decisions about children's vaccination more than about their own vaccination (Rodrigues et al., 2023).

Figure 3.6.2: Effect of media utilisation on Vaccine Hesitancy: Age groups



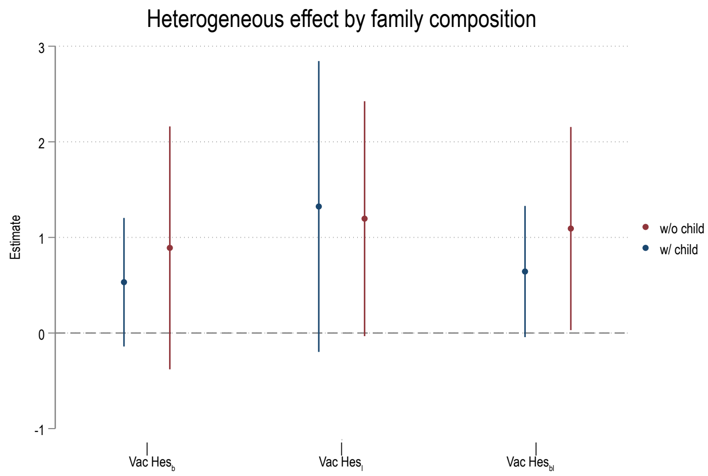
Notes: Outcome is vaccine hesitancy of respondents (Vac Hes). Estimates from IV estimations for age groups. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

Household composition could be also relevantthat is, living with children might change vaccine decisions and can either increase or decrease hesitancy, while adult-only households tend to show different patterns of concern. As shown in Figure 3.6.3, we find that when people get more vaccine information from the internet, those in households without children show a larger increase in vaccine hesitancy of households with children than individuals in households with children. In childless households, similar exposure does not meaningfully change hesitancy because there is no immediate vaccination decision (Tal et al., 2021; Al-Regaiey et al., 2022). This reveals a heterogeneous treatment effect: the impact of online vaccine information is concentrated where vaccination choices are most salient, implying that correcting online misinformation is most effective when aimed at households with children.

Stratifying the data into those living in the rural, small or large towns.In Figure 3.B.6 in the Appendix, that the results suggest a much pronounced amongst those living in small towns. This means that in small towns, internet-sourced vaccine information substantially raises the probability of being vaccine hesitant, more so than in rural areas or large cities. The fact that effects are significant for adults, parents and their children, and others in the household suggests a strong within-household spillover, once misinformation or distrust takes hold via online channels, vaccination decisions become more hesitant (Carrieri et al., 2023; Amaral-Garcia et al., 2024). Relative to individuals living in big cities, individuals living in small towns could be faced with fewer alternative and trusted information sources (specialist doctors, large hospitals, diverse media), so online narratives can have more influence on beliefs and norms. Compared with very rural areas, small towns typically have better broadband coverage penetration and social connectivity, which amplifies exposure and peer reinforcement of online vaccine misinformation, making the marginal impact of internet information on hesitancy larger and more systematic.

Other heterogenous analysis were performed considering the educational level and occupation of the respondents and presented in Figures 3.B.4 and 3.B.5. However, we do not find any significant results in these cases.

Figure 3.6.3: Effect of media utilisation on Vaccine Hesitancy: family composition



Notes: Outcome is vaccine hesitancy of respondents (Vac Hes). Estimates from IV estimations for family composition. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

3.6.2 Potential pathways

To better understand how vaccination-related information obtained from the internet influences vaccine hesitancy, we examine potential transmission mechanisms through belief channels, including trust in the internet, trust in political parties, trust in the national government, and overall institutional trust - measured by an index combining trust in political parties, local public authorities, the national government, the national parliament, and the European Union.

We assess this by examining which of these variables function as mediators. Specifically, a variable is considered a full or partial mediator if exposure to vaccine information on the internet predicts that belief, both internet information and the belief predict vaccine hesitancy, and the coefficient on internet information diminishes when both are included in the model compared with a specification that includes only internet information. Alternatively, mediation effect is indicated if internet information no longer has a significant effect on vaccine hesitancy once the belief variables are included, while the beliefs themselves remain predictive.

Results have been outlined in Tables 3.C.5 and 3.C.6 in the Appendix. Focusing on the two-stage least squares model, we find that there is a suggestive evidence that vaccine information from internet affects beliefs. That is, vaccine information from the internet appears to significantly correlate positively with trust in internet and institutions and negatively with trust in political parties and national government.

We also find that both internet-sourced vaccine information consistently has a positive effect on vaccine hesitancy of the respondents. And we find that trust in internet reduces vaccine hesitancy. Vaccine information obtained from the internet is associated with higher vaccine hesitancy, suggesting that online exposure may increase perceived uncertainty or misinformation costs and thereby weaken willingness to vaccinate. Trust in the internet, however, appears to mediate this relationship by reducing hesitancy, implying that the effect of online information depends not only on access but also on the credibility of the source. These findings are consistent with evidence that misinformation and low trust in online sources are key determinants of vaccine hesitancy (Carrieri et al., 2023).

However, we do not find evidence that trust in political parties, trust in national government and institutions$_{pca}$ on vaccine hesitancy and cannot be considered as possible mechanisms in explaining the relationship between vaccine information from the internet and vaccine hesitancy.

3.6.3 Robustness check

Various robustness checks were performed. First, we represent vaccination information by an index in Columns 2 in Table 3.6.1. The results are only marginally different from the one reported when using the binary variable and are consistent in terms of significance. We find that information on vaccination from internet suggests an increase in the vaccine hesitancy for respondents by 0.008 standard deviations. Noticeably, the effects are statistically significant in this case as well, the only difference is that the magnitude (Table 3.6.1) is much lower than compared to the one observed in the main results (0.021 in Table 3.6.1). Also, these models were estimated again using the instrumental variables approach, but then using the internet index instead. These results shown in Table 3.C.2 in the Appendix are consistent with the results in Table 3.6.2 in terms of significance although the magnitude is quite smaller.The results indicate that more access to internet-sourced vaccine information is suggested to increases the likelihood of being vaccine hesitant for respondents. We have reported similar results on considering vaccine hesitancy for children or other household members. We do not find effect on vaccine hesitancy of children, however, we find negative significant effect for vaccine hesitancy of other household members as presented in Table 3.C.3.

We control for other sources of vaccination information in our models. People usually get vaccine information from multiple channels (health workers, TV/radio, newspapers, family and friends, social media, official websites). If these other sources are correlated with both internet use and vaccine hesitancy, omitting them would bias the estimated effect of internet information because part of what looks like an internet effect would actually be due to those other channels. More specifically, we consider general practitioners (doctors), other health workers, pharmacists and health authorities as additional controls. The results are presented in Table 3.6.3, focusing on the two-stage least squares model controlling for these other vaccination information sources. We find that vaccination information from pharmacists is suggested to be relevant for vaccination attitudes of respondents. That is information from pharmacists is positively associated with hesitancy, although this association should not be interpreted causally. We find that receiving vaccination information from pharmacists is associated with a higher likelihood of vaccine hesitancy, suggesting that the content or framing of such information may contribute to reluctance toward vaccination. This result implies that vaccine hesitancy is not driven only by access to information, but also by the credibility, clarity, and trustworthiness of the source delivering it. Also, pharmacist-provided vaccine information may raise the perceived cost of vaccination if it emphasises risks, uncertainty, or side effects more than benefits, thereby increasing hesitancy. In demand terms, it can shift preferences away from vaccination by increasing the subjective price of getting vaccinated, even when the monetary price is low. The result also suggests a information-quality problem: if the signal is noisy, inconsistent, or not trusted, people may respond by delaying or avoiding vaccination rather than updating toward uptake (Wubishet et al., 2021). And the effect of internet vaccine information on vaccine hesitancy does not change much as relative to what was observed in the main results. This conclusion is also confirmed in Table 3.C.7 in Appendix. That is using internet index with additional other information sources. We find similar statistical significance, only that the magnitude of the coefficients are much smaller as compared to that in Table 3.6.3.

As a sensitivity analysis, we used information on vaccination from the internet in the past six months as the main independent variable and we estimated its causal effect on vaccine hesitancy. We find similar results in terms of statistical significance but then the magnitude of the estimates are quite smaller in Table 3.6.2 than the IV estimation in Columns (1) and (2) of Table 3.C.8 for vaccine hesitancy. Results indicate that access to information from internet sources on vaccination is more likely to lead to vaccine hesitancy of about between 0.6 and 0.7 points. Similarly, we include result on vaccine hesitancy for children and other members in the household as well. We observe similar patterns of statistical significance across specifications.

Table 3.6.3: Effect of internet use on Vaccination: including other information sources

	$2SLS_b$				$2SLS_l$				$2SLS_{bl}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Vaccine hesitancy											
Internet	0.677*	0.651**	0.645**	0.658**	1.151**	1.151**	1.135**	1.148**	0.879***	0.832***	0.822***	0.827***
	(0.346)	(0.318)	(0.316)	(0.310)	(0.469)	(0.470)	(0.465)	(0.466)	(0.335)	(0.313)	(0.311)	(0.306)
General Practitioner	0.022				0.051*				0.034			
	(0.022)				(0.030)				(0.022)			
Other health workers		0.002				0.007				0.004		
		(0.011)				(0.013)				(0.011)		
Pharmacists			0.046***				0.046**				0.046***	
			(0.016)				(0.021)				(0.018)	
Health authorities				-0.008				0.003				-0.004
				(0.012)				(0.016)				(0.012)
N	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.	12.532	14.490	14.570	15.291	10.628	10.570	10.627	10.698	8.060	8.784	8.831	9.132
CD. F stat.	12.532	14.490	14.570	15.291	10.628	10.570	10.627	10.698	8.060	8.784	8.831	9.132
F	8.746	8.906	8.979	8.869	5.624	5.594	5.701	5.622	7.289	7.584	7.677	7.635
Sargan									1.279	1.574	1.529	1.558
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	$broadband_b$				$lightning_l$				$Both_{bl}$			

Note: Outcomes are vaccine hesitancy in adults, children and others in the household. Two-stage least square(2SLS) are the IV models with broadband coverage and lightning frequency as instruments respectively. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. Controlled for NUTS II regional fixed effects. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

3.7 Conclusion

This chapter has examined the relationship between online vaccine-related information and vaccine hesitancy in the European Union, focusing on information obtained from social networks and other internet sources. Using data from the 2019 Eurobarometer and combining baseline regressions with an instrumental variable approach, the analysis provides suggestive evidence of a positive association between internet-based vaccine information and vaccine hesitancy among respondents. This outcome variable is a proxy for "vaccine hesitancy" and does not directly measure a hesitant attitude. It measures whether the respondent has not been vaccinated in the past five years. These findings contribute to the literature on media use and vaccination attitudes by addressing the endogeneity of information-seeking behaviour. The larger IV estimates, relative to the baseline results, are consistent with the interpretation that the effect identified by the instruments reflects the response of individuals whose exposure to online vaccine-related information is shifted by exogenous variation in internet access. At the same time, the analysis has a number of limitations. The data are cross-sectional and self-reported, and the dependent variable should be interpreted as a behavioural proxy related to vaccine hesitancy rather than as a direct attitudinal measure. Moreover, the analysis focuses on internet-based information and therefore does not capture the full information environment through which vaccine beliefs may be formed or reinforced. Overall, the results provide suggestive evidence that the online information environment may play an important role in shaping vaccination attitudes. From a policy perspective, this points to the value of improving the quality, accessibility, and visibility of reliable vaccine-related information online, as part of a broader strategy aimed at strengthening trust and supporting informed health decisions. Results suggests that information on vaccination from internet sources intensifies the likelihood of people being vaccine hesitant. This result is robust to several robustness checks. The heterogeneity analysis suggests larger point estimates for respondents aged 35-64, although many subgroup estimates are imprecisely estimated.

The study is characterised by some limitations. First, since the Eurobarometer survey data is measured through self-reported survey information, this introduces potential validity issues. Respondents may suffer from social desirability bias (and could be understating responses) and measurement error, for instance from questions that may not fully capture the intended concept and that this may affect the accuracy of responses. Second, the analysis is restricted to internet-based sources of vaccine information, so it does not capture the full information environment (such as traditional media, interpersonal networks), which may be important confounders or effect modifiers. Also, the study focuses on the European Union and uses Eurobarometer data, so the results may not be generalized to non-European countries with different health systems, media environments, and cultural attitudes toward vaccination. In addition, the 2019 data predate the COVID-19 pandemic, so the findings reflect hesitancy and information condition in a pre-COVID context. Vaccine attitudes, information sources, and the role of media may have changed substantially since then, limiting the external validity of the results for current vaccination campaigns.

These findings appears to suggest significant policy implications for how health institutions should respond to lessen vaccine hesitancy, particularly when there are negative side effects. From Tables 3.6.1 and 3.6.2, we can deduce that, first, information from media may be used by public health authorities, healthcare professionals and communication agencies to target certain populations with evidence-based, customised material regarding the safety and effectiveness of vaccines (Ahmad and Bali, 2024; Ahmed et al., 2022). This makes it possible for authoritative sources to quickly provide information and advice during public health emergencies like the COVID-19 epidemic, which may foster confidence and promote vaccination uptake. This method works especially well for tackling the issues that young people and adolescents face (Bhagianadh and Arora, 2022). This can help combat misinformation and address concerns, leading to increased vaccine confidence. That is, these sources of information about vaccine safety can have a beneficial impact on people's views of safety, which can lessen vaccine reluctance (Zhang et al., 2024). Also, reducing vaccination hesitancy may be more accomplished with messages that are specific to the knowledge and concerns of the groups and that uphold cultural values (Ruggeri et al., 2024). The difference between LPM and IV estimates suggests that baseline associations may understate the effect for the complier population, although the large IV estimates should be interpreted cautiously. This could be due to the unobservable traits of less hesitant individuals make them less likely to use the internet to get information on vaccines, conditional on covariates.

To mitigate the heightened vaccine hesitancy causally driven by online media, public health authorities, healthcare professionals, and communication agencies must shift from passive communication to a proactive, multi-pronged intervention strategy. Policymakers should collaborate with digital platforms to control algorithms that promote anti-vaccine misinformation while actively supporting evidence-based scientific conclusions, that is to counter misinformation. Reducing the impact of misinformation on public opinions about vaccinations and avoiding the rise in vaccine hesitancy requires a concerted effort to combat false information about vaccines on the internet. Because general public outreach faces structural limitations against misinformation, governments must implement targeted, group-specific digital communication campaigns, such as tailored video-based vaccination information. The foundation of the vaccination rollout is public outreach. In light of these findings, national public health authorities, healthcare professionals, and communication agencies must put into place trustworthy mechanisms to counteract the negative impact of false information that can intensify vaccine hesitancy. Policymakers and scientists must provide transparent messages and objective, unambiguous information on vaccines to win the public's trust and confidence. Also, given that online narratives weaponise institutional distrust, authorities must ensure absolute transparency regarding vaccine safety metrics and procurement, while simultaneously integrating strategic institutional mandates and regulatory measures to protect public health. Policymakers should aim at improving the accessibility and visibility of reliable online information, use targeted communication, strengthen trust in health information sources, monitor misinformation on social media and other internet sites.

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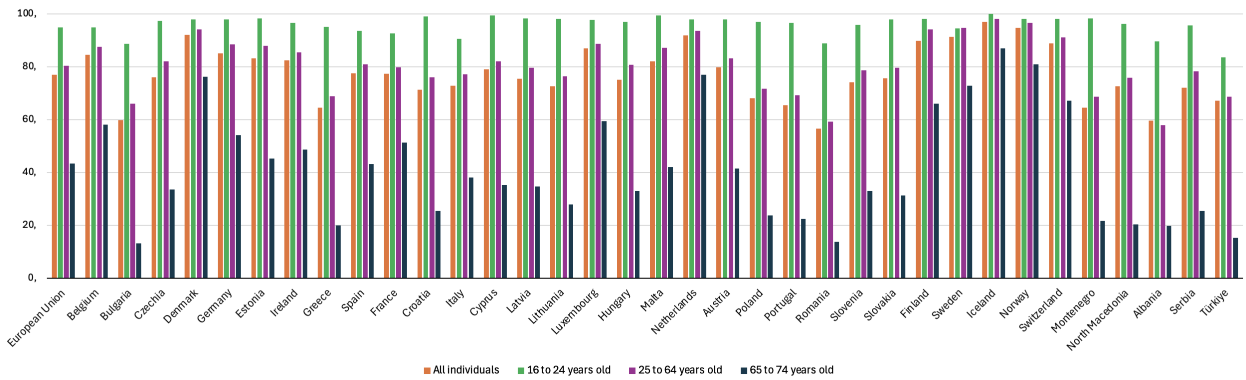
Appendix

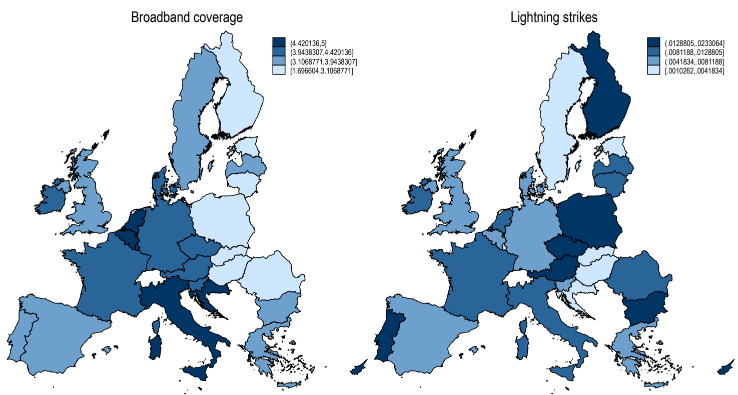
Appendix 3.A Figures

Figure 3.A.1: Frequency of Internet access: daily in 2019



The data plotted on this figure was sourced from Eurostat, 2023. The figure indicates the daily frequency of internet access for all countries in Europe and also the average for the entire Europe area.

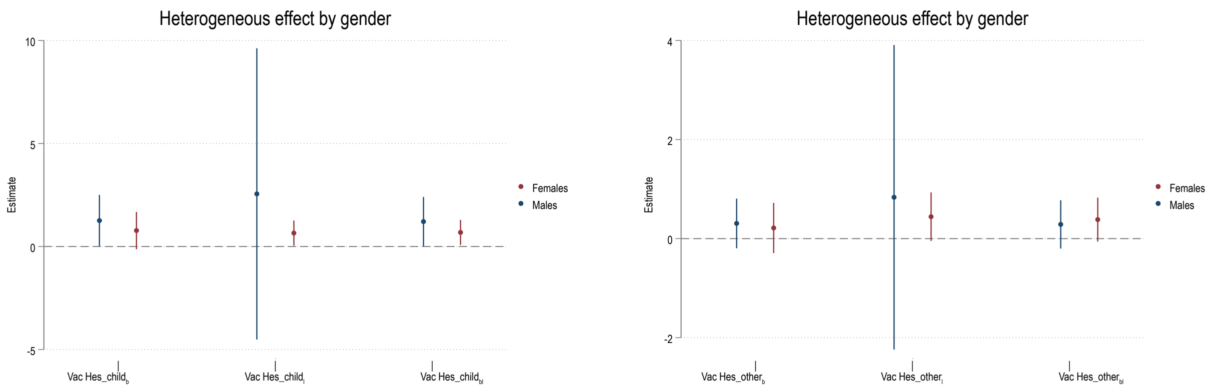
Figure 3.A.2: Intensity of lightning frequency and Broadband Coverage



Source: Authors' construction compiled from the Eurobarometer 91.2 with a shape file from the Geodata portal of Eurostat.

Appendix 3.B Heterogenous effects

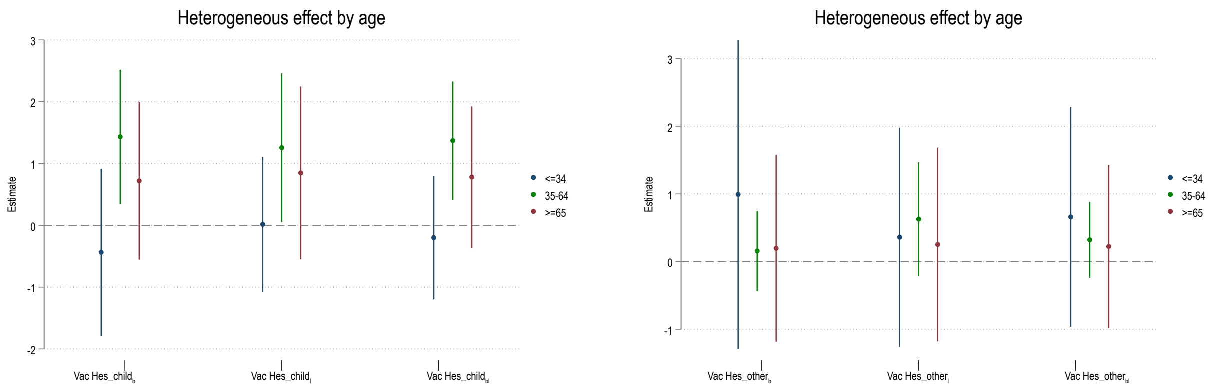
Figure 3.B.1: Effect of media utilisation on Vaccine Hesitancy: Gender



a. *Vaccine Hesitancy*$_{child}$ b. *Vaccine Hesitancy*$_{other}$

Notes: Outcomes are vaccine hesitancy for children (Vac Hes_child) and other members of the household (Vac Hes_other). Estimates from IV estimations for male and female samples. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

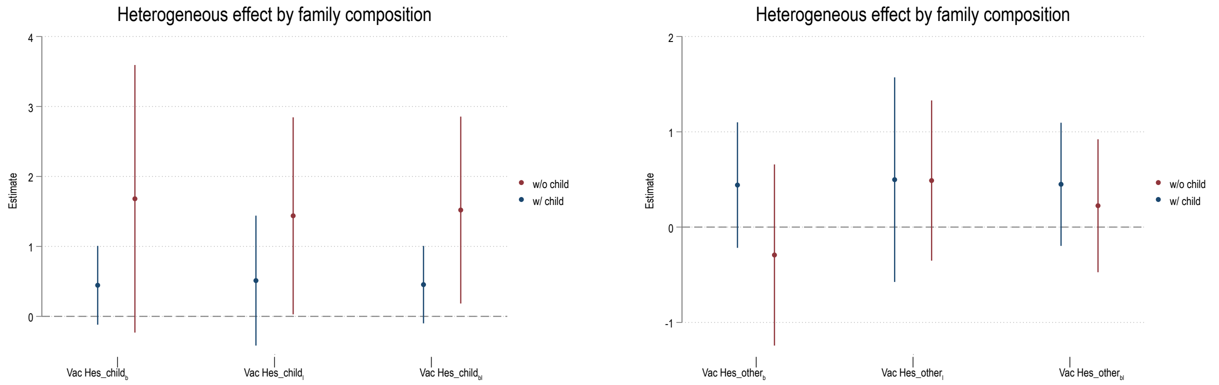
Figure 3.B.2: Effect of media utilisation on Vaccine Hesitancy: Age



a. *Vaccine Hesitancy*$_{child}$ a. *Vaccine Hesitancy*$_{other}$

Notes: Outcomes are vaccine hesitancy for children (Vac Hes_child) and other members of the household (Vac Hes_other). Estimates from IV estimations for age group samples. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

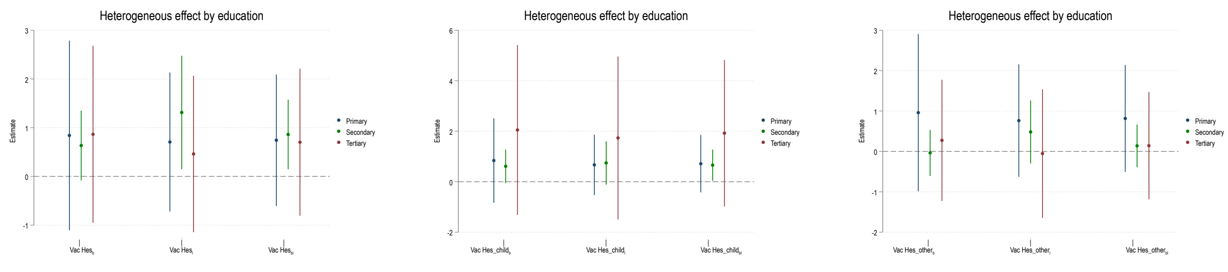
Figure 3.B.3: Effect of media utilisation on Vaccine Hesitancy: Family Composition



a. *Vaccine Hesitancy*$_{child}$ b. *Vaccine Hesitancy*$_{other}$

Notes: Outcomes are vaccine hesitancy for children (Vac Hes_child) and other members of the household (Vac Hes_other). Estimates from IV estimations for family composition. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

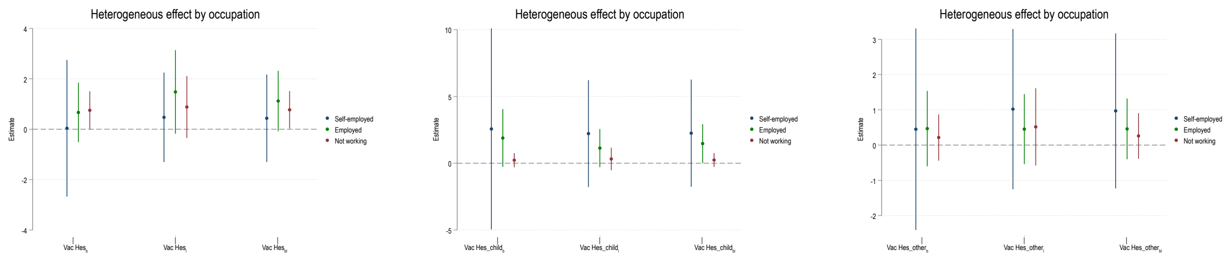
Figure 3.B.4: Effect of media utilisation on Vaccine Hesitancy: Education



a. *Vaccine hesitancy* b. *Vaccine hesitancy*$_{child}$ c. *Vaccine hesitancy*$_{other}$

Notes: Outcomes are vaccine hesitancy for respondents (Vac Hes), children (Vac Hes_child) and other members of the household (Vac Hes_other). Estimates from IV estimations for educational status. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

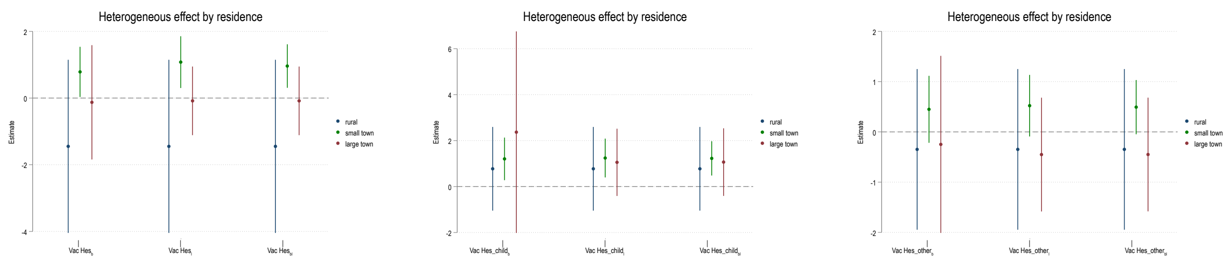
Figure 3.B.5: Heterogenous effect of media utilisation on Vaccine Hesitancy: Occupation



a. Vaccine hesitancy *b. Vaccine hesitancy$_{child}$* *c. Vaccine hesitancy$_{other}$*

Notes: Outcomes are vaccine hesitancy for respondents (Vac Hes), children (Vac Hes_child) and other members of the household (Vac Hes_other). Estimates from IV estimations for occupational status. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

Figure 3.B.6: Heterogenous effect of media utilisation on Vaccine Hesitancy: Type of residence



a. linear probability model *b. Using broadband coverage as an instrument* *c. Using lightning frequency as an instrument*

Notes: Outcomes are vaccine hesitancy for respondents (Vac Hes), children (Vac Hes_child) and other members of the household (Vac Hes_other). Estimates from IV estimations for type of residence. These are the two-stage least squares models, broadband coverage (Vac Hes$_b$) and lightning frequency (Vac Hes$_l$) are used as instruments respectively and also for both instruments (Vac Hes$_{bl}$). All these models include age, age squared, marital status, children under age 10, difficulty in paying bills, type of residence, occupation, social class, educational status, weak immune system, and vaccine ineffective as controls. Controlled for NUTS II regional fixed effects.

Appendix 3.C Additional Tables

Table 3.C.1: Effect of Media Utilisation on Vaccine Hesitancy using LPM

	Vaccine Hesitancy$_{child}$		Vaccine Hesitancy$_{other}$	
	(1)	(2)	(1)	(2)
Internet	-0.006		-0.017**	
	(0.006)		(0.007)	
Internet index		0.0003		-0.005**
		(0.002)		(0.003)
Female	-0.057***	-0.057***	0.009*	0.009*
	(0.005)	(0.005)	(0.005)	(0.005)
Age	-0.017***	-0.017***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Age2	0.000***	0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Married	-0.103***	-0.103***	-0.090***	-0.090***
	(0.005)	(0.005)	(0.006)	(0.006)
children under age 10	-0.524***	-0.524***	0.033***	0.033***
	(0.007)	(0.007)	(0.007)	(0.007)
Difficulty in paying bill	0.002	0.002	0.019***	0.019***
	(0.006)	(0.006)	(0.007)	(0.007)
Rural	0.000	0.000	-0.005	-0.005
	(0.006)	(0.006)	(0.007)	(0.007)
Large town	0.020***	0.020***	0.012	0.012
	(0.007)	(0.007)	(0.007)	(0.007)
Self employed	-0.082***	-0.082***	0.042***	0.042***
	(0.011)	(0.011)	(0.011)	(0.011)
Employed	-0.066***	-0.066***	0.027***	0.027***
	(0.006)	(0.006)	(0.007)	(0.007)
Working class	0.007	0.007	0.018**	0.018***
	(0.007)	(0.007)	(0.007)	(0.007)
Lower middle class	0.001	0.001	0.011	0.011
	(0.007)	(0.007)	(0.008)	(0.008)
Upper middle class	-0.023**	-0.023**	-0.053***	-0.053***
	(0.010)	(0.010)	(0.010)	(0.010)
Higher middle class	-0.069**	-0.069**	-0.043	-0.043
	(0.030)	(0.030)	(0.032)	(0.032)
Secondary	-0.007	-0.007	0.002	0.002
	(0.007)	(0.007)	(0.008)	(0.008)
Higher	-0.022***	-0.022***	-0.001	-0.002
	(0.008)	(0.008)	(0.009)	(0.009)
Weak immune system	0.025***	0.025***	0.041***	0.041***
	(0.005)	(0.005)	(0.006)	(0.006)
Believes vaccine are not effective	0.079***	0.079***	0.032***	0.032***
	(0.009)	(0.009)	(0.009)	(0.009)
N	22,624	22,624	22,624	22,624
R-squared	0.357	0.357	0.084	0.084
Region - NUTS II	Yes	Yes	Yes	Yes
AIC	18370	18371	21068	21070
BIC	20513	20514	23212	23213

Note: All outcomes models are estimated using linear probability regression. Columns differ in their specifications. Columns 1 and 2 vary by the variable of interest. Column 1 uses information from internet (social networks and other websites), while Column 2 uses information from the internet constructed by a PCA. NUTS II regional fixed effects are controlled for. AIC and BIC information criteria are presented, which are important metrics for model selection. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.C.2: Effect of Media Utilisation on Vaccine Hesitancy

	LPM (1)	$2SLS_b$ (2)	$2SLS_l$ (3)	$2SLS_{bl}$ (4)
	Panel A: *Vaccine Hesitancy*			
Internet index	0.008***	0.194**	0.369***	0.247***
	(0.003)	(0.090)	(0.140)	(0.089)
N	22624	22624	22624	22624
KP. Wald F stat.		22.101	13.960	12.773
CD. F stat.		22.101	13.960	12.773
F	13.546	9.877	6.480	8.801
Sargan (p-value)				2.271 (0.132)
Mean dep. var	0.216	0.216	0.216	0.216
Instruments		broadband_b	lightning_l	Both_{bl}
	Panel B: *First-stage regression*			
Dep. var (*Internet*)				
broadband coverage		-0.609***		-0.491***
		(0.129)		(0.144)
lightning frequency			-52.403***	-28.981*
			(14.026)	(15.621)
N		22624	22624	22624
F		7.205	7.171	7.191
Mean dep. var		0.022	0.022	0.022
Controls	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes

Note: Outcomes are vaccine hesitancy in adults, children and others in the household. LPM are linear probability regression and the first-stage and 2SLS are the IV models with broadband coverage and lightning frequency as instruments respectively. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. Controlled for NUTS II regional fixed effects. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.C.3: Effect of Media Utilisation on Vaccine Hesitancy

	LPM (1)	$2SLS_b$ (2)	$2SLS_l$ (3)	$2SLS_{bl}$ (4)	LPM (1)	$2SLS_b$ (2)	$2SLS_l$ (3)	$2SLS_{bl}$ (4)
	Panel A							
	Vaccine Hesitancy$_{child}$				*Vaccine Hesitancy$_{other}$*			
Internet	-0.006	1.036***	1.011**	1.027***	-0.017**	0.244	0.481	0.330
	(0.007)	(0.371)	(0.429)	(0.335)	(0.007)	(0.277)	(0.349)	(0.257)
N	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.		14.573	10.631	8.834		14.573	10.631	8.834
CD. F stat.		14.573	10.631	8.834		14.573	10.631	8.834
F	60.873	21.678	22.217	21.880	11.097	7.246	6.256	6.930
Sargan (p-value)				0.003 (0.955)				0.523 (0.470)
Mean dep. var	0.723	0.723	0.723	0.723	0.803	0.803	0.803	0.803
	Panel B							
	Vaccine Hesitancy$_{child}$				*Vaccine Hesitancy$_{other}$*			
Internet index	0.000	0.310***	0.325**	0.314***	-0.005**	0.073	0.155	0.098
	(0.002)	(0.100)	(0.128)	(0.094)	(0.003)	(0.082)	(0.109)	(0.077)
N	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.		22.101	13.960	12.773		22.101	13.960	12.773
CD. F stat.		22.101	13.960	12.773		22.101	13.960	12.773
F	60.923	26.675	25.554	26.342	11.070	7.396	6.553	7.186
Sargan (p-value)		0.000	0.000	0.016 (0.900)		0.000	0.000	0.653 (0.419)
Mean dep. var	0.723	0.723	0.723	0.723	0.803	0.803	0.803	0.803
Instruments		$broadband_b$	$lightning_l$	$Both_{bl}$		$broadband_b$	$lightning_l$	$Both_{bl}$
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Outcomes are vaccine hesitancy in adults, children and others in the household. LPM are linear probability regression and the first-stage and 2SLS are the IV models with broadband coverage and lightning frequency as instruments respectively. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. Controlled for NUTS II regional fixed effects. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.C.4: Effect of internet use on Vaccination: including other information sources

	2SLS$_b$				2SLS$_l$				2SLS$_{bl}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
					Vaccine hesitancy$_{child}$							
Internet	1.104***	1.042***	1.036***	1.026***	1.014**	1.018**	1.013**	1.010**	1.066***	1.033***	1.028***	1.020***
	(0.415)	(0.373)	(0.371)	(0.360)	(0.430)	(0.431)	(0.429)	(0.427)	(0.359)	(0.337)	(0.336)	(0.329)
General Practitioner	0.056**				0.050*				0.053**			
	(0.027)				(0.027)				(0.023)			
Other health workers		0.019				0.018				0.019		
		(0.012)				(0.012)				(0.012)		
Pharmacists			-0.006				-0.006				-0.006	
			(0.019)				(0.019)				(0.019)	
Health authorities				0.009				0.009				0.009
				(0.014)				(0.014)				(0.013)
N	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.	12.532	14.490	14.570	15.291	10.628	10.570	10.627	10.698	8.060	8.784	8.831	9.132
CD. F stat.	12.532	14.490	14.570	15.291	10.628	10.570	10.627	10.698	8.060	8.784	8.831	9.132
F	20.176	21.458	21.583	21.820	22.129	21.994	22.094	22.166	20.994	21.659	21.775	21.947
Sargan									0.041	0.003	0.003	0.001
					Vaccine hesitancy$_{other}$							
Internet	0.275	0.242	0.242	0.262	0.483	0.480	0.475	0.483	0.363	0.328	0.326	0.338
	(0.301)	(0.277)	(0.277)	(0.271)	(0.350)	(0.350)	(0.348)	(0.348)	(0.272)	(0.258)	(0.257)	(0.253)
General practitioner	0.025				0.037*				0.030*			
	(0.019)				(0.022)				(0.018)			
Other health care workersn		-0.006				-0.004				-0.005		
		(0.009)				(0.010)				(0.009)		
Pharmacists			0.022				0.022				0.022	
			(0.014)				(0.015)				(0.015)	
Health authorities				-0.017*				-0.012				-0.015
				(0.010)				(0.012)				(0.010)
N	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.	12.532	14.490	14.570	15.291	10.628	10.570	10.627	10.698	8.060	8.784	8.831	9.132
CD. F stat.	12.532	14.490	14.570	15.291	10.628	10.570	10.627	10.698	8.060	8.784	8.831	9.132
F	7.126	7.229	7.235	7.185	6.239	6.241	6.271	6.248	6.779	6.914	6.928	6.897
Sargan									0.372	0.523	0.505	0.460
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	broadband$_b$				lightning$_l$				Both$_{bl}$			

Note: Outcomes are vaccine hesitancy in adults, children and others in the household. Two-stage least square(2SLS) are the IV models with broadband coverage and lightning frequency as instruments respectively. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. Controlled for NUTS II regional fixed effects. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.C.5: Effect of internet on Beliefs

Variable	*Trust in internet* (1)	*Trust in political parties* (2)	*Trust in national government* (3)	$Institutions_{pca}$ (4)
Internet	0.103***	-0.018**	-0.021**	0.055**
	(0.003)	(0.007)	(0.008)	(0.025)
N	22,624	21,766	21,723	22,624
R-squared	0.085	0.112	0.145	0.149
Controls	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes

Note: All outcomes models are estimated using linear probability regression. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. NUTS II regional fixed effects are controlled for. AIC and BIC information criteria are presented, which are important metrics for model selection. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.C.6: Potential pathway: Effect of internet on vaccine hesitancy

	2SLS$_b$				2SLS$_l$				2SLS$_{bl}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
					Panel A: *Vaccine hesitancy*							
Internet	0.824*	0.675*	0.483	0.632**	1.504**	1.255**	1.151**	1.143**	1.061**	0.854**	0.680**	0.818***
	(0.448)	(0.346)	(0.299)	(0.321)	(0.730)	(0.568)	(0.515)	(0.476)	(0.457)	(0.347)	(0.301)	(0.317)
Trust in internet	-0.341				-0.663*				-0.453**			
	(0.213)				(0.347)				(0.218)			
Trust in Pol. parties		-0.009				0.000				-0.006		
		(0.010)				(0.014)				(0.010)		
Trust in Natl. gov't			-0.003				0.006				-0.001	
			(0.008)				(0.011)				(0.008)	
Institutions$_{pca}$				0.003				0.001				0.002
				(0.003)				(0.003)				(0.003)
N	22624	21766	21723	22624	22624	21766	21723	22624	22624	21766	21723	22624
KP. Wald F stat.	8.800	12.533	14.352	13.930	6.217	7.998	8.791	10.228	5.275	7.298	8.286	8.467
CD. F stat.	8.800	12.533	14.352	13.930	6.217	7.998	8.791	10.228	5.275	7.298	8.286	8.467
F	7.765	8.556	9.851	9.073	4.155	4.976	5.435	5.649	6.246	7.287	8.433	7.698
					Panel B: *Vaccine hesitancy$_{child}$*							
Internet	1.335**	1.189***	1.029***	1.050***	1.322**	1.265**	1.067**	1.023**	1.331***	1.213***	1.040***	1.040***
	(0.561)	(0.432)	(0.373)	(0.382)	(0.663)	(0.562)	(0.486)	(0.440)	(0.511)	(0.405)	(0.349)	(0.345)
Trust in internet	-0.586**				-0.580*				-0.584**			
	(0.267)				(0.316)				(0.244)			
Trust in Pol. parties		0.019				0.021				0.020*		
		(0.012)				(0.014)				(0.012)		
Trust in Natl. gov't			0.007				0.007				0.007	
			(0.009)				(0.010)				(0.009)	
Institutions$_{pca}$				-0.003				-0.002				-0.003
				(0.003)				(0.003)				(0.003)
N	22624	21766	21723	22624	22624	21766	21723	22624	22624	21766	21723	22624
KP. Wald F stat.	8.800	12.533	14.352	13.930	6.217	7.998	8.791	10.228	5.275	7.298	8.286	8.467
CD. F stat.	8.800	12.533	14.352	13.930	6.217	7.998	8.791	10.228	5.275	7.298	8.286	8.467
F	16.432	17.863	21.081	21.274	16.627	16.550	20.259	21.865	16.506	17.453	20.843	21.496
					Panel C: *Vaccine hesitancy$_{other}$*							
Internet	0.320	0.244	0.181	0.244	0.643	0.592	0.476	0.486	0.432	0.352	0.268	0.332
	(0.372)	(0.298)	(0.276)	(0.283)	(0.497)	(0.421)	(0.383)	(0.356)	(0.351)	(0.285)	(0.261)	(0.263)
Trust in internet	-0.148				-0.302				-0.202			
	(0.177)				(0.236)				(0.168)			
Trust in Pol. parties		0.014				0.019*				0.015*		
		(0.008)				(0.010)				(0.008)		
Trust in Natl. gov't			-0.000				0.004				0.001	
			(0.007)				(0.008)				(0.007)	
Institutions$_{pca}$				0.000				-0.001				-0.000
				(0.002)				(0.003)				(0.002)
N	22624	21766	21723	22624	22624	21766	21723	22624	22624	21766	21723	22624
KP. Wald F stat.	8.800	12.533	14.352	13.930	6.217	7.998	8.791	10.228	5.275	7.298	8.286	8.467
CD. F stat.	8.800	12.533	14.352	13.930	6.217	7.998	8.791	10.228	5.275	7.298	8.286	8.467
F	6.969	7.078	7.252	7.220	5.525	5.587	6.126	6.211	6.503	6.681	6.988	6.896
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	broadband$_b$				lightning$_l$				Both$_{bl}$			

Note: Outcomes are vaccine hesitancy in adults, children and others in the household. Two-stage least square(2SLS) are the IV models with broadband coverage and lightning frequency as instruments respectively. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. Controlled for NUTS II regional fixed effects. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.C.7: Effect of internet use on Vaccination: including other information sources

	$2SLS_b$				$2SLS_l$				$2SLS_{bl}$			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
					Vaccine hesitancy							
Internet index	0.200**	0.194**	0.193**	0.197**	0.370***	0.370***	0.365***	0.369***	0.261***	0.247***	0.245***	0.247***
	(0.097)	(0.090)	(0.090)	(0.088)	(0.140)	(0.140)	(0.139)	(0.140)	(0.095)	(0.089)	(0.089)	(0.087)
General practitioner	0.016				0.047*				0.027			
	(0.019)				(0.026)				(0.018)			
Other health care workers		0.001				0.005				0.002		
		(0.010)				(0.012)				(0.010)		
Pharmacists			0.044***				0.042**				0.044***	
			(0.016)				(0.019)				(0.017)	
Health authorities				-0.009				0.002				-0.006
				(0.011)				(0.014)				(0.011)
N	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.	19.409	22.010	22.085	23.084	13.973	13.897	13.929	14.045	11.709	12.719	12.758	13.194
CD. F stat.	19.409	22.010	22.085	23.084	13.973	13.897	13.929	14.045	11.709	12.719	12.758	13.194
F	9.757	9.838	9.902	9.803	6.478	6.447	6.548	6.472	8.530	8.763	8.845	8.798
sargan	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.973	2.270	2.206	2.232
					Vaccine hesitancy$_{child}$							
Internet index	0.327***	0.311***	0.310***	0.307***	0.326**	0.327**	0.326**	0.325**	0.326***	0.316***	0.315***	0.312***
	(0.110)	(0.100)	(0.100)	(0.098)	(0.129)	(0.129)	(0.129)	(0.128)	(0.100)	(0.094)	(0.094)	(0.092)
General practitioner	0.047**				0.047*				0.047**			
	(0.021)				(0.024)				(0.019)			
Other health care workers		0.016				0.017				0.016		
		(0.011)				(0.011)				(0.011)		
Pharmacists			-0.008				-0.009				-0.008	
			(0.017)				(0.018)				(0.018)	
Health authorities				0.007				0.008				0.007
				(0.012)				(0.013)				(0.012)
N	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.	19.409	22.010	22.085	23.084	13.973	13.897	13.929	14.045	11.709	12.719	12.758	13.194
CD. F stat.	19.409	22.010	22.085	23.084	13.973	13.897	13.929	14.045	11.709	12.719	12.758	13.194
F	25.386	26.457	26.557	26.745	25.465	25.333	25.399	25.489	25.424	26.123	26.212	26.389
sargan	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.017	0.020
					Vaccine hesitancy$_{other}$							
Internet index	0.081	0.072	0.072	0.079	0.155	0.154	0.153	0.155	0.108	0.097	0.097	0.101
	(0.088)	(0.082)	(0.082)	(0.080)	(0.110)	(0.110)	(0.109)	(0.109)	(0.082)	(0.077)	(0.077)	(0.076)
General practitioner	0.022				0.036*				0.027*			
	(0.017)				(0.021)				(0.016)			
Other health care workers		-0.007				-0.005				-0.006		
		(0.009)				(0.010)				(0.009)		
Pharmacists			0.021				0.020				0.021	
			(0.014)				(0.015)				(0.014)	
Health authorities				-0.017*				-0.012				-0.016
				(0.010)				(0.011)				(0.010)
N	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.	19.409	22.010	22.085	23.084	13.973	13.897	13.929	14.045	11.709	12.719	12.758	13.194
CD. F stat.	19.409	22.010	22.085	23.084	13.973	13.897	13.929	14.045	11.709	12.719	12.758	13.194
F	7.314	7.377	7.383	7.354	6.538	6.538	6.561	6.547	7.075	7.167	7.178	7.159
sargan	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.504	0.653	0.631	0.582
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region NUTS II	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Instruments	broadband$_b$				lightning$_l$				Both$_{bl}$			

Note: Outcomes are vaccine hesitancy in adults, children and others in the household. Two-stage least square(2SLS) are the IV models with broadband coverage and lightning frequency as instruments respectively. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. Controlled for NUTS II regional fixed effects. Robust standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.C.8: Effect of media utilisation on vaccination: robustness

	Vaccine hesitancy			Vaccine hesitancy$_{child}$			Vaccine hesitancy$_{other}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
	Two stage least squares								
Internet$_2$	0.700*	0.591***	0.600***	1.116***	0.520***	0.568***	0.263	0.247*	0.249*
	(0.406)	(0.217)	(0.217)	(0.432)	(0.181)	(0.183)	(0.195)	(0.143)	(0.138)
N	22624	22624	22624	22624	22624	22624	22624	22624	22624
KP. Wald F stat.	9.961	31.435	16.012	9.961	31.435	16.012	9.961	31.435	16.012
CD. F stat.	12.712	40.758	20.732	12.712	40.758	20.732	12.712	40.758	20.732
F	8.709	9.575	9.505	20.331	40.914	38.711	8.071	8.178	8.172
	First regression								
Dep. var (*Internet*$_2$)									
broadband coverage	-0.169***		-0.044						
	(0.047)		(0.053)						
lightning frequency		-32.731***	-30.616***						
		(5.127)	(5.711)						
N	22624	22624	22624						
F	14.818	14.942	14.888						

Outcomes are vaccine hesitancy in adults (Vac H$_{adult}$), children (Vac H$_{child}$) and others in the household (Vac H$_{other}$). All models use instrumental variables. Columns 1 and 2 are two-stage least squares models with broadband coverage and lightning frequency as instruments respectively and column 3 is a 2SLS using the two instruments. All models include age, age squared, gender, marital status, children under 10, difficulty paying bills, residence type, occupation, social class, education, immune system, and vaccine effectiveness as controls. NUTS II regional fixed effects are controlled for. Robust standard errors are in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Conclucions

This thesis presents a new analysis of some important drivers of health in the European area. Due to this, it contributes to the literature on demand for health care and the estimation of causal effects of policies. Since these issues are necessary issues for sustainable health development, the evidence outlined in this dissertation indicates appropriate measures that influence the determinants in improving health care and health in general.

In the first chapter, this thesis explains how age-dependent minimum wages on the health outcomes of young workers in the UK using data from the UK Household Longitudinal Study (”Understanding Society”) from 2016 to 2021, exploiting a Regression Discontinuity Design (RDD) framework both the standard approach and the multi-cutoff approach by Cattaneo (2020; 2021). The results indicate that the 21 year old cutoff is related to significant improvement in both physical and mental health, but no comparable effects emerge at other cutoffs. These gains in health are much more persistent among the physical health of women and mental health for men. These effects seem to be persistent also in the long run. In the short run, the effects seem to be particularly relevant for part-time workers. Our findings are confirmed by several robustness checks. Resultantly, the findings suggest that minimum wage policy is not merely a labour - market instrument but also a necessary determinant of health as well. In particular, setting a minimum wage rate at age 21 generates measurable health benefits, where maintaining lower youth rates beyond this age may forgo potential improvements in well-being. For policymakers debating reforms to the UK's age-differentiated minimum wage system, this research highlights that decisions about age thresholds and rate differentials should account not only for employment and earnings effects but also for the broader health consequences for young workers.

Considering the various debates about this policy regarding narrowing or removing the age bands, the results argue against maintaining other age cohorts aside 21 if the objective includes health and well-being, not only labour outcomes. Policymakers could therefore treat higher minimum wages as part of a preventive health strategy for precariously employed young adults, especially those in part-time, low-paid jobs who are otherwise hard to reach through standard health policy arrangements. Also, the results strengthen the case for including health impacts when the Low Pay Commission and government review youth rates and age bands. Therefore, health services and public health agencies could use this evidence to advocate for minimum wage upratings as complements to mental-health and lifestyle programmes for young workers, rather than treating pay policy as outside health of people.

Following a similar minimum wage policy in Spain, the second chapter examined how substantial increases in the Spanish minimum wage, and in particular the large 2019 increase, have affected workers' health using the Spanish Survey of Living Conditions (ES-SILC), a nationally representative data and a difference-in-difference method at multiple timing. By applying the Callaway and Sant'Anna estimator over the period 2012–2023, the analysis exploits the staggered nature and magnitude of the reforms to identify how exogenous income gains for low-wage workers translate into changes in self-reported health status. The results indicate that higher minimum wages are associated with modest but meaningful improvements in health, that is each additional euro in the minimum wage is linked to a reduced probability of reporting bad or very bad health and a higher probability of reporting good or very good health. These findings suggest that minimum wage policy can operate as a complementary public health instrument, not only improving working conditions and reducing income inequality, but also contributing to better population health and narrower health disparities. Overall, the evidence supports viewing minimum wage reforms as part of a broader social policy instrument aimed at promoting both economic security and health equity in Spain.

Debates about the appropriate level of the minimum wage should account for anticipated health gains in addition to effects on employment, productivity, and competitiveness. For Spain, observing a relatively ambitious minimum wage path, while addressing any labour-market risks for specific groups, appears consistent with both social and health policy objectives. Since minimum wage increases mainly benefit low-wage workers, who tend to be socio-economically disadvantaged, minimum wage policies may contribute to reducing health inequalities by improving health outcomes for those with worse initial health. Therefore, policymakers could treat minimum wage increases as part of a broader health-equity strategy, complementing targeted interventions in disadvantaged groups. The results also argue for closer coordination between labour, social protection, and health ministries. Also, health impact assessments of future minimum wage changes would help quantify expected gains in self-reported health and identify subgroups (by age, sector or region) where the marginal health benefit is the largest. This evidence can be used to justify further policy adjustments and to design complementary measures, such as mental health support or occupational health programmes, in sectors with high concentrations of minimum-wage workers. In addition, policymakers should continue to monitor health indicators as wages rise, investigate potential effects (such as whether very large increases leads to stronger health gains or trigger offsetting risks), and explore interactions with housing costs, debt, and access to healthcare. This will help refine the design of minimum wage policy so that it delivers the largest possible contribution to both economic implications and population health.

In the third chapter, this dissertation explained that the way people use the internet for vaccine information can have important consequences for vaccination attitudes. By exploiting regional variation in broadband coverage and lightning strikes as sources of exogenous variation, the analysis estimated a causal effect of internet-based information on vaccine hesitancy using Eurobarometer 91.2 (2019) and an instrument variable method. The results indicate that relying on the internet for vaccination information increases the likelihood of being vaccine hesitant, while women tend to be less hesitant and individuals with children are more prone to hesitancy. These patterns suggest that online information environments can amplify concerns among those with direct vaccination decisions to make, and that gendered differences in risk perception and health behaviour may shape responsiveness to online content. Overall, the evidence underscores that media use is not neutral: the channels through which people seek vaccination information and the quality of the content they encounter play a critical role in shaping attitudes. Efforts to address vaccine hesitancy should therefore focus not only on increasing the volume of information but also on improving the trustworthiness, accessibility, and targeting of online health communication, particularly for parents and other groups at higher risk of hesitancy.

As a policy, the European Union and national regulators can draw on existing platform governance instruments (such as the EU Digital Services Act) to mandate more transparency about how vaccine-related content is ranked and recommended, and to guarantee swift action against harmful viral rumours. The results also indicate that communication should be tailored to different audience groups (for example, parents versus non-parents, or people with higher versus lower levels of trust), with particular focus on parents, who in your study and others display greater hesitancy when confronted with online information. In addition, policies should allocate resources for training and digital communication support for healthcare professionals, enabling them to effectively counter misinformation and direct patients to trustworthy online sources, especially since many citizens still regard them as credible authorities and frequently check online content with them. Furthermore, involving teams and stakeholders in joint initiatives (such as media trainings and vaccination roundtables) can support journalists, influencers, and local leaders in covering vaccines responsibly and in avoiding the proliferation of fringe narratives.